The Impact of Transition Control in Different Adaptive Cruise Control Systems on Traffic Flow Efficiency and Road Safety

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The Impact of Transition Control in Different Adaptive Cruise Control Systems on Traffic Flow Efficiency and Road Safety

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Preface

This thesis represents the culmination of my masters degree in Transportation, Infrastructure, and Logistics at TU Delft. The topic of the impact of transition control of Adaptive Cruise Control (ACC) systems on traffic flow efficiency and safety has been of great interest to me, particularly because of its significance in the field of traffic dynamics. This topic also offered me an opportunity to cooperate with TNO, which is a reputation research company in the Netherlands. Through this research, I aimed to contribute a deeper understanding of how ACC systems can influence traffic flow efficiency and improve road safety. The process of completing this thesis was both challenging and rewarding. One of the main difficulties I encountered was the challenge of switching to a different traffic simulator. This transition introduced delays but helped improve the accuracy and reliability of the results in the end.

I would first like to express my deepest gratitude to my chair, Professor Haneen, for her exceptional guidance, insightful feedback, and continuous encouragement throughout this research. I would also like to extend my sincere thanks to my co-supervisors, Dr. Irene and Dr. Eleonora, for their valuable insights, constructive critiques, and unwavering support, which greatly contributed to the quality of this thesis.I am also deeply grateful to my supervisors from TNO, Dr. Gerdien and Dr. Lin. Thank you for providing me with this valuable opportunity and for your guidance and assistance throughout the entire process. I have learned a great deal from my time at TNO, and your expertise has been invaluable to my research.

I would also like to express my heartfelt gratitude to my friends and family, who have encouraged and supported me throughout this journey. Their patience, understanding, and belief in me have been invaluable, helping me stay motivated during challenging times. I am especially grateful to my parents, whose unwavering support has been a constant source of strength and inspiration.

This thesis has been a significant part of my academic development, and I have learned a lot during the journey along the way. As I look ahead, I hope that the findings of this research will contribute to further advancements in traffic management and the development of safer, more efficient transportation systems. Thank you for taking the time to read this thesis.

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Yun-An Lin
Delft, October 2024

Executive Summary

Introduction and Problem Definition

With the rapid development of autonomous driving technologies, Adaptive Cruise Control (ACC) systems are becoming increasingly common in vehicles on public roads. These systems hold the potential to significantly improve traffic flow efficiency and road safety by maintaining vehicles' speed and distance. According to the definition from SAE, ACC systems are level 1 automation, which still requires human intervention and supervision of the vehicle when the system is beyond its operational design domain (ODD). Therefore, transitions of control between human drivers and ACC systems are an integral part of this level. There are three types of transition of controls: the driver deactivates the system (DIDC), the driver activates the system (DIAC), and the system disengages due to operational limitations (AIDC). The transition of control between automated systems and human drivers could then pose challenges that need a thorough investigation to ensure the seamless integration of these technologies into existing traffic networks. For instance, in certain situations, the automated system may suddenly require the driver to take over due to operational limitations. This hand-off typically takes 3 to 5 seconds, during which the driver must regain situational awareness and assume control. Although brief, this delay can result in accidents, especially in complex or high-speed situations, as drivers may not be fully prepared to take control of the vehicle promptly. It can also cause traffic disruptions, triggering shock waves and a reduction in road capacity.

The literature on ACC systems shows progress in improving traffic flow and safety, particularly on highways, but highlights challenges during transitions between automated and manual driving. Transition control is critical in these phases, especially in complex scenarios like highway merging. However, research gaps remain in understanding the variability across different ACC systems and their broader impact on traffic safety and efficiency.

Research Objective and Method

The objectives of this research are to identify the differences in ACC characteristics across various automotive brands and to evaluate the impact of transition control in ACC systems on traffic flow efficiency and road safety. To achieve these objectives, the research applied a mixed-methods approach, utilizing empirical data, desk research, and traffic simulation models. Empirical data was analyzed from the OpenACC database and the SAE Level 2 naturalistic driving study, which included real-world driving scenarios with ACC systems. Key traffic performance indicators, including traffic flow, density, total travel time, time-mean speed, and average delay, are used to evaluate traffic flow efficiency. To assess traffic safety, metrics such as time-to-collision (TTC), deceleration rate to avoid a crash (DRAC), and time gap were selected.

In addition, simulations were conducted using PTV VISSIM, where the ACC and transition control models were implemented as external driver models through VISSIMs "External Driver Model DLL Interface."

Human-driven vehicles followed Wiedemanns 1999 car-following model, which is built into VISSIM. This model simulates human driving behavior by adjusting vehicle acceleration or deceleration based on the speed difference and distance to the vehicle ahead, utilizing psychological zones and stochastic parameters to represent various driving modes, such as free driving, following, and emergency braking. For lane-changing, VISSIM distinguishes between necessary and free lane changes, in which necessary changes are driven by route requirements or dynamic path assignment, while free changes depend on available space or speed needs. Both types must maintain safety distances and minimum clearance, with a default lane change duration of 3 seconds. The simulation network modeled a section of the Dutch A13 highway, with scenarios involving three different levels of ACC market penetration rates (MPRs): 25%, 50%, and 75%. To integrate the variability in vehicle characteristics, the simulation used random distributions to assign ACC characteristics based on market share, leading to diverse vehicle behaviors in the simulation. Three distance settings were considered: small, large, and a mix of both. The drivers take-over time after a system disengagement was modeled using a log-normal distribution to reflect realistic human reaction times. Each scenario was run 10 times to account for the randomness in each simulation, and the average values were calculated to reduce bias and ensure more reliable results.

Data Analysis and Results

The data analysis revealed differences in ACC systems between brands in terms of full speed range, acceleration capabilities, inter-vehicle spaces, time gaps, response times, and string stability. However, not all these features could be fully implemented in the simulations due to the absence of relevant ACC settings and lack of data to properly model certain behavioral aspects, leading to the exclusion of inter-vehicle space, response time, and string stability from the simulations. Moreover, for time gaps, the empirical data includes information on the medium distance setting, but it is limited to only 5 vehicles with 4 test runs. Due to this insufficient sample size, the medium-distance setting was not included in the analysis. As a result, only the small and large distance settings were considered. The simulation results revealed that traffic flow with ACC systems equipped with transition control models showed significantly higher flow efficiency compared to other scenarios, particularly as the MPR increased. On highways, which generally provide a more controlled and homogeneous traffic environment, the introduction of ACC vehicles reduced congestion compared to scenarios with exclusively human-driven cars. Scenarios with ACC vehicles showed higher TTC values, indicating improved traffic safety, and lower DRAC values, especially in conditions with higher ACC MPRs, suggesting smoother traffic flow with fewer critical braking events.

The findings indicate that ACC systems with transition control can enhance traffic efficiency and safety on highways due to their stability and predictability. Higher ACC MPRs can enhance traffic throughput and reduce congestion, particularly in small-distance settings. However, the effectiveness of these systems is constrained by their ability to maintain full-speed following within their operational design domain (ODD), especially when the ACC MPR is low. This limitation can lead to more AIDC events, as ACC systems are often unable to handle low-speed scenarios.

Limitations and Future Research

These conclusions are drawn despite several limitations in the simulations. For instance, human drivers were modeled using idealized car-following behavior, simplifying decision-making and not capturing the full range of real-world unpredictability. In addition, the simulations excluded string stability effects, where many ACC systems are string unstable in reality, amplifying speed fluctuations in traffic. The focus on highways also limits the applicability of the results to urban contexts. Future research could address these gaps by modeling more diverse driving scenarios, including string stability effects, and expanding simulations to urban roads. Improved data from naturalistic driving studies could further refine the understanding of ACC performance.

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Nomenclature

Abbreviations

Abbreviation	Definition
ACC	Adaptive Cruise Control
AV	Autonomous Vehicle
AIDC	The automation initiates the transition due to operational constraints, leading to the driver regaining control
CDF	Cumulative Distribution Function
DIAC	The driver initiates the transition, resulting in the automation assuming control
DIDC	The driver initiates the transition, with the driver resuming control subsequent to deactivation
ODD	Operational Design Domain
MPRs	Market Penetration Rates
IVS	Inter-vehicle space

Symbols

Symbol	Definition	Unit
a	Acceleration	[m/s^2]
d	Inter-vehicle space	[m]
v	Velocity	[m/s]
τ	Time Gap	[s]

1

Introduction

The development of autonomous vehicles (AVs) plays a crucial role in enhancing the safety and efficiency of transportation systems (Hu et al., 2023). As technology continues to advance, automated vehicles are steadily becoming a fixture on road networks, with the potential to reduce traffic accidents and improve traffic flow. Currently, automation systems classified as SAE Level 1 and Level 2 are increasingly being deployed on public roads. Adaptive Cruise Control (ACC), a Level 1 automation system, is one such technology, designed to maintain a set speed and a safe following distance from other vehicles, providing convenience for drivers and aiming to increase safety, reduce congestion (Wu and Boyle, 2015; Knoop et al., 2019; Varotto et al., 2022). However, despite these advancements, human drivers continue to play a dominant role in vehicle operation at these levels of automation (Levels 0 to 2), as illustrated in Figure 1.1, based on SAE's classification of automated vehicles (SAE, 2021).

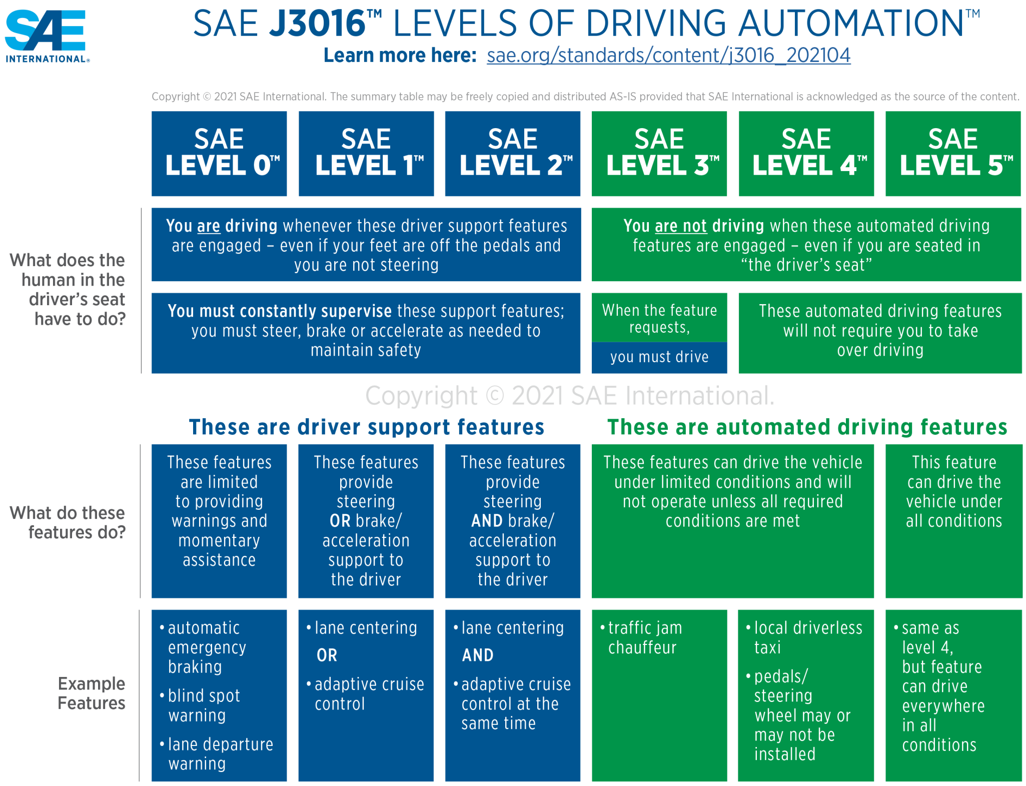


Figure 1.1: SAE J3016 LEVELS OF DRIVING AUTOMATION
(SAE, 2021)

This integration of automated vehicles then brings distinct traffic efficiency and safety implications, both of which need to be managed carefully. Automated systems such as ACC could enhance safety by reducing the occurrence of accidents that result from human error, including distraction, fatigue, or poor decision-making (Hu et al., 2023). However, safety risks arise during transition control, which refers to the switch between automated and manual driving. For instance, in certain situations, the automated system may suddenly require the driver to take over due to operational limitations. This hand-off typically takes 3 to 5 seconds, during which the driver must regain situational awareness and assume control (Vogelpohl et al., 2018). This delay, though brief, can lead to accidents, particularly in complex or high-speed environments, as drivers may not be fully prepared to take over the vehicle promptly (Lu et al., 2016). In addition, ACC systems have operational constraints, and when driving conditions fall outside the systems Operational Design Domain (ODD), such as during extreme weather or unusual traffic scenarios, the system may disengage, requiring the driver to take back control. This disengagement creates potential safety hazards, particularly if drivers do not react quickly enough (Colwell et al., 2018). While automated driving systems aim to improve traffic efficiency, their real-world impact on traffic flow must also be considered. Traffic implications arise primarily during the transition control process. When a driver must take over the control of the automated system, the delay in response can lead to disruptions in traffic flow. For example, during the transition period, drivers may brake abruptly or accelerate unpredictably, which can ripple through the traffic stream, causing slowdowns or even congestion, particularly in high-density areas (Vogelpohl et al., 2018).

On-road experiments with early ACC systems, which were limited to activation only at medium-to-high speeds, have shown that these systems influence the longitudinal control of driving behavior. Since drivers do not need to manually control speed, their driving habits shift accordingly (Alkim et al., 2007; Knoop et al., 2019; Korkiakoski et al., 2023). These studies, however, were often conducted in specific contextssuch as low-to-medium traffic density and non-critical traffic situationsand thus may not fully capture the effects in more varied conditions. The initial ACC systems were also not designed to function at lower speeds. Recent technological advancements have introduced full-range ACC systems capable of operating even in dense, low-speed traffic conditions (Knoop et al., 2019). These developments are closely tied to the concept of the Operational Design Domain (ODD), which describes the specific operating environment in which an automated system is intended to function. Monitoring ODD ensures that the system operates within its designed limits to maintain safety. ODD essentially defines the "functional system boundary" (Colwell et al., 2018).

Despite these advances, vehicles equipped with ACC systems still require human oversight and intervention under certain conditions that fall outside the defined ODD. In such cases, control must be transferred from the autonomous system back to the driver. This transition can be initiated either by the human driver or by the autonomous system, depending on the situation. The transition process involves shifting from one driving state to another, as shown in Figure 1.2. These transitions can be categorized into three main types (Lu et al., 2016):

1. Driver Deactivates the System (DIDC): The driver initiates the transition, with the driver resuming control subsequent to deactivation.
2. Driver Activates the System (DIAC): The driver initiates the transition, resulting in the automation assuming control.
3. System Disengages due to Operational Limitations (AIDC): The automation initiates the transition due to operational constraints, leading to the driver regaining control.

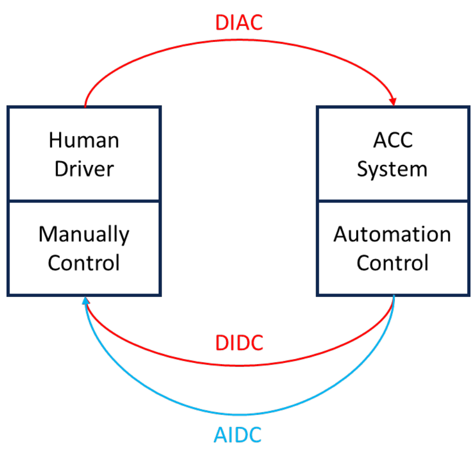


Figure 1.2: Example of transition control between different driving states

Several studies on SAE Level 1 automation have found that factors such as road conditions, traffic density, weather, and even driver characteristics significantly influence how automation systems are used (Russell et al., 2018). For instance, drivers are more inclined to use ACC in low-to-medium traffic densities on highways, particularly in clear weather conditions, which enhance the perception of safety by helping to maintain a safe time gap between vehicles (Russell et al., 2018; Nordhoff et al., 2023). However, when driving conditions exceed the system's ODD, the driver must retake control of the vehicle, typically through a manual driving state (Vogelpohl et al., 2018). These transition controls can sometimes have negative effects on traffic performance due to the reaction time needed by drivers and the minimum time required for ACC systems to activate or deactivate. For example, in the Hyundai Ioniq Hybrid owner's manual, it is noted that after a braking event, reactivation of cruise control takes approximately 3 seconds, and this delay is considered normal (Hyundai Motor America, 2018).

1.1. Problem Definition

Integrating AVs into existing road networks represents a crucial shift in transportation systems, offering significant opportunities to enhance both efficiency and safety. However, this transition also introduces complex challenges, particularly during the transfer of control between automation and human drivers. This transition of controls, especially when they occur outside the autonomous systems' Operational Design Domain (ODD), can introduce oscillations in traffic flow. Oscillations, characterized by fluctuating speeds and irregular vehicle spacing, pose significant risks to both traffic safety and flow efficiency (Tian et al., 2016). As automotive manufacturers increasingly release vehicle models equipped with ACC systems, the resulting diversity in traffic flow dynamics becomes evident. Different ACC systems exhibit varying operational characteristics and ODDs, further contributing to these complexities.

Makridis et al. have shown how the differing behaviors of commercially available ACC systems influence traffic congestion and safety. However, there remains a gap in understanding how the transition control from automation to human drivers specifically impacts traffic safety and flow efficiency across different ACC systems (Vogelpohl et al., 2018; Varotto et al., 2020). The study of these transition controls and their role in influencing traffic dynamics has been relatively limited in the literature.

1.2. Research Scope

The research considers three types of transition control: the driver Deactivates the System (DIDC), the Driver Activates the System (DIAC), and the System Disengages due to Operational Limitations (AIDC). The studied network in this research focuses on a highway segment. Several studies have indicated that merging areas are high-risk zones, both in terms of traffic efficiency and safety. From a traffic efficiency perspective, on-ramps are recognized as bottlenecks on highways, with merging behavior being a key factor affecting the continuity of traffic flow and directly influencing the capacity of the main highway line (Hall and Tsao, 1997; Ntousakis et al., 2014; Yu et al., 2022; Wang et al., 2023). In addition, Ntousakis et al. (2014) noted that merging is a significant challenge for drivers, requiring a complex sequence of observations and actions, often leading to inefficient merging maneuvers. Furthermore, Wang et al. (2023) observed that AVs face considerable difficulties when merging at highway on-ramps, especially when interacting with human-driven vehicles. For example, AVs often struggle to respond effectively to the unpredictable behavior of human drivers, such as sudden acceleration or deceleration, which can cause AVs to hesitate during merging. This hesitation is largely due to the conservative and cautious driving strategies programmed into AVs, which prioritize safety but may result in slower or delayed reactions when merging into fast-moving traffic (Wang et al., 2023). As a result, on-ramps are identified as critical bottlenecks that significantly affect traffic flow continuity and highway capacity, posing challenges for both human drivers and automated vehicles. While human drivers find merging maneuvers complex and challenging, AVs experience difficulties in interacting with human-driven vehicles during these maneuvers.

However, despite these current challenges, AV technologies are expected to bring substantial improvements in ramp merging operations over time. Specifically, AVs have the potential to reduce traffic conflicts and crashes by eliminating or mitigating the unpredictable factors introduced by human drivers (Zhu and Tasic, 2021). In advanced automated driving, particularly in merging scenarios, motion planning, and control are crucial for ensuring smooth and safe transitions (Hu et al., 2023). Thus, while AVs currently struggle with the complexities of merging, further advancements in autonomous technology could significantly enhance their performance in these situations, potentially improving both safety and efficiency.

Regarding traffic safety, merging sections are among the most accident-prone areas on highways, largely due to the lane-change maneuvers required in these areas. As illustrated in Figure 1.3, a waving section is a highway element near ramps or highway-highway connectors where vehicles must execute lane changes. Annually, a significant number of accidents occur in these sections, with roughly one-sixth categorized as severe traffic incidents (Hu et al., 2023). The high risk of crashes and conflicts arises from the varying driving styles and uncertain maneuvers of human drivers during lane changes (Yang and Ozbay, 2011; Zhu and Tasic, 2021; Liu et al., 2023). While AV technologies are expected to mitigate some of these risks by reducing human error, the complexity of motion planning in these environments remains a significant challenge. Although lane-changing models are beyond the scope of this research, it is likely that AVs may require a transition to human control (AIDC) before executing a lane change. Some studies suggest that ACC systems are predominantly used during free-flowing traffic (i.e., speeds between 70 and 90 km/h on highways) and are seldom employed during congested conditions (Pauwelussen and Minderhoud, 2008; Pauwelussen and Feenstra, 2010).

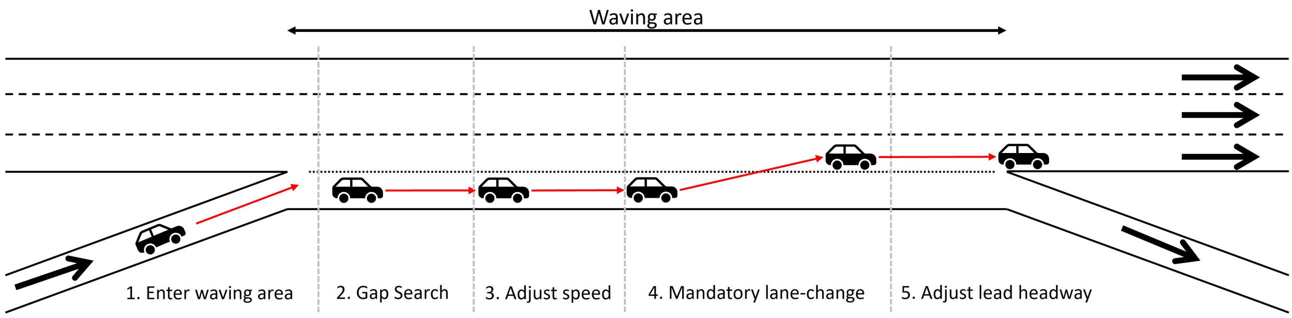


Figure 1.3: Waving Section

The simulation included the highway section as depicted in Figure 1.4. The traffic flow of the highway contains a weaving section included in the normal traffic flow at high speed, which adds a layer of complication to what would generally be a relatively simple high-speed traffic flow. These sections require the vehicles to change lanes and merge with others; thus, interactions between vehicles will be high, which might also result in a higher frequency of transition of controls. Traffic will be disturbed in the movement, making the probability of accidents also rise. These weaving sections of highways are highly important bottlenecks that have a great effect on the efficiency and safety of traffic. Therefore, it is the subject area of this research.

- Part A represents the on-ramp area, designed to explore the dynamics of vehicle merging.
- Part B depicts a main highway segment where a vehicle can be driven at the speed it wants under the free flow situation. This is also the segment where the traffic flow might be able to stabilize.
- Part C illustrates the off-ramp section, which provides the perspective on diverging behaviors.

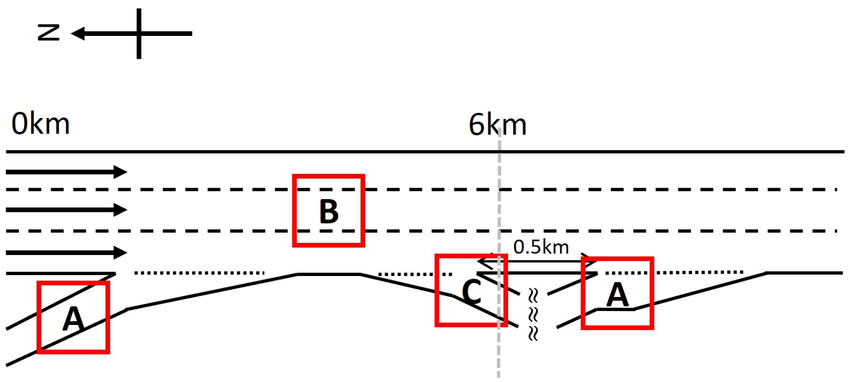


Figure 1.4: Schematic diagram of Dutch A13 highway segment

1.3. Research Gap

The existing literature has taken significant steps toward exploring transition control and disengagement within automated driving (Merat et al., 2014; Lu et al., 2016; Khattak and Fontaine, 2020; Gershon et al., 2021). However, it has largely focused on narrow vehicle specifications, often confined to specific vehicle types or the driving simulator with one ACC model only. A lack of diversity in research scope has resulted in findings that are not completely representative of real-world vehicle automation diversity. Recent studies, such as those conducted by Vogelpohl et al. (2018) and Varotto et al. (2020), have uncovered the complexities of driver behavior in response to automated driving systems and the importance of considering various automation levels as defined by the SAE (2021). However, there remains a critical gap in understanding how different vehicle brands, each with their own automation features and market penetration rates, interact within the broader system of traffic flow.

To address this gap, this research aims to assess the effects of control transitions on traffic safety and efficiency, particularly in scenarios involving vehicles equipped with ACC systems from multiple manufacturers. The research analyzes both real-world and simulated scenarios. By utilizing empirical data and traffic simulation models, this research also explores the specific behaviors of ACC systems during these transitions, providing insights into their broader impact on road safety and traffic flow.

1.4. Research Questions

Main research question: The main research question is jointly answered by the following sub-questions:

How do different automotive brands' transition control mechanisms in ACC systems affect traffic flow efficiency and safety?

The sub-questions are:

1. What key performance indicators can be used to assess the impact of ACC systems and the transition control models on traffic flow efficiency and safety?

   The introduction discusses the potential for AV to improve safety and efficiency on roads but also highlights risks during transition control, such as disruptions in traffic flow and accidents caused by delays in driver response when taking over control. To measure these effects, it is essential to identify the key metrics that reflect how ACC systems and transition control models influence both traffic efficiency and safety. This sub-question is to establish the performance metrics that will be used to evaluate the impacts of ACC systems.

2. How do ACC transition control mechanisms and characteristics vary across different automotive brands?

   The introduction indicates that the deployment of ACC systems is growing, but human drivers still play a critical role in vehicle control. In addition, different vehicle brands implement ACC systems with varying characteristics and operational limitations. Understanding these variations is critical, as they directly influence how different systems interact with traffic flow and safety dynamics. This sub-question addresses the need to explore how different ACC systems handle transitions.

3. What are the variables and their corresponding ranges for simulating transition control?

   The introduction discusses the complexities of ACC systems, especially their limitations during the switch from automated to manual control. To simulate the differences between ACC systems and the transition control models, as well as their impact on traffic, it is crucial to define the relevant variables and their ranges. This sub-question aims to establish the parameters for simulation to ensure that the study accurately represents more realistic conditions.

4. What is the market penetration of different brands?

   The introduction mentioned the growing presence of AVs and ACC systems in traffic, which includes multiple brands with varying levels of market penetration. The influence of these systems on traffic flow and safety depends not only on their technical performance but also on their prevalence on the roads. This sub-question addresses the need to find the market penetration of different brands, which is crucial for creating a more realistic traffic simulation models and understanding their cumulative impact.

5. What are the implications of transition controls on traffic flow and safety?

   The introduction highlights that transition controls, where a driver must take back control from the automated system, can lead to traffic oscillations, disruptions, and safety risks, particularly in complex environments like highway merging sections. This sub-question aims to analyze how these transition controls affect traffic efficiency and safety, particularly in scenarios that involve both automated and human-driven vehicles. The insights from this analysis will have a better understanding on the broader impacts of ACC systems on the road.

Table 1.1 shows the research questions and where they are answered and explained in the chapter.

Table 1.1: Research questions and the corresponding method

Research question	Method
1. Key performance indicators for the assessment	Literature review (Section 2.4)
2. ACC transition control mechanisms and characteristics vary across different automotive brands	Literature review (Section 2.5); Data Analysis (Chapter 4)
3. The variables and their corresponding ranges for simulating transition control in each scenario	Data Analysis (Chapter 4)
4. The expected market penetration of different brands	Statistical result from authority (Chapter 4)
5. The implications of transition control models with different ACC brands variation on traffic flow and safety	Simulation setup (Section 3.4); Conducting simulation (Chapter 5)

2
Literature Review

The purpose of this literature review is to closely examine existing research on transition control in automated vehicles, with a focus on ACC systems. The review explores the factors influencing these transitions in section 2.1, the reasons for system disengagement in section 2.2, and the effects of ACC vehicles and transition control on traffic safety and efficiency in section 2.3. Following this, section 2.5 discusses the variability in ACC systems' characteristics. Section 2.6 summarizes the general ODDs mentioned in several car owners' manuals. Finally, the conclusion of the literature review is presented in section 2.7.

2.1. Influential Factors in Drivers' Decision-Making for Transition Controls

Understanding factors influencing drivers' decision to activate or deactivate ACC systems is one of the important to enhance the realism of the simulation. The following attempts to address influential psychological and situational factors that drive transition decisions based on cognitive psychological theories about human behavior. Key factors for the influence on perceived safety and usefulness of automation systems are limitations, responsibility, dynamics, and efficiency Goodrich and Boer (2003); Flemisch et al. (2012); Vlakveld (2015). Further, driver performance can be interpreted through the U-shaped model that Hoeger et al. (2008) proposed with respect to workload and task characteristics in terms of performance, situational awareness, and automation needs. Another factor influencing the driver's decision about initiating a transition control is the driver's lack of trust in the automated system. This distrust can arise when drivers believe that the system may fail to handle complex or dynamic situations effectively, especially under difficult or unpredictable conditions, such as bad weather, sensor malfunctions, or complicated traffic scenarios (Vlakveld, 2015; Lu et al., 2016; Vogelpohl et al., 2018).

The process of making decisions with regard to transitional control is quite dominated by cognitive psychological factors as far as drivers are concerned. Automation changes driving in many ways, such as workload, situational awareness, confidence, locus of control, habitual adaptation, and anticipation of hazards (Vlakveld, 2015). Hoeger et al. (2008) argued that, across levels of difficulty, driver performance could be conceptualized as a U-shaped function. There would, accordingly, be an optimum level of performance at moderate driving difficulty. Figure 2.1 illustrates that driver performance deteriorates when the driving demands are either too simple, leading to underload and reduced vigilance, or too high, causing overload and task saturation. In both extreme situations, there is an increasing need for automation to provide support. When the driver is not carrying a heavy load, automation should help maintain attention. On the other hand, when the driver is overwhelmed, automation should assist in managing potentially stressful situations.

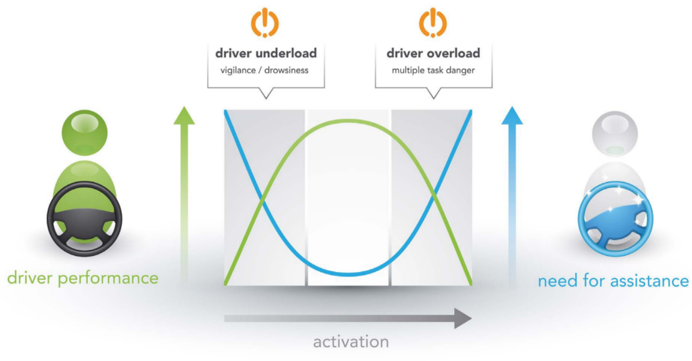


Figure 2.1: U-shape function between driving difficulty and driver performance (Hoeger et al., 2008)

For the type of DIAC transition controls, where drivers actively choose to hand over control to automation, workload reduction can be a primary factor. When drivers use ACC systems, their workload is typically low because the system manages most driving tasks, potentially leading to decreased situational awareness. Situational awareness is defined as "the perception of elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future" (Endsley, 1995). Research by Reagan et al. (2021) found that prolonged reliance on partial automation systems can lead to disengagement, where drivers become less attentive and more likely to engage in non-driving activities, such as taking their hands off the wheel or using a cell phone. When a transition of control is necessary, this disengagement may result in slower reaction times, raising safety risks, particularly during DIAC transitions.

In contrast, Driver-Initiated Deactivation of Control (DIDC) transitions occur when drivers choose to resume manual control from automation, often in response to a perceived safety threat or complex driving conditions. Trust in the automation system is a key factor in these transitions. Nordhoff et al. (2023) suggested that drivers are more likely to deactivate automation when they feel unsafe or uncertain about the systems capabilities. Complex driving conditions, such as dense traffic or the need to execute a lane change, can also prompt drivers to deactivate automation in favor of manual control. ACC systems typically focus on longitudinal control (maintaining speed and following distance) but may struggle with lateral control tasks, such as maneuvering the vehicle during lane changes (Vogelpohl et al., 2018). Drivers may therefore prefer to take over in such scenarios, where precise control is required.

The findings from Nordhoff et al. (2023) about the SEM (Structural Equation Model) study provide further insight into the decision-making processes of drivers. The research emphasizes that if drivers don't trust the automated system or feel that the driving conditions are unsafe or confusing, they are more likely to switch to manual driving. Additionally, drivers may deactivate automation because they prefer manual driving or feel that automation is unnecessary in some conditions. These findings highlight the significance of perceived safety and trust in automation in deciding whether a driver will keep using or deactivate the ACC system.

In real-world situations, there are many instances where ACC systems may need human intervention. For instance, in urban areas, ACC systems may struggle to make quick decisions, such as avoiding a pedestrian at a traffic signal (Li et al., 2019). These scenarios demonstrate the limitations of current ACC models and the necessity for prompt human response to prevent potential dangers. Additionally, in heavy traffic, drivers may choose to deactivate ACC in order to regain full control of the vehicle before making complicated maneuvers like changing lanes (Varotto, 2018; Klunder et al., 2009).
In conclusion, the influential factors of the drivers' decision can be organized as follows:

1. Driver Initiates transition, and Driver in Control after (DIDC)
    - Safety perception: When the driver feels unsafe or unfamiliar with the automation system, they might deactivate the automated system.
    - Complex driving conditions: When the driver is in conditions such as dense traffic or before lane changing, the driver might deactivate the system to handle these situations. Speed adaptation before a lane change maneuver is common since only Level 2 automated vehicles have longitude control.
    - Overruling due to defensive or offensive driving behavior, where defensive driving behavior of the driver can be defined as less sudden acceleration and deceleration and the aggressive behavior means higher acceleration and more sudden braking (Peng et al., 2022).
2. Driver Initiates transition, and Automation in Control after (DIAC)
    - Task overload: The driver may activate the automated system when the driving tasks become overloaded or complex, so they ask for driving assistance.
    - Boredom with driving: When the driving experience is boring for the driver or when the driver feels sleepy, the driver might activate the automated system.

2.2. System Disengagement

The last type of transition control is AIDC, which is the disengagement of ACC systems and requires the driver to take over the control of the vehicle. An ACC system may disengage when sensor failures occur or when the system reaches the limits of its ODD (Varotto et al., 2018; Vogelpohl et al., 2018; Lu et al., 2016). In these cases, the system is no longer able to perform its tasks safely, triggering a transition control of AIDC, which requires the driver to take over the control of the vehicle. During this transition, drivers are removed from the active control loop and need time to re-engage with the driving task. This process, referred to as a take-over request (TOR), typically takes 3 to 5 seconds, during which drivers must regain situational awareness and fully take control of the vehicle (Vogelpohl et al., 2018). Building upon the experimental framework defined by Vogelpohl et al. (2018), assessments of reaction time involve the initiation of both acoustic and visual warning signals to alert the driver (Gold et al., 2015; Louw et al., 2015; Vogelpohl et al., 2018; Lu, 2020). The endpoints for measuring reaction times were systematically categorized into four distinct stages:

Orienting Response, Preparation for Action, Implementation of Action, and Vehicle Stabilization, and the definition is shown in Table 2.1 (Schömig et al., 2015; Vogelpohl et al., 2018).

Table 2.1: Overview of the measures used for the reaction time of the Take-Over Control (Vogelpohl et al., 2018)

Measurement Category	Measure	Definition	Average Reaction Time (seconds)
Orienting Response	Eyes on Road	Time between the TOR and the first fixation of the road center	1.14 - 1.90
Preparation for Action	Hands On	Time between the TOR and the moment where participants had at least one hand grasping the steering wheel	3.28 - 3.90
Implementation of Action	Automation Off	Time between the TOR and the deactivation of the automation through the brake pedal or the lever behind the steering wheel	4.59 - 5.07
Implementation of Action	Brake Reaction	Time between the onset of the event and a brake pedal position >10%	N/A
Implementation of Action	Gaze Side Mirror	Time between the TOR and the first fixation of the side mirror	N/A
Implementation of Action	Gaze Speed	Time between the TOR and the first fixation of the speedometer	N/A
Vehicle Stabilization	SDLP	Standard deviation of lane position from the center of the lane measured between the TOR and the end of each scenario (500 m)	N/A

The situation awareness might also influence the driver's reaction time. When the situation awareness is lower, and tensions are lower, the reaction time is longer(Vogelpohl et al., 2018; Zhang et al., 2019a; Weaver and DeLucia, 2022). They may require additional time and assistance to fully perceive and understand complex trafc situations and to reach a level of situation awareness comparable to manual drivers (Vogelpohl et al., 2018). The distracted conditions could take the driver visually, mentally, and physically out of the loop (Vogelpohl et al., 2018). The tasks that result in the distracted conditions could be an intrinsic motivation (e.g., performing ofce tasks, gaming) (Beggiato et al., 2015). In addition, the overall summary of the studies on transition control and disengagement in automated driving can be found in Appendix B.

In conclusion, the reason for system disengagement can be organized as follows:

- A sensor failure: The sensor's functionality is compromised in some scenarios, such as under conditions of poor visibility attributed to adverse weather or due to specific road geometries and conditions. For example, the inability to operate effectively when entering a sharp curve or when the sensors fail to detect lane markings.

- Encountering the limitations of system support in a safety-critical situation: When the speed or acceleration of the vehicle is beyond the upper or lower bound of the system's support constraints. The driver needs to take over the control to avoid collisions (Varotto, 2018).

2.3. Impact of ACC Vehicles and Transition Control on Traffic Flow and Safety

The use of ACC and other in-vehicle systems can have an impact on the efficiency, sustainability, and safety of the transportation network (Wu and Boyle, 2015). ACC systems are designed for convenience to maintain a desired speed and specified distance from a lead vehicle. Before discussing the impact of transition controls on traffic, the research on how ACC systems influence traffic flow and safety is examined first.

Impact of ACC Vehicles

Several studies have demonstrated that ACC systems can enhance traffic flow efficiency by maintaining consistent vehicle speeds and reducing stop-and-go conditions. For instance, high penetration rates of ACC vehicles have been shown to increase road capacity and reduce congestion, leading to smoother traffic flow and decreased travel times (Stern et al., 2019). In addition, the ability of ACC systems to maintain safe following distances helps to reduce traffic disruptions, particularly in controlled environments like highways, where vehicle interactions are more predictable (Yu et al., 2021; He et al., 2019). The implementation of ACC has also been linked to improved safety, as it increases the Time to Collision (TTC) by ensuring vehicles maintain adequate spacing, thus reducing the likelihood of rear-end collisions (Stern et al., 2019). In addition, Li et al. (2017) indicated the safety effects are largely affected by the simulation parameter settings. If the settings are proper, such as larger time gap values and greater maximum deceleration rates in emergencies, it can have a positive impact on reducing collisions in congested traffic flow.

However, some studies also pointed out potential drawbacks of ACC, particularly in mixed-traffic environments where ACC vehicles interact with human-driven vehicles. Calvert et al. and He et al. have shown that low market penetration rates (MPRs) of automated vehicles in mixed traffic would initially have a small negative effect on traffic flow and road capacities. In addition, some research has indicated that ACC can sometimes decrease traffic flow efficiency by enforcing overly conservative following distances, which may lead to reduced road capacity and increased travel times in congested conditions (Liu et al., 2018). Furthermore, safety concerns have been raised regarding ACC's impact on TTC, especially in scenarios where ACC systems react with a time lag to sudden decelerations. This delayed response can decrease TTC and heighten the risk of rear-end collisions, particularly in environments with variable traffic dynamics (Li et al., 2021). According to the findings of Qin et al. (2019), unstable ACC systems are a key factor contributing to negative safety outcomes, especially when compared to cooperative adaptive cruise control (CACC) systems. While CACC systems are beyond the scope of this research, these findings highlight the limitations of current ACC systems in maintaining traffic stability and safety.

Impact of Transition Control

There are three types of transition controls within the research scope, which are DIDC, DIAC, and AIDC. It can be classified that DIDC is a self-activated transition, and thus a type of active transition, and AIDC and DIAC, which are triggered interventions, are passive transitions (Lu, 2020). In active transitions, the agent who initiates the transition is the same as the agent who ends up with control. Therefore, the agent who initiates the transition is usually prepared to take over control afterward. On the other hand, in passive transitions DIAC and AIDC, the initiating agent and the resulting driving agent are different, and whoever is in control after the transition may have been forced to take over control from the other agent. A lack of preparation may lead to unsafe situations. In a mandatory DIAC transition, the driver is in control before the transition, and automation control could be unstable after the automation has been forced to take over control of the car, depending on the situation and environmental conditions. As for AIDC transitions, if drivers do not respond promptly and properly, the transition could lead to an accident (Lu, 2020). The fact that AIDC transitions are essential to the safety of automated driving may explain why these transitions have been extensively studied in driving simulator experiments by human factors researchers (Reagan et al., 2021; Wu and Boyle, 2015; Gold et al., 2015; Vogelpohl et al., 2018). These studies reveal a concerning trend: drivers' engagement levels diminish significantly as they become familiar with utilizing automation systems. The authors observed that there was a marked increase in the likelihood of drivers removing both hands from the steering wheel or engaging with a cell phone, compared to when driving manually. Furthermore, Papadimitriou et al. (2020) indicated that prolonged exposure to automated driving systems increases self-reported trust in automation and is associated with reduced perceived safety benefits. Therefore, the disengagement resulting from prolonged use of automation is linked to an increase in takeover time during AIDC transitions due to diminished situational awareness.

Regarding traffic flow efficiency, potential instability in traffic flow may be attributed to the passive transition control. Varotto et al. (2018) have suggested that transitioning from ACC to manual control (AIDC) significantly impacts driver behavior, affecting traffic flow. This transition is marked in driving patterns that the drivers tend to reduce, which is a compensation strategy for drivers' vehicles ahead of time when ACC is deactivated. It is a compensation strategy for drivers to reduce perceived risk in complex traffic scenarios. However, these kinds of adjustments could lead to instability in the traffic flow. On the other hand, when the drivers override, ACC is characterized by increased speed and acceleration. This adaption in driving behavior represents another form of state change, which may similarly contribute to the instability of traffic flow (Varotto, 2018).

2.4. Traffic Efficiency and Safety Indicators

Highway safety and efficiency are two of the most important concerns for traffic systems around the world (Yang et al., 2010; Yang and Ozbay, 2011; Hu et al., 2023). Therefore, the following subsection is about the indicators used for assessing traffic flow efficiency and safety.

2.4.1. Traffic Efficiency

Traffic flow efficiency is a crucial aspect of transportation, assessed through various indicators and methods. This includes the traditional macroscopic variables such as flow (q), density (k), and average speed (u), alongside methodologies such as highway capacity manual (HCM) method (Hoogendoorn and Knoop, 2013; Sharma et al., 2021). The average speed can be classified into three perspectives: time-mean speed (TMS), space-mean speed(SMS), and time-space-mean speed (TSMS) and the definitions are as follows (Jamshidnejad and De Schutter, 2015):

- TMS: The average speed across a time interval at a fixed location. A stationary observer, such as a loop detector that has a sampling period of T_A and is placed at a fixed position $x_{loop,A}$ observes the vehicles during its sampling period, T_A, at the position $x = x_{loop,A}$. Hence, from the given definition, the arithmetic mean of the speeds observed by the loop detector is the TMS.
- SMS: The average speed across a section of the road at a specific time. Therefore, for a traffic detection system such as a traffic camera that provides a data set covering a stretch of road of length L_A at a specific time, the arithmetic mean of the speeds observed in the photograph is the SMS.
- TSMS: The fundamental traffic equation relates two fundamental concepts (i.e. the flow and the density), one of which is defined across a time interval, and the other one is defined across a length interval.

When it comes to the integration of Connected and Automated Vehicles, Guériau and Dusparic have introduced indicators such as the Congested Index (CI), Travel Rate (TR) expressed in minutes per kilometer, and Total Time Spent (TTS) to evaluate traffic flow efficiency comprehensively (Guériau and Dusparic, 2020). In addition, Heikoop and Hekens suggested that the V/C ratio could also be an indicator because it points out the level of service (LOS) for the highway and examines the probability that congestion would occur given 30 minutes of traffic at a given volume-to-capacity ratio as shown in Table 2.2 (Heikoop and Henkens, 2016). However, the traffic volume might not be able to be measured accurately from the simulator used in this research, so LOS is not used as the indicator in the result analysis.

Table 2.2: Probability of congestion at different volume-to-capacity ratios (Heikoop and Henkens, 2016)

V/C ratio	Probability of congestion within 30 minutes	LOS
< 0.3	0%	A
0.3 - 0.8	< 1%	B - D
0.8 - 0.9	< 20%	E & F (congestion)
0.9 - 1.0	20% - 100%	E & F (congestion)
> 1.0	100%	F (congestion)

To conclude on the traffic flow efficiency indicators, the following outlines the indicators and the corresponding formulas:

1. Traffic Flow ($q(A)$): This is the rate at which vehicles pass an area A on a roadway, typically measured in vehicles per hour (vph).

$$q(A) = \frac{1}{|A|}\sum_{i=1}^{n_A} d_i(A) \tag{2.1}$$

   where

n_A is the number of vehicles observed in area A
$d_i(A)$ is the distance traveled in the area A by vehicle i

2. Traffic Density (ρ): It is defined by the number of vehicles being enclosed by the area A.

$$q(A) = \frac{1}{|A|} \sum_{i=1}^{n_A} t_i(A) \tag{2.2}$$

where
n_A is the number of vehicles observed in area A
$t_i(A)$ is the travelled time spent in the area A by vehicle i

3. Total Time Spent (TTS) (Guériau and Dusparic, 2020): A total of each vehicle's journey time on the section studied.

$$TTS = \sum_{i=1}^{n} t_i \tag{2.3}$$

where
t_i represents the travel time of the i^{th} vehicle
n is the total number of vehicles observed

4. Time-mean Speed ($\bar{v}_{TMS}$)

$$\bar{v}_{TMS} = \frac{\sum v_i}{n} = \frac{\sum \frac{d}{t_i}}{n} \tag{2.4}$$

where
d is the distance traveled or length of roadway segments
t_i is the travel time of i th vehicle
n is the total number of vehicles observed

2.4.2. Traffic Safety

Generally, traffic safety measures can be classified into four groups: time-based, distance-based, deceleration-based, and other composite measures (Yang et al., 2010). Among time-based metrics, Time-to-Collision (TTC) is one of the most widely utilized (Yang et al., 2010; Wang et al., 2021). TTC estimates the time remaining until a collision occurs if two vehicles continue at their current speed and direction. This measure is useful for understanding the criticality of vehicle interactions, but it is limited to assessing potential collisions on a microscopic levelbetween individual vehicleswithout considering the broader context of the traffic environment. Minderhoud and Bovy (2001) introduced two variants that build upon TTC: Time Exposed Time-to-Collision (TET) and Time Integrated Time-to-Collision (TIT). These metrics provide a cumulative assessment of how long and how frequently vehicles are exposed to dangerous interactions. TET and TIT are commonly used to compare a "do-nothing" scenario with one where intelligent driver support systems are implemented. However, as surrogate measures, these indicators cannot fully capture the real risks or drivers' perceptions in complex driving environments. They infer potential safety issues but do not provide direct insight into actual crash risks.

From the perspective of deceleration-based metrics, the Deceleration Rate to Avoid Crash (DRAC) is frequently applied. DRAC quantifies the deceleration required by the following vehicle to avoid a rear-end collision with the lead vehicle (Saccomanno et al., 2008; Yang et al., 2010; Sharma et al., 2021). This measure also relies on assumptions about driver behavior and vehicle dynamics, which may not fully reflect real-world conditions where unpredictable events and driver reactions occur. While DRAC can provide information in understanding how vehicle interactions contribute to crash risk, it remains a surrogate measuremeaning it offers an approximation of risk rather than a direct measurement of crash likelihood (Chen et al., 2023).

Despite the widespread use of these surrogate safety measures, it is important to recognize their limitations. First, they are microscopic indicators that focus primarily on individual vehicle-to-vehicle interactions. This means that while they can provide detailed insights into the criticality of specific maneuvers (e.g., braking, lane changes, or car-following behavior), they do not capture the overall safety level of the entire traffic network (Guo et al., 2021). They are designed to infer the potential for collisions or near-miss events but do not assess real-world risks or the subjective perceptions of drivers, which are essential components of safety. Studies have emphasized that surrogate measures, while useful for identifying near-crash events, are proxies for real safety outcomes and may not align perfectly with actual crash data (Hussain et al., 2019; Zhao et al., 2020). Furthermore, these measures do not account for broader network-level safety, which limits their ability to provide a comprehensive understanding of overall traffic safety (Xu et al., 2022).

Furthermore, because these measures are surrogates, they are limited in their ability to predict actual crash outcomes. Surrogate measures provide an approximation based on modeled behaviors and interactions rather than empirical crash data. This is especially relevant in intelligent transportation systems, where automated and human-driven vehicles interact in complex, often unpredictable ways. Surrogates may under-represent or over-represent risks depending on how well they reflect real-world behavior and vehicle capabilities (Salmon et al., 2014; Chen et al., 2023). Therefore, while surrogate measures are valuable for examining vehicle-to-vehicle interactions, they should be supplemented with network-level safety evaluations and driver behavior assessments to obtain a more comprehensive picture of traffic safety.

In conclusion, while these surrogate safety measures are commonly used in traffic safety research to evaluate and compare safety-critical situations, they have limitations. They are not direct measurements of risk and do not fully represent the complexity of real-world traffic safety. These metrics are useful for identifying areas of potential concern, especially in the absence of comprehensive crash data, but they should be supplemented with broader safety assessments that consider driver behavior, network-wide safety, and real crash occurrences. As such, researchers and practitioners should be cautious in relying solely on these indicators to evaluate traffic safety and should recognize the need for more comprehensive risk assessments.

1. Time to collision (TTC): The time until a collision between the vehicles would occur if they continued on their current speed and direction.

$$TTC_{i,t} = \frac{IVS_{i,t}}{v_{i,t} - v_{i-1,t}} \qquad if \quad v_{i,t} > v_{i-1,t} \tag{2.5}$$

2. Time Exposed Time-to-Collision (TET): Summation of all moments that a driver approaches a front

vehicle with a TTC below a threshold value. This is suitable for microscopic simulation.

$$TET^* i = \sum_{t=0}^{T} \delta_i(t) \cdot \tau_{sc}, \quad \delta_i(t) = \begin{cases} 1 & \text{if } 0 \leq TTC_i(t) \leq TTC^* \\ 0 & \text{otherwise} \end{cases} \tag{2.6}$$

where

δ is a switching variable. Its value is 1 in case a driver i at instant t experiences a TTC-value between 0 and the specified threshold value TTC*. Otherwise, its value is 0.

τ_{sc} is a small time step (e.g. 0.1 s) (Saccomanno et al., 2008)

3. Deceleration rate to avoid the crash (DRAC): It is a measure to estimate the required rate of deceleration to avoid a collision based on the relative velocities of the vehicles and the distance between them.The greater the DRAC value, the higher the crash risk (Fu and Sayed, 2021).

$$DRAC_{i,t+1} = \frac{(V_{i,t} - V_{i-1,t})^2}{(V_{i-1,t} - V_{i,t}) - L_{i-1,t}} \tag{2.7}$$

4. Time Headway: The time difference between the front bumper of the leading and the front bumper of the following vehicle.

$$TH = \frac{IVS_i + L_i}{V_{i+1}} \tag{2.8}$$

5. Time Gap: The desired time gap does not consider the length of the vehicles. Therefore, the time difference between the leading vehicle's rear bumper and the following vehicle's front bumper is shown.

$$TG = \frac{IVS_i}{V_{i+1}} \tag{2.9}$$

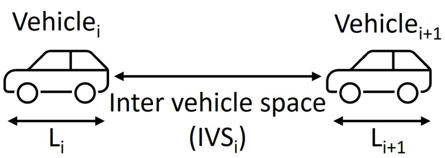


Figure 2.2: Illustration of Inter-vehicle Space

The following context is about the threshold of each indicator. Defining a standard Time-to-Collision (TTC) threshold has been contentious in evaluating collision risks (Das and Maurya, 2020). Previous research has proposed various thresholds ranging from 0.90 to 5 seconds, tailored for different traffic and driving scenarios. Hogema et al. (1996) found minimum TTC values of 3.5 seconds for non-supported drivers and 2.6 seconds for supported drivers when approaching a queue, with the 2.6-second TTC regarded as a safety concern. Guériau and Dusparic (2020) proposed TTC thresholds of 2.5 and 3 seconds to distinguish unsafe car-following maneuvers. Other researchers have also recommended a critical threshold of 3 seconds. Overall, the literature suggests that conflict severity largely depends on the TTC threshold, though no definitive standard exists. A 3-second TTC is commonly recommended for rear-end collision avoidance systems (Das and Maurya, 2020), identifying unsafe car-following maneuvers and assessing traffic conflict exposure.

For the TTE, according to Minderhoud and Bovy, the threshold of TET depends on the TTC value. For example, if the TCC value is 3 seconds, the TTE is approximately 19.5 seconds (Minderhoud and Bovy, 2001). On the aspect of DRAC, according to the American Association of State Highway and Transportation Officials, it is suggested that a deceleration rate above 3.6 m/s^2 is considered unsafe (Sharma et al., 2021). When it comes to time headway, Ayres et al. indicated that the time headway between vehicles varies between 1 and 2 seconds for a range of traffic speeds during rush hours (Ayres et al., 2001). Time headway for the speed above 80 km/hr is recommended as 1.8 seconds (Vogel, 2003; Khansari et al., 2020) while the police use a time headway of 1 second as orientation for imposing fines in Sweden. Drivers in the Netherlands, Sweden, and France are taught that a time interval of 2 s is considered safe Risto and Martens (2013). It can be assumed that the threshold for a safe time headway is 2 seconds, and the critical time headway for traffic safety is 1 second (Khansari et al., 2020).

2.5. Variability in ACC System Characteristics

In the context of evaluating ACC systems across different vehicle brands and their impact on traffic flow and safety, several studies have been conducted, providing valuable insights into this field, as shown in Table 2.3.

Knoop et al. (2019) conducted research utilizing vehicles to understand the interactions between SAE level-2 vehicles driven as a platoon and the vehicles on public roads (Knoop et al., 2019). Although it was focused on the interaction of the platoon in traffic instead of the different characteristics among different brands, the AVs' behaviors and how they will impact the traffic flow could be observed and concluded. Their results indicated that low-speed platoons could lead to the formation of moving bottlenecks, and despite high capacity values in the Netherlands, manual intervention was often required for maneuvers such as lane changing. The study concluded that current SAE level-2 systems are not ideally suited for platooning due to instabilities in car-following behavior. They suggested that the research can be useful for other studies setting up field tests (Knoop et al., 2019).

Makridis et al. (2020a) conducted a detailed investigation into four commercial ACC systems tested on the OpenACC (AstaZero) platform, revealing significant differences in response time, time headway, and string stability across the systems. In their systematic approach, response time was defined as the time taken by the ACC system to react to a change in the speed of the lead vehicle, from the moment the lead vehicle decelerates to when the ACC system initiates a response. The study found that the response time varied between 1.7 and 2.56 seconds across the tested vehicles, with these measurements being critical for understanding how different ACC systems handle traffic dynamics. These findings underline the importance of consistent reaction times, particularly in platooning scenarios where variability in response can lead to disturbances in string stability and overall traffic efficiency.

Li et al. (2021) carried out an experiment involving a 3-vehicle platoon but did not specify the brands involved. The study focused on the response time, average deceleration and acceleration rates, oscillation amplitude and growth, and overshooting. The results revealed that sensor delays in ACC systems are comparable to human reaction times, and amplification and overshooting are more pronounced at lower traffic speeds. In a subsequent study, Li et al. (2022) explored various experiments, including MA, work, OpenACC, and GA experiments, without mentioning specific vehicle brands. The MA experiments involved a three-vehicle platoon, where two ACC-equipped vehicles followed a human-driven vehicle, focusing on car-following behavior under different headway settings and driving conditions. The work experiments aimed to evaluate string stability by testing different ACC models in car-following scenarios with human-driven vehicles leading, exploring the impact of headway settings and speeds on traffic stability. The OpenACC experiments were part of a larger campaign that tested over 20 ACC models in various configurations, including 2- to 10-vehicle platoons, to examine their effects on traffic flow and energy consumption. The GA experiments concentrated on ACC performance in urban environments, specifically analyzing how ACC-equipped vehicles behave when following a human-driven leader and stopping at intersections, providing insights into jam spacing and urban driving dynamics. These experiments collectively highlighted the variability in ACC behavior. They introduced the headway coefficient (τ) and a constant coefficient (δ) for the space-speed relationship, concluding that ACC jam spacing could be significantly larger than human traffic, which potentially reduces network storage capacity.

Raju et al. (2022) took insight from the owner's and operator's manuals of the following brands: Nissan, Tesla, Volvo, Mercedes Benz, BMW, and Toyota to examine ACC features such as speed control, following time and distance, acceleration values, and response time. The research concluded that meantime gaps ranged from 0.7 to 2.1 seconds, with ACC response times comparable to human drivers, though not instantaneous. Ye et al. (2023) used the OpenACC database from the AstaZero campaign to evaluate ACC systems from Ford, Kia, Mitsubishi, Peugeot, and Volkswagen, focusing on string stability and disturbance growth. The findings suggested that ACC systems were string unstable compared to Human-Driven Vehicles (HDVs) and that stability varied across high and low-speed ranges, with the Ford platoon exhibiting more stability at higher speeds and the Mitsubishi platoon at lower speeds. In addition, the Ford-ACC system's behavior was most similar to that of human drivers with low instability. On the other hand, the Peugeot-ACC system was the most divergent and showed aggressive behavior with high instability. This divergence is primarily attributed to the system's tendency to react more abruptly to changes in the driving environment compared to other ACC systems. For instance, larger variations in acceleration and deceleration were exhibited by the Peugeot-ACC system, contributing to oscillations in speed that propagated through the traffic flow. This aggressive response to vehicle spacing and speed changes often resulted in the amplification of disturbances, leading to string instability. The system's inability to maintain consistent headways, combined with its propensity for frequent and sharp adjustments in speed, were key factors that contributed to its classification as highly unstable and aggressive.

Table 2.3: Summary of ACC System Evaluations from Previous Studies

Authors (Year)	Database/ Vehicle involved	Different features among the brands	Conclusion
Knoop et al. (2019)	1. BMW 530i (2017) 2. Mercedes E-class(2017) 3. Audi A4 (2017) 4. Tesla Model S (2017)	The research aimed to understand the interaction of the platoon in traffic	1. If the speed of the car-platoon is lower then 10km/hr, the platoon will form a moving bottleneck 2. Capacity values in the Netherlands are high, so drivers are used to small headways in normal conditions 3. While drivers tried to rely on the vehicle systems as much as possible, sometimes manual intervention was needed (for instance, for lane changing, braking, or catching up) 4. Current SAE level-2 systems are not suitable for driving as platoons of more than typically three to four vehicles, because of instabilities in the car-following behavior
Makridis et al. (2020)	OpenACC (AstaZero) 1. Audi A8 (2018) 2. Tesla Model 3 (2019) 3. BMW X5 (2018) 4. Mercedes A-Class (2019) 5. Audi A6 (2018)	1. Response time 2. Time headway 3. String stability	1. Studies on how four commercial ACC systems function in relation to response time, time headway, and stability. 2. Provides quantified results on response times and time headway values that can be used in microsimulation modeling of ACC systems. 3. Analyzes empirically the string instability of the car-platoon illustrating quantified results from perturbations of variable magnitudes and at different speeds.
Li et al. (2021)	MA experiment 3-vehicle platoon But did not mention about the real brand	1. Response time 2. Average deceleration rate 3. Average acceleration rate 4. Oscillation amplitude 5. Oscillation growth 6. Overshooting	1. There are sensor delays and the values are comparable to human driver 2. ACC response varies with headway setting, speed level and stimulus 3. Amplification and overshooting are more likely to occur when the traffic speed is low
Li et al. (2022)	1. MA experiments 2. Work experiments 3. OpenACC experiments 4. GA experiments	1. Headway coefficient (τ) 2. Constant coefficient (δ) (for $s - v$ relationship) $s = \tau_0 v + \delta_0$	1. At the minimum ACC headway setting, equilibrium capacities in excess of 3500 vehicles per hour are observed, together with an extremely fast equilibrium wave speed of 100 kilometers per hour. These fast waves are unfamiliar to human drivers, and may pose a safety risk. 2. Suggestion about that ACC jam spacing can be much larger than in human traffic, which reduces the network storage capacity
Raju et al. (2022)	Owner's/ Operator's manual 1. Nissan Leaf ProPilot 2. Tesla 3. Volvo 4. Mercedes Benz 5. BMW X5 6. BMW X6 7. Toyota	1. ACC speed control 2. ACC following time 3. ACC following distance 4. Acceleration values 5. Response time	1. The measured mean time gaps in the current study ranged between 0.7 s to 2.1 s 2. Response times were larger when reaching higher speeds 3. Response times of ACC systems are comparable to those of human drivers and not instantaneous
Ye et al. (2023)	OpenACC (AstaZero) 1. Ford 2. Kia 3. Mitsubishi 4. Peugeot 5. Volkswagen	1. String stability 2. Disturbance growth 3. Desired time headway 4. Maximum acceleration	1. Evaluating the similarities of parameter distributions between ACC vehicles and HDVs 2. From the perspective of string stability, all the ACC systems are string unstable and more unstable than HDVs 3. Within high-speed range, the Ford platoon is more stable 4. For low-speed range, Mitsubishi platoon is more stable 5. Behavior of the Ford-ACC system is most similar to human drivers with a relative low instability 6. Peugeot-ACC system behaves most differently to human drivers, and aggressively with the highest instability

Based on the review of the literature, it can be concluded that the performance attributes of ACC systems present variability across different brands. These variations can be vehicle-specific characteristics that influence the ACC system's functionality:

1. Response Time: The latency between stimulus and the ACC system's reaction.
2. Desired Time Headway Setting: The desired time headway maintained between the ACC-equipped vehicle and the preceding vehicle.
3. Acceleration Capability: The spectrum of acceleration rates the ACC system can command in response to dynamic traffic conditions.

2.6. The General ODD of ACC Systems from the Owners' Manual

The owner's manual is read to have a piece of knowledge on the system design and limits, such as under what situations the ACC systems would deactivate automatically and cause an AIDC transition control from the official documents. The following list shows the general system limits from several owners' manuals, which can be assumed as the technology limitations nowadays (MINI, 2017; Hyundai Motor America, 2018; Volvo, 2018; Volkswagen, 2018; Peugeot, 2018; Toyota, 2019; BMW, 2018b,a). Therefore, these limitations could be considered when modeling the transition control in the simulation. Besides, some limitations, which are considered rare during highway driving, such as opening the door or disengaging the selector lever position D, are not included in the list.

1. On curves: When the set speed is too high for a curve, the speed is reduced slightly. Due to the camera's limited field of view, it is imperative to approach curves at a speed that ensures safe maneuverability, as the camera may not detect the curve in sufficient time to allow for anticipatory adjustments. Situations can arise in tight curves where a vehicle driving ahead will not be detected or will be detected very late. As a curve is approached, vehicles in the adjacent lane may be momentarily detected by the system due to the curvature of the road. Should the system initiate deceleration, compensation through brief acceleration may be required. Upon release of the accelerator pedal, the system will reactivate and resume autonomous control of the vehicle's speed.

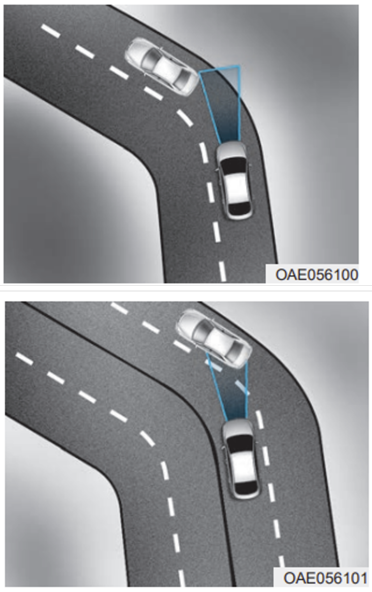


Figure 2.3: On Curves (Hyundai Motor America, 2018)

2. Lane changing: When a vehicle merges into the same lane ahead suddenly, the system may not automatically re-establish the preset distance. Restoration of the selected distance may not always be feasible, such as in scenarios where the ego vehicle's speed exceeds that of the vehicles ahead, for example, when closing in quickly on a truck. If the system reliably detects a vehicle ahead, it will signal the need for driver intervention through braking and, if necessary, an evasive maneuver.

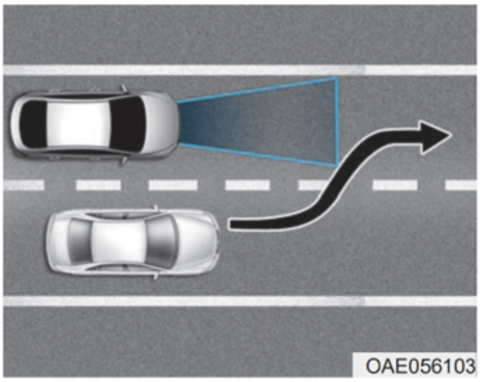


Figure 2.4: Lane Changing (Hyundai Motor America, 2018)

3. On inclines: During uphill or downhill driving, a moving vehicle within the same lane may not be detected by the ACC system, which could result in unintended acceleration to the preset speed. In addition, a rapid decrease in vehicle speed may occur when a vehicle ahead is suddenly recognized. On inclines, it is recommended that an appropriate set speed be selected and the brake or accelerator pedal be applied manually if necessary.

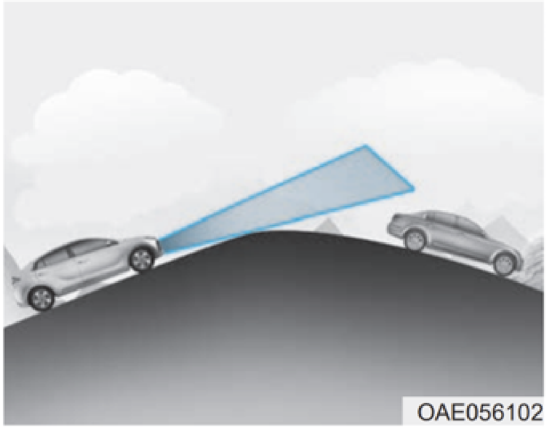


Figure 2.5: On inclines (Hyundai Motor America, 2018)

4. Detecting Vehicles: Certain vehicles in the same lane as the ego vehicle may not be detected by the ACC system's sensors, particularly narrow vehicles like motorcycles, bicycles, or pedestrians. This issue can also occur with vehicles that are offset to one side, slow-moving or suddenly decelerating vehicles, stopped vehicles, or those with small rear profiles, such as trailers without loads. In the Netherlands, where motorcycles are permitted on highways, this limitation could lead to ACC system disengagement, as the sensors may fail to recognize these smaller vehicles.

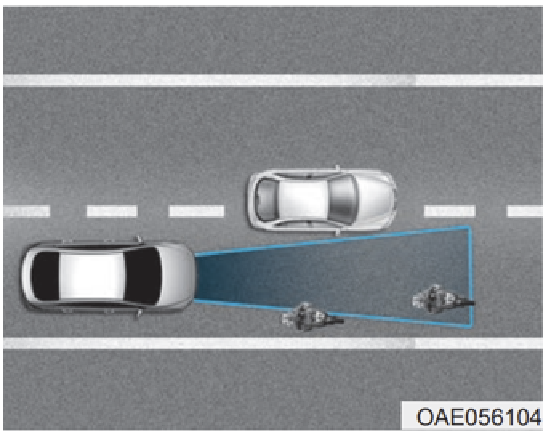
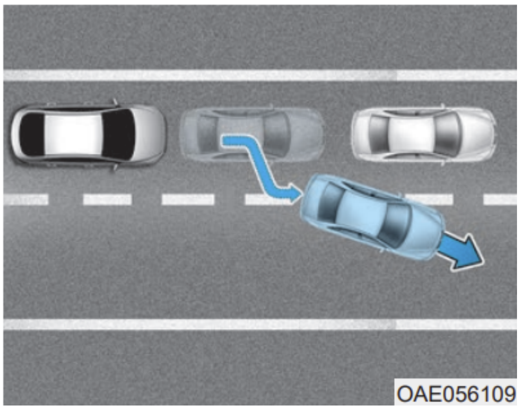
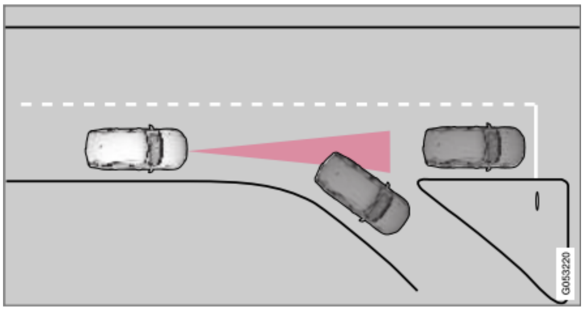


Figure 2.6: Detecting vehicle (Hyundai Motor America, 2018)

5. Changing of the target: When the vehicle directly in front exits the lane, the ACC system may experience a delay in detecting a new leading vehicle. It is essential for the driver to maintain a safe following distance and manually apply brakes if necessary to ensure safety.



(a) Change of the target
(Hyundai Motor America, 2018)



(b) Change of the target (Volvo, 2018)

Figure 2.7: Changing of target

6. The accelerator pedal is continuously depressed for more than one minute. If the driver continuously depresses the accelerator pedal for an extended period (e.g., over one minute), the ACC system might disengage. This is because the system interprets prolonged manual control of acceleration as the driver's intent to override the automation. Continuous engagement of the accelerator effectively signals to the ACC system that manual intervention is desired, prompting a transition to manual driving.
7. The ACC cannot detect the stationary obstacles. The limitations of ACC sensors often result in the system being unable to detect stationary objects, such as parked or stationary vehicles. Most ACC systems are designed to track moving objects and adjust the speed accordingly. Stationary objects may not be detected, especially if they are outside the ACCs expected operational context, such as when the vehicle is moving at highway speeds.
8. Front-collision warning (FCW) is activated. In situations where the front-collision warning (FCW) system is triggered, the ACC system may disengage. The FCW system is designed to alert the driver of an imminent collision by providing visual and/or auditory warnings. When activated, the system typically assumes that the driver needs to take immediate control of the vehicle, as the ACC system may not be able to handle emergency braking scenarios effectively on its own. This action prompts the driver to intervene and manually steer or brake to avoid an accident.
9. The vehicle has been stopped for a certain time period (3 or 5 minutes) after the vehicle is braked to a full stop by the ACC system. ACC systems often include a time limit for how long they can keep the vehicle stopped. If the vehicle remains stationary for an extended periodtypically 3 to 5 minutes after being brought to a halt by the ACC systemthe system will automatically disengage. This safety measure ensures that the driver is still attentive and that the vehicle does not remain under automated control indefinitely in traffic situations, where prolonged inactivity could occur. The driver must reengage the ACC system or take manual control after such a prolonged stop.
10. Electronic stable control (ESC) is activated. ESC systems are designed to prevent loss of vehicle control in situations such as skidding or oversteering. If the ESC system is activatedindicating that the vehicle is losing stability due to road conditions like wet or icy surfaces, or sudden maneuversthe ACC system may disengage. This is because ESC activation suggests that the vehicle is in a critical situation where full driver control is necessary to navigate safely. The ACC system may be unable to appropriately respond to these sudden changes in vehicle dynamics, thus necessitating driver intervention.

11. Autonomous emergency braking (AEB) is activated. AEB systems are intended to automatically apply the brakes when a collision is imminent, and the driver has not reacted in time. When AEB is activated, the ACC system will typically disengage. The situation is considered too critical for the ACC to handle alone, so the autonomous emergency braking system takes over. The driver must then manually regain control after the AEB system has finished braking.
12. When braking manually/ When the driver depresses the brake pedal. If the driver manually depresses the brake pedal while the ACC system is active, the system will disengage. This action signals that the driver intends to take over control of the vehicle's deceleration. The ACC system interprets this input as an override and hands control back to the driver to ensure safety, especially in situations where the driver may be reacting to something the ACC system did not account for.
13. When driving under bad weather conditions, such as foggy, heavy rain, or snow, which might influence the functionality of the cameras and the sensors. In adverse weather conditions such as fog, heavy rain, or snow, the cameras and sensors that ACC systems rely on can become impaired. These systems depend on clear visibility and sensor accuracy to detect other vehicles, road markings, and obstacles. When weather conditions reduce sensor efficacy, the ACC system may disengage because it cannot reliably maintain a safe distance or speed. This requires the driver to manually control the vehicle until conditions improve.
14. When the sensors cannot detect lane marks. Lane detection is a critical component of many ACC systems, particularly those with lane-keeping or lane-centering features. If the sensors fail to detect lane markingsdue to faded lines, poor road conditions, or obstructionsthe ACC system may disengage because it can no longer ensure that the vehicle will stay safely within its lane. This limitation means that on roads with poor or missing lane markings, drivers must remain especially vigilant and prepared to take over control.

2.7. Conclusion

In summary, the literature on ACC systems reveals the current progress in the impact on traffic flow efficiency and safety for both ACC systems themselves and the transition control between ACC systems and human drivers. Studies have indicated the importance of transition control mechanisms, particularly during the switch between automated and manual driving, as a critical factor influencing traffic dynamics. Existing research has identified that while ACC systems contribute to smoother traffic flow and reduce the risk of accidents under more controlled environments, such as highways, their effectiveness is often constrained by operational limitations, especially during transition control phases and the interaction with human drivers. Despite the progress, gaps remain in understanding the variability in the ACC systems and the transition control mechanisms across different automotive brands and their corresponding impact on traffic safety and efficiency since the existing research tends to focus on one or two ACC models, neglecting the broader implications of diverse vehicle types operating simultaneously on the road. In addition, there is a lack of comprehensive analysis of how different ACC systems handle disengagements, particularly in complex traffic environments like highway merging sections.

The indicators identified in section 2.4 for evaluating traffic flow efficiency and safety are applied in this research for the subsequent analysis. In addition, the general ODD described in section 2.6 is utilized to enhance the transition control model in this research.

3
Methodology

This chapter presents the research methodology, divided into two main sections. section 3.1 outlines the research framework, while the first part focuses on data collection and processing, which aims to identify the differences and precise parameter values in ACC systems and transition control mechanisms, as described in section 3.2. The following section, 3.3, explains how these findings are used as inputs for simulations in VISSIM, with the simulation setup detailed in section 3.4. The simulations utilize both external ACC and transition control models. Finally, the indicators selected for performance assessment are explained in section 3.5.

3.1. Research framework

Figure 3.1 illustrates the framework of this research. The core method involves data processing and running simulations in VISSIM. Before conducting these simulations, several preparatory steps are taken to configure the simulation settings to achieve the research objectives. The first step is the analysis of two databases, the OpenACC database and the SAE L2 database, which contain output data from field experiments with different commercial brands and vehicles. This analysis, detailed in Chapter 4, provides the necessary input parameters for the ACC vehicles within the simulation, allowing them to represent vehicle dynamics more realistic. Once the input parameters are defined, the simulation is run according to the settings described in Section 3.4. The VISSIM simulation results are then analyzed using vehicle trajectory data and predefined indicators that evaluate traffic efficiency and safety. These indicators are discussed in Section 2.4.

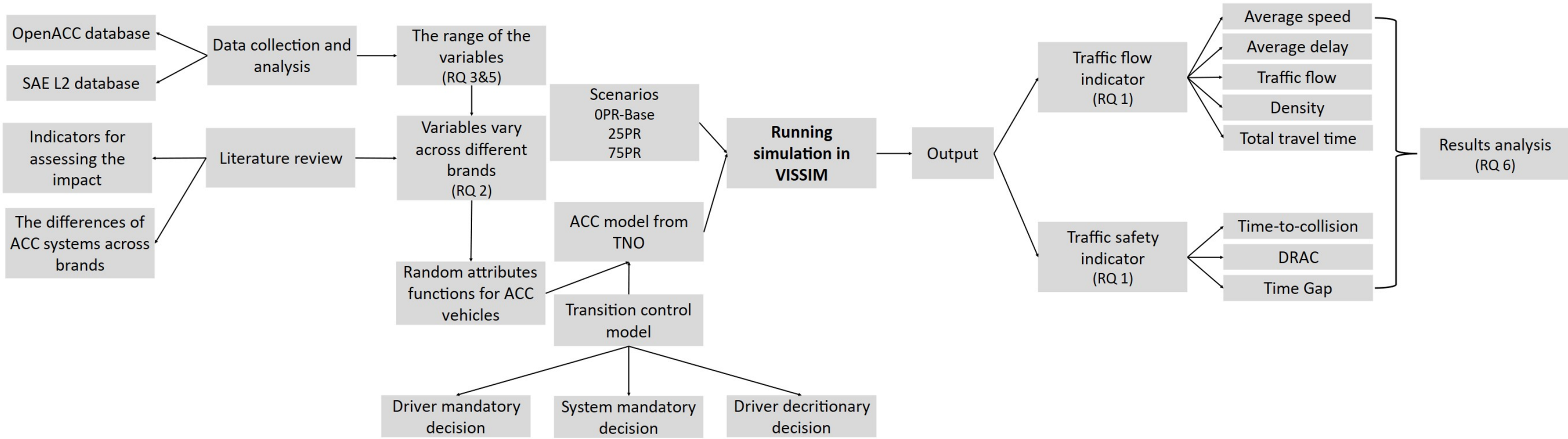


Figure 3.1: Research Framework

3.2. Data Process

Two empirical databases are used for the data process. The first one is the OpenACC database, which is an open source from European Commission, Joint Research Centre (2020). There are four campaigns from the OpenACC database. Two of the tests were conducted on public roads during non-peak hours to minimize interference from other road users, while the other two took place in controlled test environments. These experiments were designed to evaluate the performance of various ACC systems from different experimental designs. The other one is the SAE L2 database from TNO. There are two types of outputs expected from the data analysis. The first one is the transition control-related data, and the second one is the differences in characteristics of ACC systems.

The transition control moment

The transition control is identified by a parameter known as "driver" in the OpenACC database or "acc_state_enum" in the SAE L2 database, which differs from the preceding time step. Therefore, transition control can be classified into two categories: human to ACC and ACC to human. Based solely on the numeric data, whether the transition control from ACC to human is AIDC or DIDC cannot be judged. In the following context, the distribution is based on the transition control from ACC to human since this research would like to discuss the characteristics of the different ACC systems. During some cases, especially stop-and-go scenarios, the time gap values are extremely large because of the very low-speed values, so these data will also be filtered out as they do not represent the actual time gap setting. The data is filtered as the following steps:

1. Finding the two rows with different values in column "driver" or "acc_state_enum." Each pair is seen as a transition control moment.
2. Keeping the first rows, representing the moment just before a transition control.
3. Filtering the speed value is larger than 2 m/s, and the time gap value is between 0 and 5 seconds.
4. Filtering by the column value of "ACC" or "ACTIVE" means there will be a transition control from ACC to Human.
5. Extracting the data for further analysis.

After filtering the data, the time gap and Time-to-Collision (TTC) were analyzed to determine whether transition controls could be the decision based on safety concerns, considering the drivers' perspective. If deemed relevant, the resulting time gap or TTC distributions could be modeled and incorporated into the simulation.

The characteristics of different ACC systems

Since the OpenACC database comprises a series of campaigns with varied experimental designs aimed at testing the performance of ACC systems, the characteristics of these systems are collected from each campaign based on the objectives and information requirements. In addition, it is important to note that the OpenACC database does not include information on acceleration values or time gaps. Therefore, these two variables were calculated based on the other recorded information. Eq. 3.1 is the formula for calculating acceleration based on the speed difference. $a_i(t)$ means the acceleration value of vehicle i at time t. The data is recorded at 10Hz, so the time difference is 0.1 seconds to get the acceleration values for each step except the first time step. Eq. 3.2 represents how the time gap is calculated. Because no inter-vehicle space (IVS) is recorded for the first vehicle, d_i means the inter-vehicle space between vehicle i and vehicle $i+1$. For example, d_1 refers to the inter-vehicle space between vehicle 1 and vehicle 2. The time gap is defined as the time difference between the rear of a vehicle and the front of its follower (Loulizi et al., 2019) and $\tau_i(t)$ means the time gap value of vehicle i at time t. Both acceleration and time gap are calculated based on the vehicle speed v, measured in meters per second.

$$a_i(t) = \frac{v_i(t) - v_i(t-1)}{\Delta t} \tag{3.1}$$

$$\tau_i(t) = \frac{d_i(t)}{v_{i+1}(t)} \tag{3.2}$$

Table 3.1 summarizes the different characteristics of ACC systems recorded in the OpenACC database. Each characteristic has been sourced from various campaigns, designed to evaluate particular aspects of ACC performance. The table lists these characteristics along with the respective campaigns or sources from which the data was collected.

Table 3.1: ACC characteristics and the data sources

ACC Characteristics	Source
Full speed range	1. Owners Manuals
Acceleration capabilities	1. Campaign Zalazone 2. Campaign Cherasco 3. Campaign Viclungo
Inter-vehicle space	1. Campaign Zalazone 2. Campaign Cherasco 3. Campaign Viclungo
Time gap	1. Campaign Zalazone 2. Campaign Cherasco 3. Campaign Viclungo
Response time	1. Campaign AstaZero
Standstill distance	1. Campaign AstaZero
String stability	1. Campaign AstaZero 2. Campaign Zalazone

3.3. Traffic Simulator - VISSIM

In this research, simulations are conducted using VISSIM, a leading traffic simulation software tool renowned for its microscopic-scale traffic pattern reproduction. VISSIM operates as a behavior-based, multi-purpose traffic flow simulator, accurately recalculating the position of each vehicle every 0.1 to 1 second using several mathematical models, which can be set, ensuring high precision in simulation results (Fellendorf and Vortisch, 2010). This research is conducted in collaboration with the TNO SUMS department, which integrates the ACC model into VISSIM to enhance its simulation capabilities. This includes the implementation of the transition control model, which will be explained in detail in the following subsections. For human-driven vehicles, VISSIM applies the psycho-physical perception model developed by Wiedemann (1974) (PTV Group, 2024). This model is based on the concept that a driver of a faster-moving vehicle begins to decelerate upon reaching their perception threshold relative to a slower-moving vehicle. Due to the inability to accurately gauge the slower vehicle's speed, the faster vehicle's speed decreases below that of the slower vehicle until the driver reaches another perception threshold and begins to accelerate slightly. This results in a pattern of slight, steady acceleration and deceleration. The model accounts for varying driver behaviors through distribution functions of speed and distance behavior (PTV Group, 2024).

3.3.1. Models utilized in VISSIM

This research aims to investigate the impact of transition control in ACC systems within mixed traffic conditions. In real-world traffic, the market penetration rates (MPRs) of ACC-equipped vehicles are not yet fully widespread, meaning that human-driven vehicles still dominate the roads alongside ACC vehicles. Therefore, it is important to simulate mixed traffic conditions where both human-driven vehicles and ACC-equipped vehicles coexist, reflecting the current reality of traffic systems.

The following subsections discuss the models used in VISSIM. The human driving behavior is modeled using Wiedemanns 99 car-following model, which is built into VISSIM. In contrast, the ACC and transition control models are not native to VISSIM and are implemented as external driver models via VISSIM's "External Driver Model DLL Interface." According to PTV Planung Transport Verkehr AG (2022), this interface allows users to replace the default driving behavior in VISSIM with custom, user-defined behavior for some or all vehicles during a simulation. During the simulation, VISSIM communicates with the external model by calling the DLL code for each relevant vehicle at every simulation time step. VISSIM provides the current state of the vehicle and its surroundings to the DLL, which then calculates the vehicle's longitudinal dynamics, such as acceleration and deceleration, as well as any lane-changing maneuvers. The DLL then sends these computed values back to VISSIM to be applied in the current time step. In addition, to activate the external driver model for a specific vehicle type, users can navigate to the Vehicle Type dialog box, select the External Driver Model tab, and check the Use external driver model option. From there, a driver model DLL file and an optional parameter file can be chosen. Once enabled, the selected DLL calculates the driving behavior of all vehicles of that type (PTV Planung Transport Verkehr AG, 2022). In this research, the external driver model is applied to ACC vehicles only, while human-driven vehicles use VISSIM's built-in model.

Furthermore, since ACC systems mainly do longitudinal control, the velocity and acceleration discussed

here are exclusive to longitudinal dynamics. Lateral dynamics are outside the scope of this research. The following subsections outline the process of generating ACC vehicles within the VISSIM simulation environment. The first step explains how vehicles are generated with varying parameters. This is followed by the explanation of the ACC model and the transition control model applied to the generated vehicles.
For the lane-change model, VISSIM distinguishes between two types of lane changes: necessary and free. Necessary lane changes are triggered by vehicle routes, dynamic path assignments, or the COM interface, with the deceleration depending on the emergency stop distance. Free lane changes occur when more space is available or when maintaining a desired speed, ensuring that safety distances are respected between vehicles. A default lane change takes 3 seconds, and while "aggressiveness" cannot be altered, the safety distance can be adjusted in the car-following model parameters. Both lane change types must respect the minimum clearance. For overtaking, vehicles consider their maximum speed and lane change behavior, preventing heavy goods vehicles (HGVs) from overtaking on gradients where they cannot reach their desired speed.

Human Driving Model - Wiedemann 99

In this research, Wiedemanns 1999 car-following model was used to represent human driving behavior. This model is widely implemented in microscopic traffic simulations to simulate individual vehicle interactions. It relies on psychological zones and stochastic parameters to define how a vehicle reacts to the vehicle ahead, focusing on speed, distance, and acceleration (PTV Group, 2024). The model triggers acceleration or deceleration based on the current distance, speed difference, and predefined perception thresholds and the following formulas are from Leutzbach and Wiedemann (1986).

The model calculates the speed difference between the subject vehicle and the lead vehicle, given by:

$$\Delta v = v_s - v_l$$

where v_s is the speed of the subject vehicle, and v_l is the speed of the lead vehicle. When this difference exceeds certain thresholds, the subject vehicle either accelerates or decelerates to maintain a safe following distance.

The desired safety distance between vehicles, which increases with the vehicle's speed, can be expressed as:

$$d_s = a \cdot v + b$$

where d_s is the desired distance v is the current speed of the subject vehicle, and a and b are driver-specific parameters.

The model also includes the time gap, τ_{human}, which is the time gap that the following vehicle maintains relative to the lead vehicle. The time gap is calculated as:

$$\tau_{human} = \frac{d}{v}$$

where d is the distance between the two vehicles and v is the speed of the following vehicle. Drivers adjust their speed to maintain this time headway, depending on the current traffic conditions.

The acceleration a is determined by the speed difference (Δv) and the distance gap (d) between the following vehicle and the lead vehicle. The model is designed to mimic human behavior by using thresholds to transition between driving modes, such as free driving, closing in, and following. The acceleration can be generalized as a function of these parameters:

$$a = f(\Delta v, d)$$

where Δv is the speed difference between the subject vehicle (v_s) and the lead vehicle (v_l), and d is the distance between the two vehicles. The exact relationship is governed by stochastic parameters and psychological zones within the model. Depending on the scenario, the vehicle accelerates, decelerates, or maintains a constant speed to keep a safe following distance.

Vehicle Generation Process

Figure 3.2 illustrates the vehicle generation process in the external driver model to VISSIM. The green and italics text means that it is a function, and the red and bold text means it is a variable. This process represents the ACC vehicles generated to the network during the simulation. This example focuses on the 'SL' scenarios. For scenarios involving either small or large distance settings, the condition that governs the variable x, which determines the applied distance setting, is adjusted accordingly. For example, in the small distance setting scenario, if $x \leq 100$, the small distance setting is applied. Conversely, in the large distance setting scenario, the condition becomes $x \leq 0$. Since this condition will never be met, the large distance setting will always be applied in this case.

Figure 3.2: ACC vehicle generation process in VISSIM

ACC Controller Model - TNO

The ACC controller model used in this research was developed by TNO and was originally designed for a Tier 1 supplier, and is therefore confidential. It has been simplified and adapted for use in a micro-simulation model. Detailed specifications are not included in this thesis. The following description is a summary of the adapted version of the original algorithm as implemented into VISSIM.

The basic operating principle is that the controllers simultaneously calculate the desired acceleration of the vehicle. The model contains three main functions and several auxiliary ones. The main functions are Cruise Control (CC), Adaptive Cruise Control (ACC), and Gap Closing (GC). These three functions serve as "control laws" or algorithms, with only one being active at a time to manage the vehicle. Therefore, they can be considered distinct 'driving modes.' When no object is detected within 120 meters in front of the ego vehicle, the CC mode is activated, which maintains a desired user-set speed. Once an object (another vehicle) enters the specified range in front of the ego vehicle, the ACC mode engages, maintaining a desired user-set time headway toward that object. The GC algorithm was designed to close the gap between the ego vehicle and a new predecessor smoothly, with less emphasis on minimizing fluctuations in headway. In situations where headway changes rapidly due to traffic conditions, such as during merging maneuvers of other vehicles, the GC algorithm is primarily employed to smoothly close the gap with the new predecessor in a way that enhances driving comfort. The key inputs to the ACC controller are ego vehicle information, such as speed, and object information of the most important object in front, such as relative distance, speed, and acceleration. The output of ACC is a desired acceleration. To be noted, there is no setting related to the response time, so the string stability is not captured in this model. Figure 3.3 illustrates the dynamic behavior of ACC controllers among different modes.

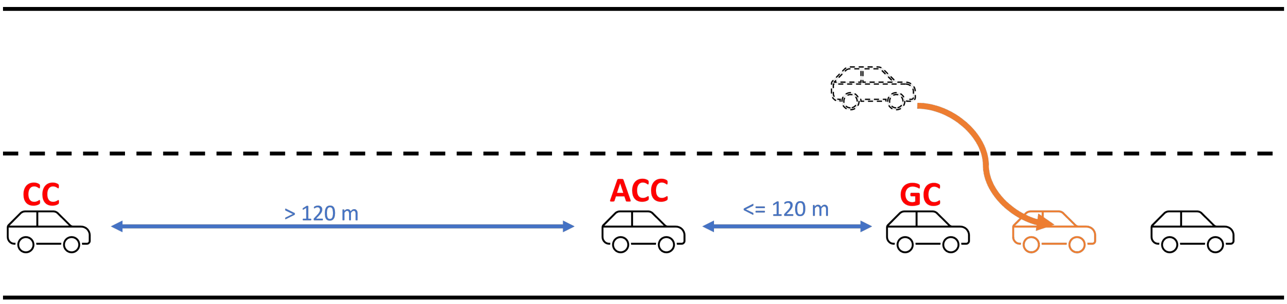


Figure 3.3: Dynamic ACC modes

The formulas for calculating the acceleration are as follows:

- CC

$$a_{CC}(t) = k_v \cdot (v_{set} - v_x) \quad \text{if } d_x > 120 \tag{3.3}$$

  - $a_{CC}(t)$ is the acceleration in cruise control mode at time t [m/s^2].
  - K_v is the speed gain in the CC controller [s^{-1}].
  - $v_{desired}$ is the desired setspeed of the vehicle. (The setting of the desired setspeed is explained in section 3.4.7.)
  - $v_x(t)$ is the current speed of the vehicle [m/s].
  - d_x is the distance to the object ahead [m].

- ACC

$$a_{ACC}(t) = K_{ACC} \times (K_{dx}(d_x - d_{x_{max}}) + K_{dv} \times \Delta v(t)) + K_{ACC_{ff}} \times a_{object} \tag{3.4}$$

where:
  - $a_{ACC}(t)$ is the acceleration in ACC mode at time t [m/s^2].
  - K_{ACC} is the overall gain of the ACC controller [-].
  - K_{dx} is the gain on distance error in the ACC controller [s^{-1}].
  - d_x is the inter-vehicle space between the ego vehicle and the object vehicle [m].
  - $d_{x_{max}}$ is the required maximum distance headway for the calculation of cruising setpoint [m].
  - K_{dv} is the gain on speed error in the ACC controller [s^{-1}].
  - $\Delta v(t)$ is the speed difference between the ego vehicle and the object vehicle at time t [m/s].
  - $K_{ACC_{ff}}$ is the gain on the feedforward [-].
  - a_{obect} is the acceleration of the object vehicle [m/s^2].
- GC

$$a_{GC}(t) = -K_{p,GC} \cdot (\Delta v(t) - v_{threshold}) \tag{3.5}$$

where:
  - $a_{GC}(t)$ is the acceleration in GC mode at time t [m/s^2].
  - $K_{p,GC}$ is the gain for gap closing control [s^{-1}].
  - $\Delta v(t)$ is the speed difference between the ego vehicle and the object vehicle at time t [m/s].
  - $v_{threshold}$ is the approach velocity threshold [m/s].

All acceleration formulas are subject to the inherent limitations of ACC vehicles. Once the driving mode is determined and the corresponding acceleration values are calculated, the final acceleration value, denoted as $a_{following}$, is constrained by the vehicle's performance limits. If $a_{following}$ is less than the minimum allowed acceleration (a_{min}), the final executed acceleration return to VISSIM, $a_{executed}$, is set to a_{min}. Conversely, if $a_{following}$ exceeds the maximum allowed acceleration (a_{Max}), the final acceleration returned to VISSIM, $a_{executed}$, is restricted to a_{Max}.

$$a_{min} \leq a_{excuted}(t) \leq a_{Max} \tag{3.6}$$

where:

- a_{min}: Minimum allowed acceleration (deceleration or braking limit) [m/s^2].
- a_{Max}: Maximum allowed acceleration [m/s^2].

Transition Control Model - TNO

Figure 3.4 shows the logic of the transition control model in the external driver model. The original structure of the model is developed by, with original contributions from D. Altgassen et al. This document is also not publicly accessible. The model's final decision results in one of four outcomes: DIDC, DIAC, AIDC, or no transition. These four outcomes are represented as boolean variables, and all are initially set to $False$. If the respective conditions are met, the corresponding variable will be set to $True$. The decision process consists of three layers. The first layer is the system's mandatory decision, which can also be understood as the conditions of ODD. Forward Collision Warning (FCW), as defined by Kiefer (2000), uses a logistic (sigmoid) function to calculate a final probability p. If this probability p is greater or equal than the threshold of 0.75, which is suggested by Kiefer, the FCW is triggered and set to $True$. The outcome of this layer determines whether an AIDC will occur. The second layer involves the driver's decisions, which are divided into two categories: mandatory and discretionary. The mandatory decisions include actions such as lane changes or responding to slower vehicles ahead, which are essential for the driver to execute. For instance, if the driver intends to exit the highway, they must change to the rightmost lane to leave the highway. Discretionary decisions, on the other hand, involve the driver choosing to activate the ACC system with a 50% probability.

Finally, the third layer is the final decision layer. In this layer, the priorities are ranked: DIDC takes the highest priority, followed by AIDC, and then DIAC. If none of the transition control conditions are met, the outcome will be no transition control.

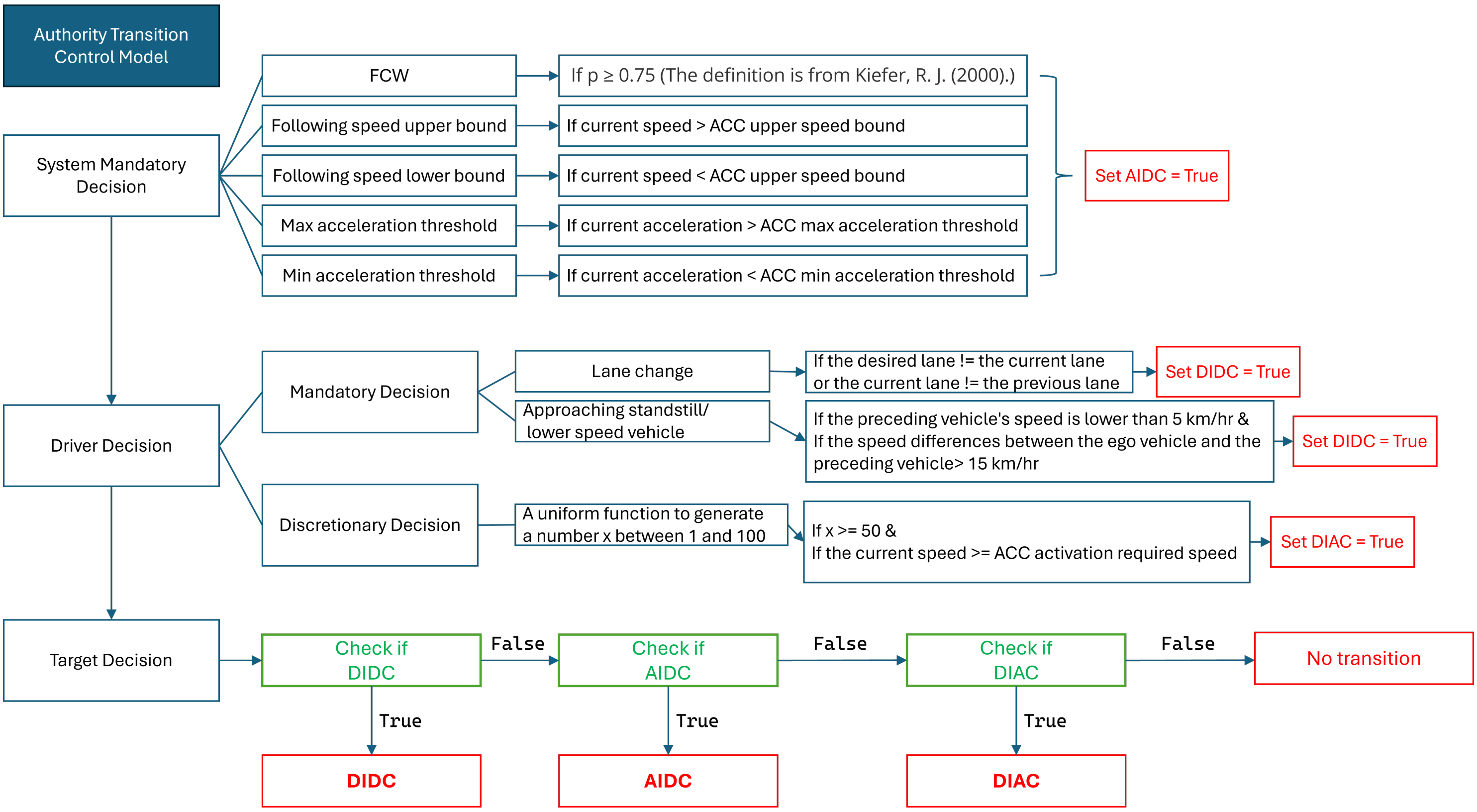


Figure 3.4: Transition control model logic (a modified version based on D. Altgassen et al. 2023)

3.4. Simulation Setup

This section is about the simulation setup in VISSIM. Guidance is provided on the set up of the VISSIM simulation environment and selecting appropriate parameters. By the end of this section, the setup framework is outlined, providing a comprehensive understanding of the simulation setup required to achieve the research objectives.

The objective of the simulation is to investigate the impacts of the transition control of different ACC systems on traffic flow and integrate different vehicle brands' characteristics. The simulation introduces the vehicles equipped with ACC systems from different brands with their MRPs. According to the Dutch government, the A13 highway, as shown in Figure 3.6, in the Netherlands is one of the busiest highways in the Netherlands (Statistics Netherlands, 2014; Rijkswaterstaat, 2024). Therefore, it is chosen as the simulation network. The corridor is 17 km long with 5 on-ramps and 6 off-ramps from the Hauge to Rotterdam. In the opposite direction, from Rotterdam to The Hague, there are 9 on-ramps and 6 off-ramps. It is a dual-carriageway with three lanes in each direction. For this research, the simulation focuses on the section of the A13 highway with the direction from The Hague to Rotterdam.

Figure 3.5 provides a schematic drawing of the highway infrastructure along the A13, starting from Den Haag and extending to the first exit in Rijswijk. This diagram is presented to visualize how traffic merges onto and exits the highway, as these areas often involve changes in the number of lanes (e.g., lane additions and lane drops). Along the A13 highway, the roadway typically consists of three lanes but expands to four lanes near on-ramps and off-ramps to accommodate merging and exiting traffic. In this diagram, 'O1' and 'O3' are entry points onto the freeway, matching the locations shown in Figure 3.6. The exit points are labeled 'D1' and 'D0', where 'D1' corresponds to the same exit depicted in Figure 3.6, and 'D0' represents exits for other segments of the highway, not a specific existing in the figure. Because the merging maneuvers are significant in traffic flow, the anticipated network design will incorporate segments for on-ramp and off-ramp traffic (labeled as D1 and D0, respectively). Simultaneously, the network maintains vehicles' input and output at the highway's original points (labeled as O1 and D1), ensuring a comprehensive representation of vehicular movement and interactions. The simulation is designed to run from 7 AM to 10 AM, spanning both the morning peak and off-peak hours. This time frame will facilitate an examination of free-flowing traffic conditions as well as congestion recovery strategies. The research will then analyze the impact on high-density and low-density traffic flow, providing a comprehensive understanding of various traffic dynamics. D4 and O6 are the entrance and exit for the highway rest area.

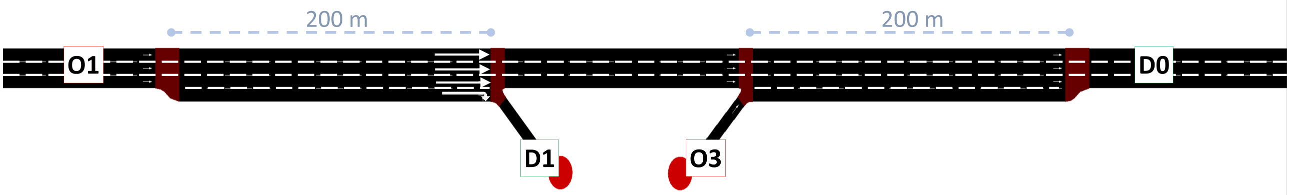


Figure 3.5: A13 Schematic Diagram

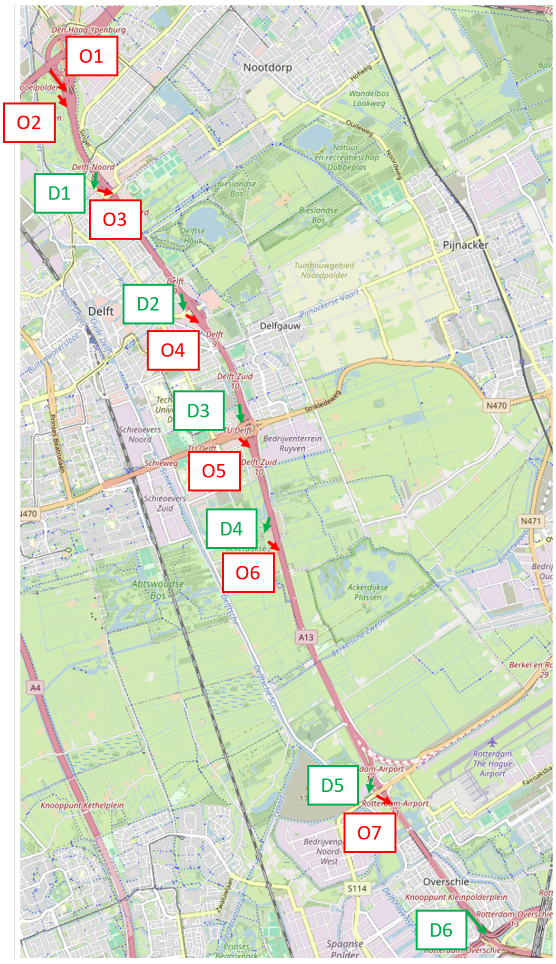


Figure 3.6: A13 Highway (based on OpenStreetMap contributors (Accessed: 2024))

Table 3.2: The location of the highway in kilometers

Origin/ Exit	Location along the highway
O1	0
D1	6
D2	7.5
D3	9.6
D4	11.6
D5	15.0
D6	17.8

Table 3.3 presents the configurations for a series of traffic flow simulation scenarios executed using VISSIM. The focus is on varying vehicle dynamics and traffic conditions. The table details each parameter, including brief reasons for and comments on each configuration. In the following part, a comprehensive breakdown and explanation of each variable and the corresponding values are provided.

Table 3.3: Simulation Setup

Simulation seed for each scenario	10		
Simulation variables	Level description	Level values	Reason/ Comment
ACC MPRs (%)	-	0	All HDV model (human-driven vehicles) **Base Scenario**
	-	25	Low ACC MPRs
	-	50	Medium ACC MPRs
	-	75	High ACC MPRs
Vehicles involved The corresponding distance setting	All	- S: 50% L: 50%	Build the distributions for each attribute of the ACC and utilize these distributions as input. Each vehicle will then be randomly assigned a value from its respective distribution. The brands of the vehicles will remain anonymous.
		All small distance setting S: 100% L: 0%	The short time gap might negatively impact the weaving section as there will be less space for vehicles from on-ramps to merge into the main traffic flow.
		All large distance setting S: 0% L: 100%	The large time gap might influence the capacity of the road, and in contrast to the small distance setting, there might be more space for the vehicles to make the lane changes.
		Min speed is not zero S: 50% L: 50%	Vehicles that cannot follow the full-speed range will deactivate when their velocity is below certain thresholds. It may cause more congested traffic flow if the average travel speed is low or there are many stop-and-go situations.
Truck MPRs (%)	-	6	Fixed value for all scenarios
Total number of scenarios	13		
Total number of simulations	130		

3.4.1. Simulation Seed for Each Scenario

The simulation seed is configured to run each scenario ten times. This repetition accounts for the inherent randomness in vehicle behaviors. Firstly, the heterogeneity of human-driven vehicles is considered, incorporating variations in speed distribution and acceleration behavior to achieve more realistic results. Secondly, the random distribution of vehicle generation, informed by the results from Chapter 4 regarding small and large distance settings, is also considered. Consequently, each scenario is executed ten times to obtain an average with a more comprehensive result.

3.4.2. ACC Market Penetration Rates (MPRs)

The ACC market penetration rates (MPRs) are considered at 0%, 25%, 50%, and 75%. A scenario with 100% ACC vehicles is discarded, as it is relatively unrealistic in real-world conditions in the near future.

3.4.3. Number of Brands and Corresponding Distance Setting Percentages

The vehicles with ACC systems are assigned the values of the characteristics from the results after the data processing of the characteristics of different ACC systems and is shown in Table 4.12 in Chapter 4. In this method, vehicle characteristics are assigned randomly from a distribution, resulting in anonymous vehicles with characteristics derived from various brands. The approach involves creating lists for each characteristic, where the weight of each value's appearance corresponds to its market share. During the simulation, a uniform distribution is used to randomly select a value from each list to assign to the vehicle's characteristics, thereby increasing the heterogeneity of the simulation. For instance, a vehicle might possess the time gap value of a Tesla and the acceleration capabilities of a Hyundai based on distribution data. Although the database contains only 22 models, this method allows for a broader representation of real-world variability by simulating different combinations of vehicle parameters and behaviors. While some of these combinations may not actually exist in the real world, this is considered acceptable because the goal is to capture the vehicle behaviors of different ACC systems rather than strictly adhering to current market offerings. In addition, there are usually four to five levels for the distance setting can be set for the driver. Some vehicles' minimum time gap from the empirical data could be the second-level distance setting, where the first-level distance setting is the minimum one. Figure 3.7 shows an example of the random distribution built from the data analysis, which is used as an input for the simulations.

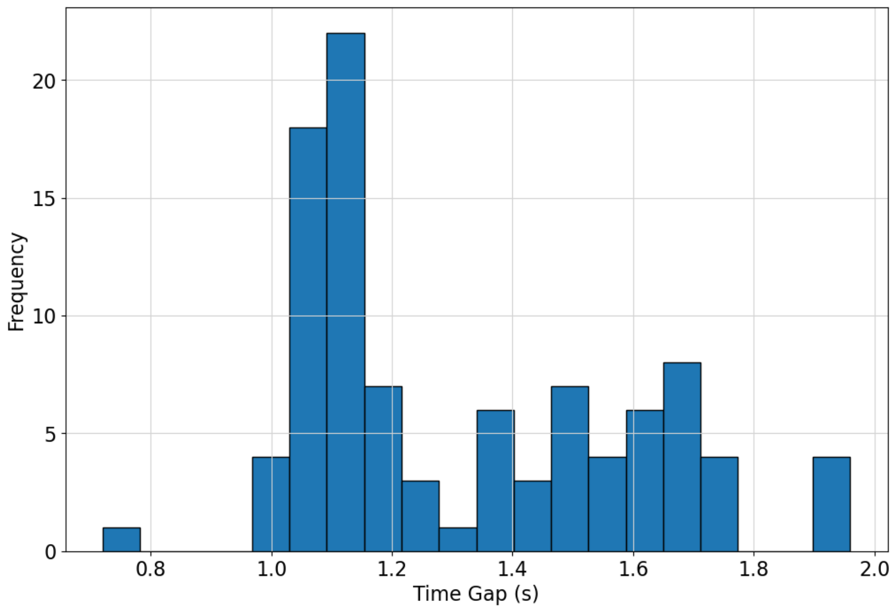


Figure 3.7: Random Distribution for Time Gap - Small Setting

1. All Distance Settings: Includes a mix of distance settings.
2. Small Distance Setting Only: Focuses on scenarios where vehicles only have small distance distances, potentially leading to more challenging lane-change behaviors and increased congestion. The dis-

tance setting is considered a significant factor that might influence transition control. It is assumed that smaller distance settings could complicate lane-change maneuvers, resulting in more congested traffic patterns.

3. Large Distance Setting Only: Considers scenarios where vehicles only use large following distance settings. The large time gap might influence the capacity of the road, and in contrast to the small distance setting, there might be more space for the vehicles to make the lane changes.
4. Min speed is not zero: Vehicles that cannot follow the full-speed range will deactivate when their velocity is below certain thresholds. It may cause more congested traffic flow if the average travel speed is low or there are many stop-and-go situations.

If scenarios are not clearly defined for the distance setting (such as specifying only small distance settings), the distance settings will be equally distributed between small and large settings, which is 50% for each distance setting.

3.4.4. Truck MPRs

The choice of truck MPRs for highway traffic simulation is based on the specific traffic composition observed in the Netherlands. According to Yang et al. (2019), the Netherlands experiences high traffic intensity due to its dense population and significant freight traffic. In this context, freight transportation, primarily by trucks, accounts for 6%. Given this distribution, setting the truck MPRs at 6% can reflect the real-world conditions of Dutch highways. This realistic representation ensures that the simulation outputs are both relevant and reliable for planning and analysis purposes. The value is fixed for every scenario since the trucks are not the main focus of the research.

3.4.5. Human Driver's Take-Over Time

In automated driving research, it is important to take the driver's take-over time (TOT) into account (Vogelpohl et al., 2018; Zhang et al., 2019b). According to Zhang et al. (2019b), the TOT can be defined as the time it takes for drivers to regain control from automated driving following a critical event in the environment or after receiving a take-over request (TOR). In this research, this is not the main research point. There is already research investigating this question. Therefore, the setting of the driver's take-over time used the results from Vogelpohl et al. (2018); Zhang et al. (2019b).

After AIDC

The mean and standard deviation values are chosen based on the findings of Zhang et al. (2019b), which provide a series of scenarios for assessing driver performance. The values of mean and standard deviation for the reaction time are chosen from the results of scenarios where only no visual non-driving tasks (NDT) are involved. The mean value is 2.49, and the standard deviation is 1.12, which can be visualized in Figure 3.8 in log-norm distribution.

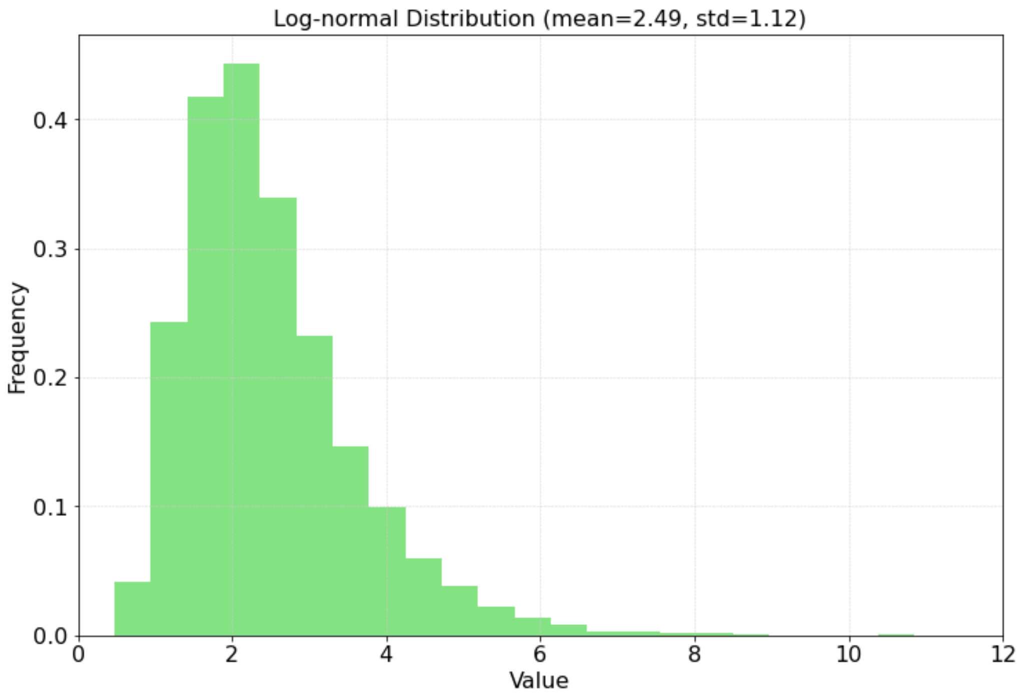


Figure 3.8: Driver's take-over time under visual non-driving task

After DIDC

For the DIDC transition control, it is assumed that the driver initiates the transition control. This means the driver should already be aware of the driving situation and is usually prepared to take over control afterward (Lu and De Winter, 2015). Therefore, the reaction time for it is 0 seconds.

3.4.6. Time Gap of Human Drivers

The dataset from TNO (2022) containing real-world traffic information, which included time gap recordings, was applied to analyze time gap distribution patterns. By calculating the percentiles of the time gap values in this empirical dataset, the cumulative distribution function (CDF) can be plotted. This is one of the input formats for the VISSIM to set the distribution. Therefore, by incorporating these percentile values, the VISSIM simulation was able to represent the traffic dynamic more realistic.

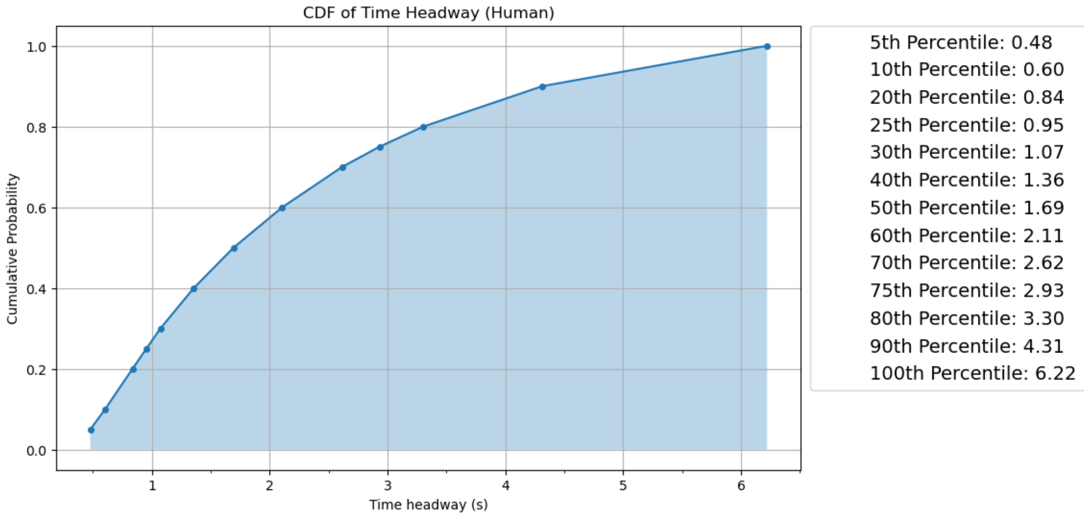
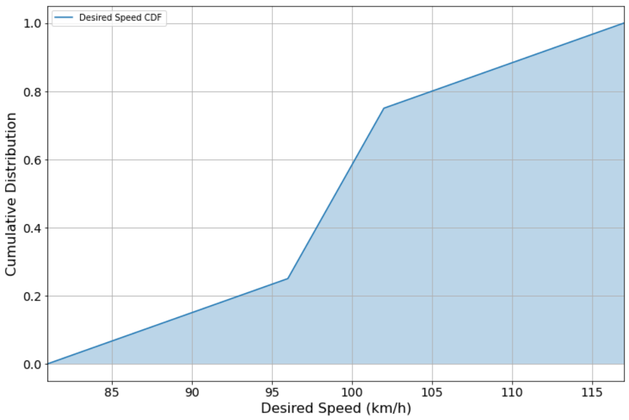


Figure 3.9: Cumulative Distribution Function for Time Gap (TNO, 2022)

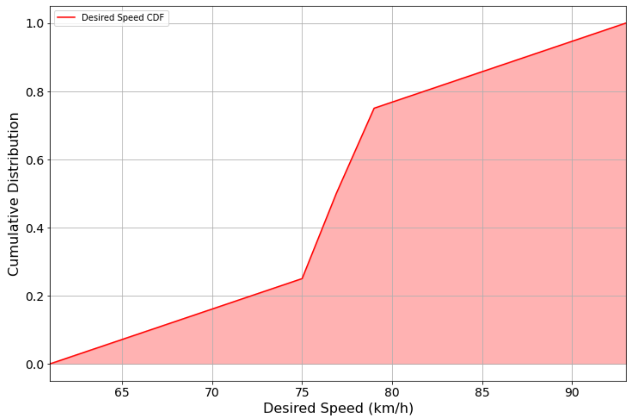
3.4.7. Desired Speed and Setspeed

There are two different speed limits on the network, which are 100 kilometers per hour and 80 kilometers per hour. Therefore, there are two different desired speed distributions. The distributions are based on real-world traffic data from the same network (Nationaal Dataportaal Wegverkeer (NDW), 2022). The speed values are taken from a free-flow situation between 6 AM and 7 AM before any congestion occurs. For the 100 km/h speed limit, the desired speed values are filtered from sections of the road with this limit, and a cumulative distribution is generated for use in VISSIM, as shown in Figure 3.10a. Similarly, for the 80 km/h desired speed, the relevant road sections are filtered, and the speed data is extracted to create a cumulative distribution, illustrated in Figure 3.10b.

In the external driver model described in the previous section, for the CC acceleration formula (3.3), the set speed is a key factor in determining both acceleration and deceleration. The model transfers the driver's desired speed to the set speed parameter within the tactical layer, which is then passed on to the operational layer for execution.



(a) 100 km/hr



(b) 80 km/hr

Figure 3.10: Desired Speed CDF (Nationaal Dataportaal Wegverkeer (NDW), 2022)

3.4.8. Final Scenarios

Table 3.4 shows the final scenarios that will be simulated in this research.

Table 3.4: Simulation Scenario Number

Scenario NO.	Name*	ACC MPRs	Vehicles involved
1 (base)	0PR-Base	0%	All human-driven vehicles
2	25PR-All-SL	25%	All in random distributions
3	25PR-All-S	25%	All in random distributions with small distance setting only
4	25PR-All-L	25%	All in random distributions with large distance setting only
5	25PR-Speed-SL	25%	All vehicles that cannot follow for full speed
6	75PR-All-SL	75%	All in random distributions
7	75PR-All-S	75%	All in random distributions with small distance setting only
8	75PR-All-L	75%	All in random distributions with large distance setting only
9	75PR-Speed-SL	75%	All vehicles that cannot follow for full speed
10	50PR-All-SL	50%	All in random distributions
11	50PR-All-S	50%	All in random distributions with small distance setting only
12	50PR-All-L	50%	All in random distributions with large distance setting only
13	50PR-Speed-SL	50%	All vehicles that cannot follow for full speed

*The principle of the names:

ACC MPRs - the vehicle involved - the distance setting applied

3.5. Indicators Selection

Based on the literature review, the indicators used for the following analysis are as follows: In this research, the following indicators shown in Table 3.5 will be used as indicators to assess traffic efficiency and safety. These indicators are crucial for analyzing the potential congestion and the overall efficiency of traffic flow and inferring the potential for collisions or near-miss events without relying on historical crash data, which is often limited. Some indicators are output directly from VISSIM, such as traffic flow and time-mean speed. These indicators are measured at specific user-defined points, referred to as "Data Collection Measurements." Traffic flow represents the total number of vehicles passing through these points, with the data output provided at one-minute intervals. The time-mean speed is also recorded at these points and reflects the average speed of vehicles during that period.

Table 3.5: Assessment indicators for traffic flow efficiency and safety

Category	**Indicator**	**Formula**
Traffic Flow Efficiency	Traffic flow q	Direct output from VISSIM
	Traffic Density ρ	$\rho = \frac{q}{\text{time-mean speed}}$
	Total Time Spent (TTS)	$TTS = \sum_{i=1}^{n} t_i$ ()
	Time-mean Speed $\bar{v}_{TMS}$	$\bar{v}_{TMS} = \frac{\sum v_i}{n} = \frac{\sum \frac{d}{t_i}}{n}$ (Direct output from VISSIM)
	Average Delay	$\frac{Total \quad delay}{n}$ (Direct output from VISSIM)
Traffic Safety	Time-to-collision (TTC)	$TTC_{i,t} = \frac{IVS_{i,t}}{v_{i,t} - v_{i-1,t}} \qquad if \quad v_{i,t} > v_{i-1,t}$
	Deceleration rate to avoid the crash (DRAC)	$DRAC_{i,t+1} = \frac{(V_{i,t} - V_{i-1,t})^2}{(V_{i-1,t} - V_{i,t}) - L_{i-1,t}}$
	Time Gap (TG)	$TG = \frac{IVS_i}{V_{i+1}}$ (Direct output from VISSIM)

4
Data Analysis

This chapter provides an overview of the databases used in this research. Two databases are utilized: the OpenACC database and the SAE L2 database. Both contain empirical data from ACC tests across various vehicle brands, which are described in detail in section 4.1. The general ODDs and their integration with the model are discussed in section 4.2. Furthermore, the results of the data analysis are presented in section 4.3 for transition control-related data and in section 4.4 for ACC characteristics. Finally, a summary table presents the distinct characteristics of each vehicle model and brand from the databases in section 4.6.1. This table is a key input for configuring the ACC settings in the simulation.

4.1. Database

4.1.1. OpenACC Database

The OpenACC database is from a series of car-following experiments involving vehicles with ACC systems. The objective of the OpenACC Database is to provide data about ACC behavior to the scientific community to understand better the properties of ACC vehicles and how their widespread use may influence traffic dynamics to anticipate possible related problems. It is an open-access database of car-following experiments involving 28 vehicles, 22 equipped with state-of-the-art commercial ACC systems, as shown in figure 4.1. Experiments were carried out in the framework of four test campaigns. The campaigns have been designed to study, among others, vehicle dynamics in real-world conditions, the behavior of ACC systems, and car-following patterns (Makridis et al., 2021). Table 4.1 represents the standard variables collected from the experiments.

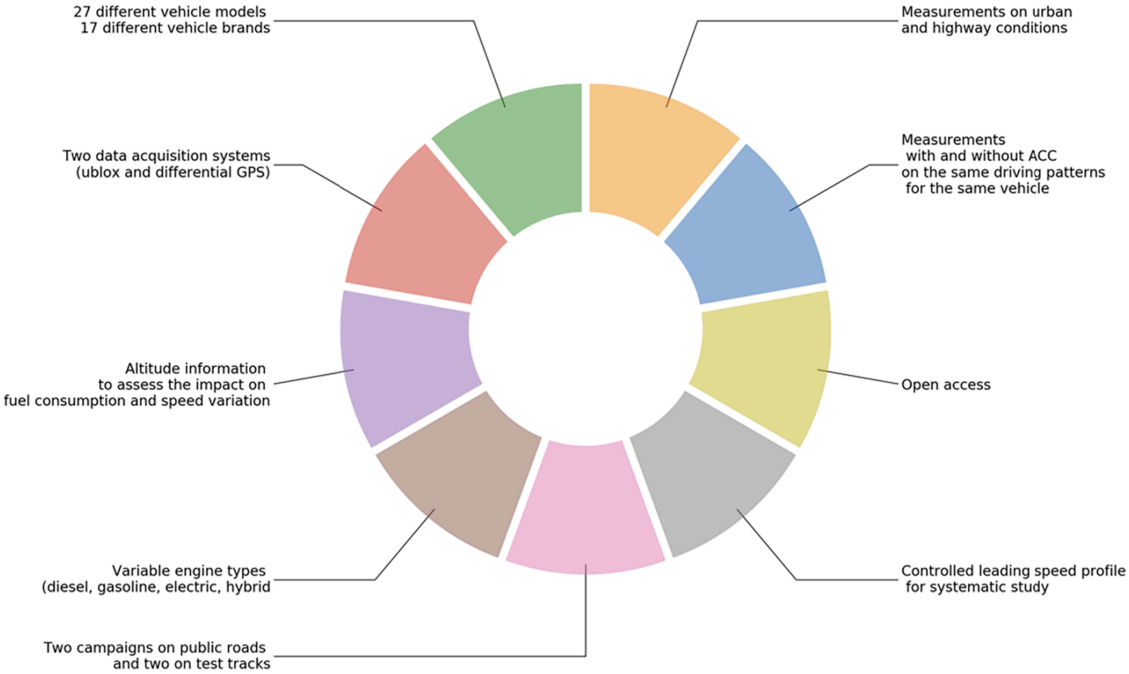


Figure 4.1: The overview of OpenACC database (Makridis et al., 2021)

Table 4.1: Variables in OpenACC Database

Variable	Description
Time	Common time frame for all vehicles (s)
Speed	Raw Speed (Doppler) (m/s)
Lat	Latitude (rad)
Lon	Longitude (rad)
Alt	Altitude (m)
E	East (x) coordinate in the local ENU plane (common center for all vehicles) (m)
N	North (y) coordinate in the local ENU plane (common center for all vehicles) (m)
U	Up (z) coordinate in the local ENU plane (common center for all vehicles)
VE	Speed in the East direction of the local ENU plane (m/s)
VN	Speed in the North direction of the local ENU plane (m/s)
VU	Speed in the Up direction of the local ENU plane (m/s)
IVS	Inter-Vehicle Spacing computed from GNSS data after bumper-to-bumper correction (m)
Driver	The driver of the vehicle: 'Human' for manual driving, 'ACC' for ACC driving

The following subsections are the short introductions of each campaign included in the database, and the information is based on (Makridis et al., 2021).

Cherasco

This campaign was conducted in the last quarter of 2018 and involves two days of car-following testing, either with two or three vehicles in car-platoon formation on the public freeway roads from Ispra(VA) to Cherasco (CO) in northern Italy. The tests were scheduled for non-peak hours to minimize the disturbances from other road users. The leader was instructed to drive manually and perform occasional random deceleration and accelerations over a desired speed in a realistic way. The followers, whenever possible, were driving with ACC on, apart from a day when manual driving situations were tested.

Figure 4.2: The layout of Cherasco campaign (Makridis et al., 2021)

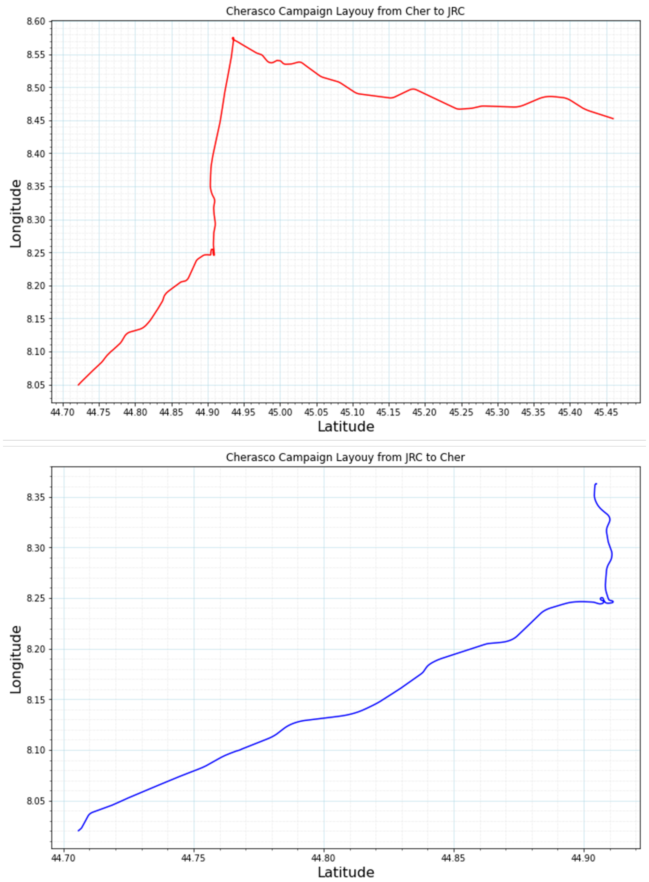


Figure 4.3: The layout of the Cherasco campaign (plotted using longitudinal and latitudinal data recorded in the OpenACC database)

Vicolungo

This campaign was conducted in the first quarter of 2019 and involved three days of car-following testing from Ispra (VA) to Vicolungo (NO) and the other way around in northern Italy. The testing was performed with five vehicles of various brands and models driving on car-platoon formation. The tests were scheduled for non-peak hours in order to minimize the disturbances from other road users. The leader was instructed to drive manually and perform occasional random deceleration and accelerations over a desired speed in a realistic way. The followers, whenever possible, were driving with ACC on, apart from a day when manual driving situations were tested.

Figure 4.4: The layout of Vicolungo campaign (Makridis et al., 2021)

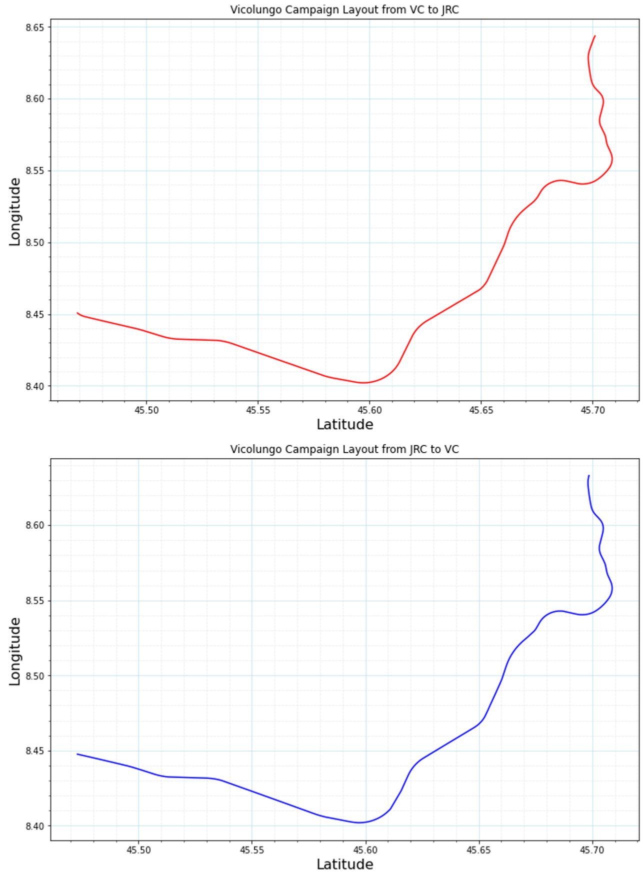


Figure 4.5: The layout of the Vicolungo campaign (plotted using longitudinal and latitudinal data recorded in the OpenACC database)

AstaZero

The campaign was conducted on the Rural road section of the AstaZero test track in Sweden, which spans approximately 5.7 kilometers. Five high-end vehicles were involved, each from a different manufacturer and model. The initial campaigns revealed issues such as high response times of the Adaptive Cruise Control (ACC) controllers, large headway settings, and instability. This campaign was organized to serve as a research tool to address the limitations of on-road experiments and facilitate a more systematic study. It took place within a controlled and protected environment to minimize risks and avoid the constraints associated with public roads. The experiments were structured as laps, with each lap corresponding to the path depicted in Figure 4.6. In all tests, the leading vehicle was equipped with ACC and driven with this feature, enabled to maintain a stable desired speed, thus minimizing fluctuations caused by manual driving. Two different car-following patterns were applied to the following vehicles:

1. Car-platooning with a constant speed.
2. Car-platooning with perturbations in the target speed, involving deceleration to a new desired speed from an equilibrium point.

For the second pattern, a radio-based communication system between the drivers of the first and last vehicles ensured that the speed of the last vehicle remained stable at the desired speed. This arrangement allowed the car platoon to approach an equilibrium state before applying a new perturbation. Each perturbation was initiated by the driver setting the desired speed of the ACC system to a lower value. Consequently, the vehicle autonomously decelerated, and when the new desired speed was reached, the driver reset the desired speed to the previous setting. The duration of the perturbation was automatically adjusted based on the deceleration strategy applied by the controller. This methodology was chosen to carry out the various perturbations in a controlled manner, closely resembling the behavior of vehicles equipped with ACC on real roads. For safety reasons, the desired speeds were fixed at 13.916.7 m/s along curves and 2527.8 m/s on straight sections during each lap.

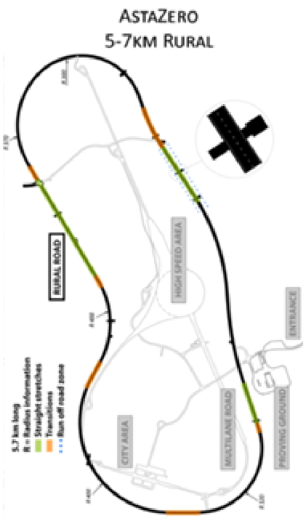


Figure 4.6: The layout of Vicolungo campaign (Makridis et al., 2021)

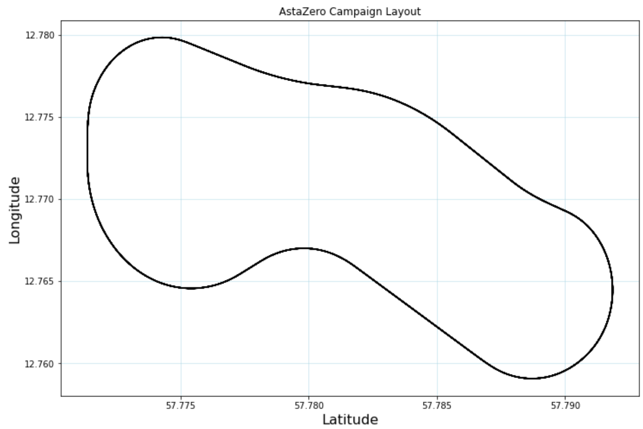


Figure 4.7: The layout of the Vicolungo campaign (plotted using longitudinal and latitudinal data recorded in the OpenACC database)

ZalaZone

This campaign included two test tracks, the Dynamic Platform and the Handling Course, located at the ZalaZone ground in Hungary (see Figure 3). The Dynamic Platform boasts a diameter of 300 meters, providing available space for executing a wide range of maneuvers without safety concerns. The Handling Course comprises curves and inclines and covers a distance of 2.2 kilometers, with a uniform asphalt lane width of 12 meters. The primary objective was to evaluate various ACC systems at low speeds with different vehicle orders and ACC settings. Therefore, various time gap settings, including short, long, medium, and mixed, were applied during these experiments.

Tests conducted on the Dynamic Platform were centered on the circular road section, where researchers assessed general ACC performance and related string stability. The test design involved maintaining a steady speed and introducing perturbations in the form of rapid decelerations to reach a new speed, followed by subsequent accelerations to restore the desired speed. The Smart BME ADdv always assumed the role of the leader vehicle and executed all perturbations. Radio-based communication among all drivers ensured that each vehicle attained the desired speed before the initiation of a new perturbation. Specifically, decelerations triggered by the leader were executed at a target deceleration of -3 m/s^2, while accelerations were performed at a rate of 1 m/s^2. The automated leader vehicle guaranteed precise replication of each individual perturbation, irrespective of the equilibrium speed or the magnitude of the perturbation.

Tests conducted on the Handling Course were geared toward studying the impact of road geometry on ACC performance. In this setting, tests were organized in laps, with vehicle speeds consistently set to a predetermined desired speed. Each experiment comprised two complete laps around the track. At the conclusion of the second lap, vehicles came to a stop on the straight section of the Handling Course, employing ACC to simulate stopping at traffic lights.

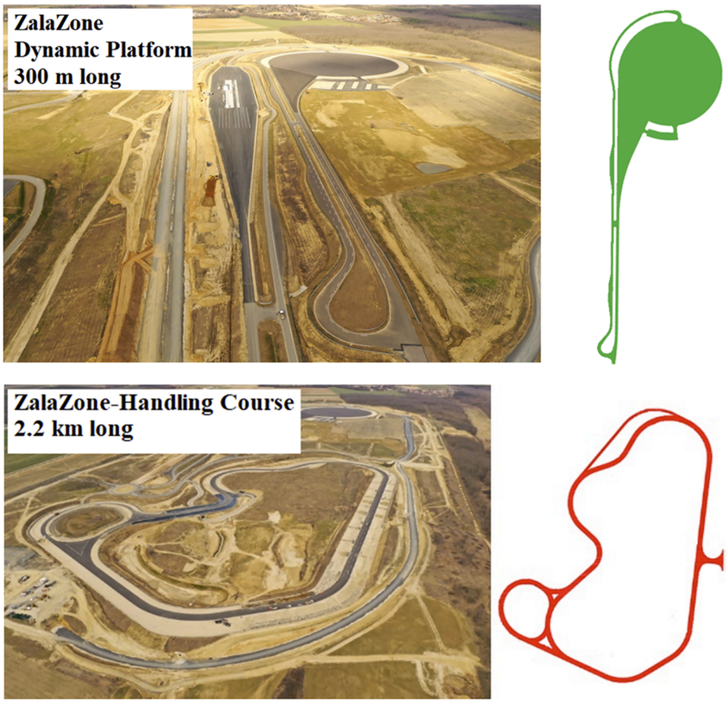


Figure 4.8: The layout of Zalazone campaign (Makridis et al., 2021)

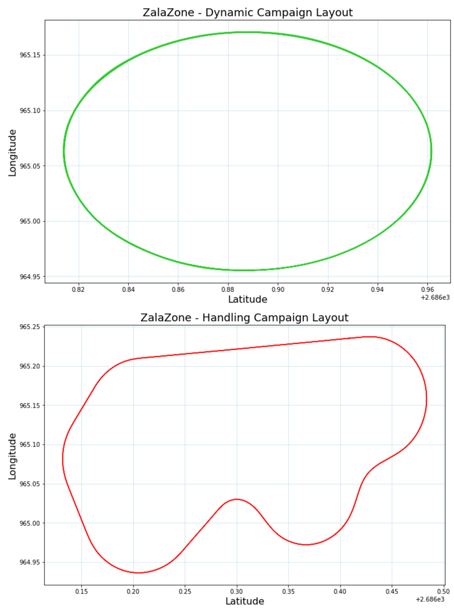


Figure 4.9: The layout of the Zalazone campaign (plotted using longitudinal and latitudinal data recorded in the OpenACC database)

4.1.2. TNO Database - SAE L2 Naturalistic Driving Study

SAE L2 database is from TNO (2019). This naturalistic driving data of 9 vehicles of different brands, where 20 volunteers drove for one month without ADAS and two months with ADAS. CAN-bus, MobilEye, GPS, and internal/external video are recorded. The goal was to analyze how drivers use ACC and LKS systems in naturalistic circumstances and how this changes their behavior. Data is map matched on a snapshot of the OpenStreetMap (OSM) network, resampled to 10Hz for ease of analysis, and a link is made to the NDW data to determine the traffic characteristics (speed and intensity) the vehicle was driving in. The most accessible way to work with the data is using the MySQL database (see resources for connection information). It contains the data itself but also a description of tables and columns. Although the experiment utilized both ACC and LKS, only data from ACC systems will be used in this research.

Table 4.2: SAE L2 Data Description (TNO, 2019)

Column	Type	Label	Description
id	numeric	Unique row ID	
trip_id	numeric	Unique trip ID	Identifies all data belonging to a single trip, which is the movement between engine start and stop.
date_and_time	timestamp	Local date and time	Local "naive" datetime when the data was recorded. No information is stored on timezone or DST.
time_in_trip	numeric	Seconds since start of trip	
acc_follow_distance	numeric	ACC follow distance setting	Range depends on car brand; a small number indicates the follow distance is closer than a large number.
acc_overrule	numeric	ACC overruled by throttle	No, Yes
acc_state_enum	text	ACC state	OFF = ACC is switched off by driver; NOTACTIVE = ACC is switched on by driver, but not actively regulating speed; ACTIVE = ACC is switched on and actively regulating speed
acc_status	text	Chosen speed control function	OFF = driver has deactivated all speed control functions; ACC = driver selected adaptive cruise control; LIM = driver selected speed limiter
button_enum	text	Button presses	Description of which button is pressed
brake_position	numeric	Brake pressure	Brake pressure applied by user, range = 0:100, invalid signal when < 0, unit = %
cc_set_speed	numeric	Set (A)CC speed	Requested target speed, invalid = {210, 250, 320}, unit = km/h
indicator_left_status_enum	text	Left turn indicator	Description of left indicator status

Table 4.2 – *SAE L2 Data Description*

Column	**Type**	**Label**	**Description**
indicator_right_status_enum	text	Right turn indicator	Description of right indicator status
vehicle_speed	numeric	Speed (km/h)	Vehicle speed derived from wheel speeds, (converted) unit = km/h

4.2. The General ODD of ACC systems and the Integration with the Model

In section 2.6, the general ODD of the ACC systems is introduced. This section explains whether ODD constraints can be incorporated into the external driver model used in the research and considered during simulation, along with the reasoning behind it.

Table 4.3 presents the limitations that have been integrated into the transition control model within the external driver model. While it is not possible to account for every limitation, several key factors, such as lane-changing and front-collision warnings, have been incorporated. These elements are particularly relevant to the research focus on traffic flow efficiency and safety on highways.

Table 4.3: General limitations from the owners' manuals and the application for the transition control model

Limitation	**Already in the model**	**Can be added in the model**	**Comment**
Driving on curves	N	N	There is insufficient data on ACC systems driving on curves to accurately model the limitations of these systems, particularly in determining at what level the systems will disengage.
Lane change	Y	-	The lane-change model has already been taken into account. When there is a lane change, there will be a DIDC transition control.

Continued on next page

Table 4.3: Limitations from the manuals and the simulator (continued)

Limitation	**Already in the model**	**Can be added in the model**	**Comment/ Reasons**
Driving on inclines	N	N	The external driver model used for this research cannot control the delay in the vehicle receiving the information, and there is a lack of empirical data to judge the delay seconds under inclined situations. Therefore, this constraint has not been considered in this research.
Detecting narrow vehicles	N	N	Although motorcycles are permitted to ride on highways in the Netherlands, their presence is relatively low, and there is limited empirical data on how ACC systems interact with them. Therefore, motorcycles have been excluded from this research.
Changing of target	N	N	There is a lack of empirical data to say the delay is second under inclined situations. Therefore, it is not included in the scope of the simulation in this research.
Continuously depressing the accelerator pedal	N	N	It is a driver-related behavior that cannot be simulated in VISSIM, and it is not the main focus of this research.
Detecting stationary obstacles	Y	-	This constraint has been taken into account. When approaching the slower or stationary vehicle, there will be a DIDC transition control.
Front-collision warning (FCW)	Y	-	The rule of FCW is based on the paper from (Kiefer, 2000). If there is an FCW, there will be an AIDC transition control.

Continued on next page

Table 4.3: Limitations from the manuals and the simulator (continued)

Limitation	**Already in the model**	**Can be added in the model**	**Comment/ Reasons**
The vehicle has been stopped for a certain time period	N	Y	This constraint can be added to the Transition Control model in the external drive system. If a vehicle's speed remains at 0 m/s for either 180 seconds or 300 seconds after a complete stop initiated by the ACC system, it will trigger an AIDC event. These time intervals are based on the specifications provided in the owners manuals for different brands.
The activation of Electronic stable control (ECS)	N	N	The external driver model used in the research does not have a model related to Electronic stable control currently, so it can not be modeled.
The activation of Autonomous emergency braking (AEB)	N	N	The external driver model used in the research does not have a model related to Autonomous emergency braking currently, so it can not be modeled.
Braking manually/ When the driver depresses the brake pedal.	N	N	It is driver-related behavior that cannot be simulated in VISSIM, and it is not the main focus of this research.
Driving under bad weather conditions	N	N	VISSIM cannot simulate the weather conditions, nor can any other traffic simulations simulate them at the moment.
The sensors cannot detect lane marks	N	N	It is assumed that this kind of situation rarely happens on the highway section.

4.3. The Transition Control Moment from the Empirical Data

After filtering both databases with the steps mentioned in section 3.2, three vehicles provide a sufficient quantity of transition control data to build up distributions for the deactivation of ACC systems, and the descriptive statistical analysis is shown in Table 4.4. These vehicles are the Hyundai Ioniq-Hybrid, the BMW 530i, and the Volvo XC40. Among the vehicles, the Hyundai Ioniq-Hybrid and Volvo XC40 are from the

OpeanACC database, and the BMW 530i is from the SAE L2 naturalistic driving study. As shown in Table 4.4, while all vehicles maintain relatively similar meantime gaps, the BMW 530i has the smallest mean and maximum time gaps, as well as the lowest standard deviation, indicating a more consistent time gap during the transition from ACC to human control. On the other hand, the Hyundai Ioniq Hybrid and Volvo XC40 show larger variations in time gaps, as indicated by their higher standard deviations and maximum values. In addition, it can also be observed that BMW 530i has a significantly higher frequency of the number of transition controls. This difference is because the OpenACC database primarily focuses on testing ACC performance, with only two public road campaigns conducted under specific time constraints, such as driving during non-peak hours. In addition, the Cherasco campaign only lasted two days, and the Viclungo campaign lasted three days. In contrast, the SAE L2 database captures natural driving data from the same individual over a period of three months. The limited duration and experimental design of the on-road experiments in the OpenACC database contribute to higher standard deviations and maximum values for time gap measurements during the transition control moment. Furthermore, these factors result in a significantly smaller number of transition control data points.

Table 4.4: Descriptive statistical overview of transition control from ACC to Human in terms of time gap

Vehicle	Hyundai (Ioniqhybrid)	Volvo XC40	BMW 530i
Count	18	12	376
mean	1.523	1.507	1.336
std	0.949	0.883	0.565
min	0.531	0.705	0.300
25th Percentile	0.923	0.984	0.900
50th Percentile (Median)	1.111	1.092	1.200
75th Percentile	1.742	1.670	1.800
max	3.741	3.687	2.500

The initial idea is to try to identify a possible pattern for the transition control mechanism in a way that would rather be understood at a macroscopic level and analyze variables recorded in the data rather than plot the geographic data and see a possible underlying reason for every incident. It is the idea of building a distribution for the time gap in which the ACC system is deactivated.

Figure 4.10 presents the frequency of and time gap observed during the transition of control from the ACC system to the human driver for all three vehicles, which are Hyundai, Volvo, and BMW 530i within a single visual framework to facilitate a clearer comparative analysis. However, the time gap distributions do not show a pattern for ACC deactivation for the three vehicles. The data in the figures tend to indicate that large time gaps do not correspond to critical safety issues that would cause system disengagement. This makes it unreasonable to develop a time gap distribution based on which one can make an assertion on the event of the system disengagement likely occurring at the time gap value considered safe, such as over 3 seconds.

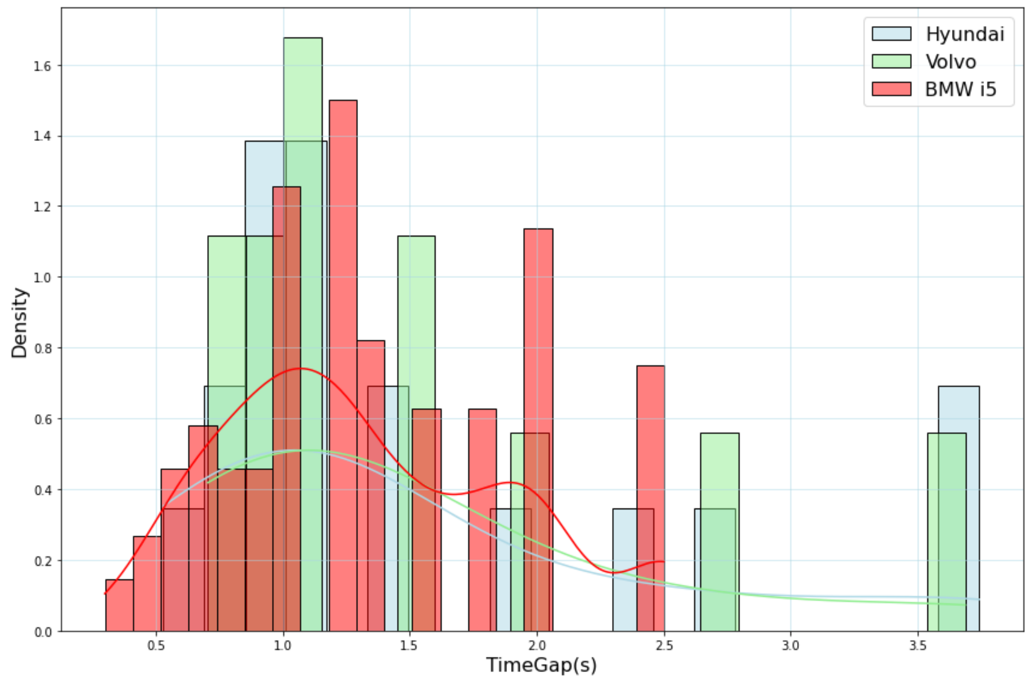


Figure 4.10: Time gap distribution for the three vehicles

The following paragraphs are about time-to-collision (TTC) around the transition control moment, which is a critical indicator when it comes to traffic safety. For each transition control moment, it was identified that the min TTC value lay within a 4-second interval preceding the control moment. It is assumed that the moment that the minimum TTC occurred is not always the moment that transition control occurred. This gap is due to the delay in human perception and reaction or the vehicle's mechanical response times, such as braking or steering adjustments, requiring a buffer period for drivers or ACC systems to detect and respond. In research of Makridis et al. (2019), it was assumed that the response time for both ACC and manually-driven vehicles could not be more than 4s in the present work.

Table 4.5 presents data on speed, IVS, acceleration, time gap, and TTC at the point with the minimum TTC value. It is important to note that the table excludes 15 data points for which the minimum TTC values are infinite, as these values correspond to scenarios with negligible safety risk. It is observed that the time difference values are all zero, which indicates that the minimum TTC occurred with the moments of control transition. It is mentioned specifically that this table includes only those cases where ACC disengagement occurs. In addition, cases with TTC being infinity represent the condition of the leading vehicle driving with a higher velocity and are not listed in the table. The data presented in the table reveals that the minimum (TTC) recorded is 9.6 seconds. This value is significantly larger than the critical threshold of 2.6 seconds typically associated with the safety parameters of ACC systems Hogema et al. (1996). Therefore, it can be concluded that the transition controls, especially for the ACC disengagement, are not safety-concern decisions.

Table 4.5: Transition control moment data from OpenACC database (Hyundai Ioniq Hybrid and Volvo XC40)

Model	Time Difference (s)	Speed (km/hr)	IVS (m)	Acceleration (m/s^2)	TimeGap (s)	TTC_min (s)
Hyundai Ioniq Hybrid	0	116.5329	45.47	-0.4652	1.4047	10.9344
	0	125.9780	33.65	-0.4210	0.9615	27.8495
	0	1.5954	12.32	-0.4646	27.8028	28.0741
	0	98.7610	24.72	-0.1383	0.9009	35.9882
	0	112.7096	25.76	0.4922	0.8227	42.8014
	0	1.6918	21.34	0.3007	45.4039	47.6162
	0	0.5652	8.67	-0.4127	55.2055	59.9175
	0	0.3577	11.72	0.1805	117.9703	229.5776
Volvo XC40	0	108.4769	23.98	-1.2962	0.7958	9.6132
	0	2.2140	12.99	0.6462	21.1183	23.5776
	0	4.6161	13.07	0.3940	10.1921	30.2890
	0	37.1412	20.08	0.7172	1.9464	118.8710
	0	0.7386	26.31	0.5990	128.2582	132.3834
	0	101.4552	27.80	0.2796	0.9864	144.0558
	0	102.6936	27.83	0.4611	0.9757	386.5666

Time Difference: Transition control timing - Min TTC occurred timing

Table 4.6 presents the data on the minimum TTC for transition control in BMW 530i, which is extracted from the SAE L2 database. There is only one case with a minimum TTC of 0.742 seconds and a speed of 133.75 km/hr that stands out as a critical safety concern. Taking an insight into the trip where this minimum TTC was recorded, it showed that the ACC system was deactivated, possibly due to safety concerns. It is worth mentioning that the driver reactivated the ACC just one second later, at which point the TTC dramatically increased to 24 seconds. The majority of the other data points with small minimum TTC values correspond to relatively low speeds, suggesting that the ACC system is more frequently deactivated in low-speed or potentially congested traffic scenarios. In addition, the acceleration data indicate substantial deceleration moments, but there is no clear evidence of emergency braking, as the acceleration values remain above -1 m/s^2 or even reach positive figures. Given these observations, it is hard to conclude that the ACC system deactivation is primarily related to safety concerns.

Table 4.6: Data on minimum time to collision (TTC) during ACC to OFF transition control

Time Difference	Min TTC (s)	Speed at Min TTC (km/hr)	Acceleration at Min TTC (m/s^2)
0.3	0.742	133.75	-0.880
4.2	0.787	15.05	-0.907
3.1	1.105	2.63	0.939
8.2	1.127	10.31	-1.008
2.2	1.182	2.77	-0.927
8.1	1.231	6.47	0.955
9.8	1.265	31.91	-0.774
1.1	1.273	7.67	0.957
3.5	1.279	6.86	0.000
5.9	1.325	7.20	-0.918
8.5	1.409	8.23	0.935
1.3	1.736	18.55	-0.997
6.9	1.918	11.28	-0.933
9.5	1.980	11.00	0.931
5.7	2.111	1.72	-0.908
4	2.125	17.23	0.934
5.4	2.154	30.20	0.922

Time Difference: Transition control timing - Min TTC occurred timing

4.3.1. Conclusion for the Transition Control Moment Data

It is concluded that the transition control was not safety-concern-based based on empirical data. This is mainly due to safety precautions during the experiments, which prevented the systems from being tested at their limits, especially on public roads. In addition, it suggests that the systems' ODD covered most of the driving scenarios present in the data.

Although the transition controls observed are not safety-based, the reason that could be behind them is as follows. It should be noted that the percentages are calculated based on the transition control number and not on the potential reasons number. For example, in the reason 'lane-change ego vehicle,' the percentage is 28.0, which means that 28.0% transition control happened is about lane-change, not 28% of lane-changing behavior will have a transition control. Table 4.7 outlines the potential reasons for the transition control deactivation as recorded in the SAE Level 2 and OpenACC databases. Generally, these reasons can be classified into five main categories. Among these reasons, re-acceleration after a full stop could potentially explain system limitation 9, as discussed in Section 4.1, which states that ACC systems may deactivate after a vehicle has been stationary for a certain duration. Furthermore, some ACC systems may automatically deactivate when the vehicle's speed falls below a certain threshold. This observation is consistent with the empirical data presented in the databases, aligning with the descriptions provided in the vehicle manuals. It is worth noting that the sum of the percentage is not 100%. It is because these events were not independent, and multiple factors could contribute to the deactivation of the ACC system. For example, a driver could have deactivated ACC while approaching a slower-driving vehicle and changing lanes afterward.

Table 4.7: Percentages of deactivations where between 10s before and 10s after ACC deactivation

Potential reason	SAE L2	OpenACC database
Lane changes ego vehicle	28.0	19.23
Change of road type	23.5	19.23
Change of speed limit	62.4	-
Approaching slower vehicle (vel_rel < 10km/h)	53.4	
Re-acceleration after a full stop	-	30.77

4.4. The Characteristics of Different ACC Systems

The OpenACC database contains 27 different ACC systems, while the SAE L2 naturalistic driving study includes one ACC model. To narrow down the models for the simulation, the data was filtered to identify ACC systems with sufficient data to account for heterogeneity.

4.4.1. Full Speed Range

The data from OpenACC were collected through controlled experiments, which did not capture the full range of vehicle speeds and ACC system capabilities due to safety limitations. As a result, the speed range settings for each ACC system were sourced from vehicle owner manuals, and the findings are summarized in Table 4.8. The table contains three main columns pertaining to the ACC speed requirements. The first column shows the minimum set speed, which is the lowest speed at which the ACC system can operate. For example, if the desired speed is below this minimum (e.g., 20 km/h), but the minimum set speed is 30 km/h, the vehicle will maintain 30 km/h instead. Most vehicles have a standard ACC activation speed of 30 km/h, though some, like the Mercedes-Benz A-class, can activate ACC at lower speeds (e.g., 20 km/h). This can also reflect the current technological constraints of ACC systems for most vehicles.

In the second and third columns, values are separated by a forward slash ("/"). The value preceding the forward slash represents the speed requirement in the absence of a preceding vehicle, while the value following the forward slash indicates the requirement when a vehicle is present ahead. For instance, in some vehicles, ACC can be active even at 0 km/h if the system is capable of adapting to a complete stop. However, certain vehicles have operational speed limits for their ACC systems. If the vehicle's speed drops below this limit, the ACC system automatically disengages. The third column provides the operational speed range of the ACC system, directly related to the minimum speed at which the system can engage. ACC systems with a minimum operating speed above 0 km/h can do a full-speed following if there is a vehicle ahead. For example, in a Hyundai, if no vehicle is detected ahead, the ACC system operates within a speed range of 30 km/h to 190 km/h. However, when a vehicle is present, the ACC system can follow at speeds as low as 10 km/h. In cases where the minimum speed threshold is not 0 km/h, the ACC system will disengage if the vehicles speed falls below this limit, resulting in a transition to manual control (AIDC).

This research focuses rather on the lower bound of the ACC operational speed range due to its more importance assumed with respect to the practical relevance in typical traffic conditions. At the speed range, reaching the top is less likely even when the traffic flow is comparably less congested; some vehicles have the upper bound at 150 km/hr, and some vehicles are even above 200 km/hr.

Table 4.8: Adaptive Cruise Control Systems Speed Limitation

Vehicle Brand	Model	Min Set Speed for ACC (km/hr)	Speed required to activate ACC (km/hr) *	ACC speed range (km/hr) *	Note
Hyundai	Ioniq Hybrid	30	30/ 10	30-190/ 10-190	• ACC deactivates under 10 km/h. • Cruise control activates after approx. 3 sec delay post braking.
Volvo	XC40	30	15/ 0	15-200/ 0-200	Adaptive Cruise Control uses approx. 40% of the capacity of the foot brake. If the car needs to be braked more heavily than the adaptive cruise control is capable of and the driver does not brake, the warning lamp and acoustic warning are activated to alert the driver that immediate intervention is required.
Volkswagen	Golf E	30	30/ 10	30-150/ 0-150	
Peugeot	3008 GTLine	30	30/ 10	30-180/ 10-180	The driver must press the accelerator to move off after complete stop.
Kia	Niro	30	30/ 0	10-160/ 0-160	ACC deactivates if the vehicle stops for 5 minutes.
Ford	S-Max	30	30/ 10	30-190/ 10-190	
Mitsubishi	Outlander PHEV	40	40/ 10	30-180/ 10-180	ACC auto cancellation alert by buzzer if no brake within 2 sec after stop.
BMW	**I3**	30	30/ 0	30-180 / 0-180	
	X5	30	30/ 0	30-180 / 0-180	
	530i	30	30/ 0	30-180 / 0-180	
Toyota	**RAV4**	30	30/ 30	30-190/ 30-190	
Tesla	**Model X**	30	30/ 0 (if a preceding vehicle is within 1.5m)	30-150/ 0-150	
	Model S	30	30/ 0 (if a preceding vehicle is within 1.5m)	30-150/ 0-150	
	Model 3	30	30/ 0 (if a preceding vehicle is within 1.5m)	30-150/ 0-150	
Audi	**A4**	30	30/ 0 (if the vehicle is not stationary for more than 3 minutes)	30-150/ 0-150	
	A6	30	30/ 0 (if the vehicle is not stationary for more than 3 minutes)	30-150/ 0-150	
	A8	30	30/ 0 (if the vehicle is not stationary for more than 3 minutes)	30-150/ 0-150	
	E TRON		30/ 0 (if the vehicle is not stationary for more than 3 minutes)	30-150/ 0-150	
Mercedes	**GLE450**	20	20/ 20	20-210/ 0-210	ACC automatically pulls away within up to 60 seconds and with moderate steering maneuvers.
	A Class	20	20/ 20	20-160/ 0-160	ACC auto follow the vehicle in front if drive resumes within 30 sec after a stop.
JAGUAR	**I PACE S**	32	32/ 0	32-200/ 0-200	ACC automatically accelerates the vehicle away from a standstill, if the targeted vehicle pulls away within a few seconds. A short press of the accelerator pedal is required if the targeted vehicle is stationary for longer than a few seconds.
Mazda	**3**	30	30/ 0	30-145/ 0-145	

*: The value if there is no vehicle ahead/ The value if there is a vehicle ahead

Light blue texts: The data on vehicles is from the Cherasco Campaign in the OpenACC database.

Green texts: The data on vehicles is from the Vicolungo Campaign in the OpenACC database.

Bold texts: The data on vehicles is from the ZalaZone Campaign Dynamic part in the OpenACC database.

Dark orange texts: The data on vehicles is from the AstaZero Campaign in the OpenACC database.

Dark blue text: The vehicle is from the SAE L2 database.

Red text: The assumptions are made for the values.

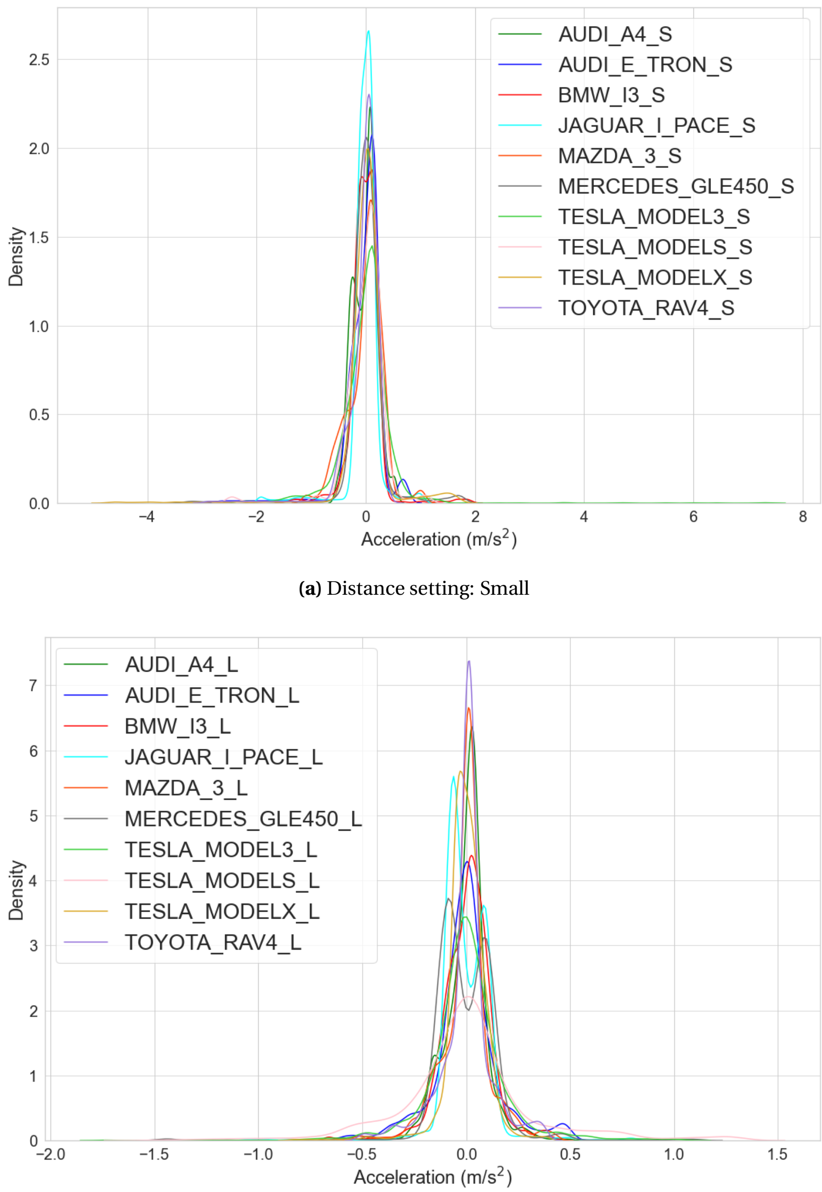
Underlined text: The data is sourced directly from the owner's manual

4.4.2. Acceleration Capabilities

The maximum deceleration rate of vehicles usually does not have empirical data available for it since experimentation would involve safety risks. In the OpenACC database, which is shown in Figure 4.13, some vehicles have a maximum deceleration value of less than -3 m/s^2. This is not considered reflective of a real vehicle's maximum deceleration and may reflect the data failing to display the real limitation in acceleration for the vehicle. In addition, the setting of the desired speed in the experiments restricted the vehicles' performances and cannot represent the real acceleration limitation since the observed maximum acceleration/deceleration rates across different ACC manufacturers all suggest that the acceleration/deceleration constraints decrease linearly with vehicle speeds (Zhou et al., 2022). Furthermore, the distance settings of the vehicles also affect their acceleration performance during the experiments. Vehicles with smaller distance settings can achieve higher maximum deceleration rates, while those with larger distance settings generally have lower maximum deceleration rates. This is because a larger time gap results in greater space between vehicles, reducing the frequency of critical moments that require sudden deceleration. Therefore, vehicles with small distance settings need higher maximum deceleration rates to respond quickly to immediate changes in their environment, while those with larger distance settings can decelerate more gradually. As for the experiments held on the public roads, such as the data from OpenACC-Cherasco and Viclungo Campaign and SAE L2 database, it indicates a wider acceleration range based on the full-speed test environments, as shown in Figure 4.12.

The international rules of ACC systems, according to ISO 15622, specify that the acceleration of the vehicle should be not less than -3.5 m/s^2 and not more than 2.5 $m/m/s^2$. In accordance with this regulation, research by Zhou et al. (2022) indicated that the ACC systems show different features in acceleration and deceleration among manufacturers. The study also found that maximum acceleration rates are similar across various engine modes but with changes in the case of free motion and car-following scenarios. Furthermore, maximum deceleration rates are closely related to the minimum time to collision, signaling a tailored approach to safety and performance differences across various vehicle brands and models. Therefore, the owners' manuals were reviewed to determine if the manufacturers reference limitations on acceleration. However, according to the manuals, no such references are made. Subsequently, this issue may pertain to the forward collision warning and autonomous emergency braking for the maximum acceleration allowed to avoid an accident, as Li et al., 2020 indicated that maximum deceleration shows a strong correlation with min TTC. Nonetheless, this is not specified for the actual values. According to the manuals, settings can only be adjusted for the sensitivity of the forward collision warning, which could be early, middle, and late and is typically defaulted to "middle." Besides, there is no information in the manuals about the exact values of the acceleration capabilities.

Figure 4.11 shows the aggregated acceleration distributions across different vehicles. The acceleration distributions for all vehicles are centered around 0 m/s^2, which suggests that, on average, the cars maintain a steady speed rather than accelerating or decelerating. Figure The data presented in Figure 4.13 indicates that the median acceleration value for each vehicle hovers around 0 m/s^2. While subtle differences in acceleration patterns are noticeable among the various vehicle models, the overall distribution remains tightly clustered around the neutral point. However, a distinct peak is observed in the data for the Tesla Model 3 under small distance settings. This could be due to the larger time gaps recorded during the experiment. Most time gap values for the small distance settings typically ranged between 1 and 2 seconds. However, when the time gap exceeded 4 seconds, higher acceleration values were also observed. It's important to note that all of these data were recorded under the control of the vehicles' ACC systems. This supports the proficiency with which ACC systems have been designed to operate within a consensual framework of safety and efficiency: the synthesis of acceleration behaviors across the represented models. The graph further shows a homogeneous system response but with different vehicle specifications. This can indeed point toward a harmonized vehicular dynamics ethos that pervades the present landscape of ACC technology. This, the empirical evidence so collated, of course, points to the robust calibration practices employed across the automotive industry to yield a congruous performance spectrum within the regulatory restraints.



(a) Distance setting: Small

(b) Distance setting: Large

Figure 4.11: Acceleration distribution of each vehicle - ZalaZone Campaign

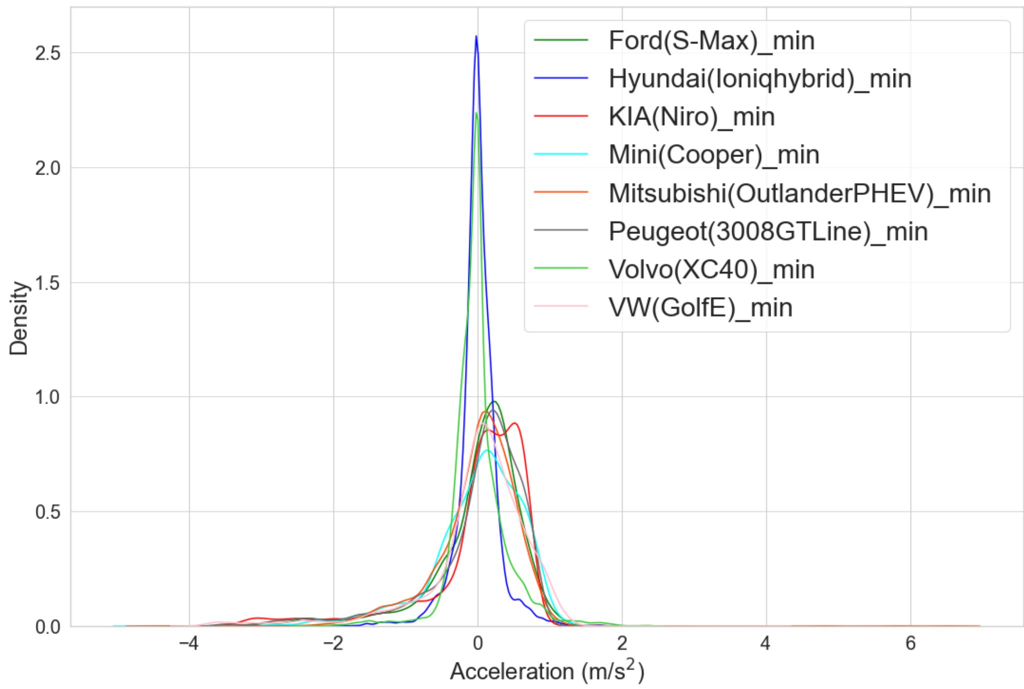


Figure 4.12: Acceleration distribution of each vehicle - Cherasco and Vicolungo Campaign

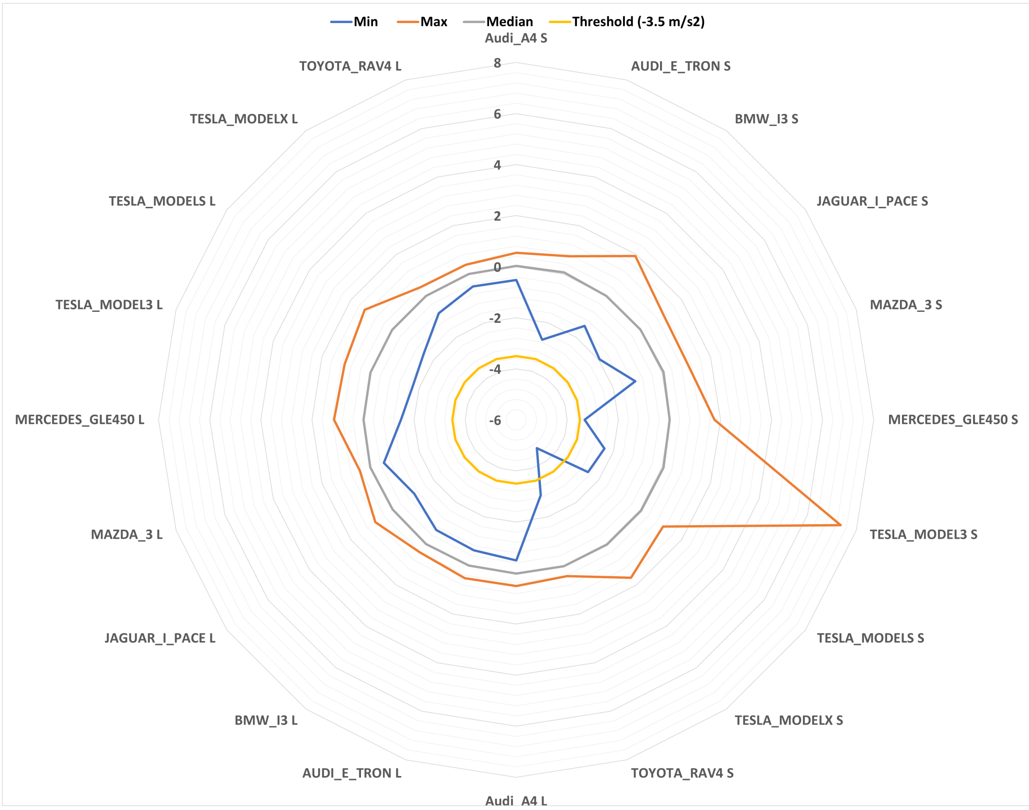


Figure 4.13: Acceleration descriptive statistics of each vehicle - ZalaZone Campaign

4.4.3. Inter-vehicle Space (IVS)

The inter-vehicle space is an essential parameter within the ACC systems and is often emphasized in the distance control section of the user manuals. The data in this comes from the OpenACC database of the Zalazone Campaign. There are three different settings that can be set as small (S), medium (M), and large (L). The medium had two trials, with four vehicles each, and consequently, it was the least represented setting. The dataset presented a number of vehicles from the manufacturers Audi, BMW, Jaguar, Mazda, Mercedes, Tesla, and Toyota, all having a unique pattern within the IVS. Bar graphs in Figure 4.14 give the mean IVS for different vehicles at S and L settings. For instance, in the S setting, it can be seen that the Jaguar I_PACE and Tesla Model X have some of the higher average IVS values, while the Mercedes GLE450 and BMW I3 have some of the lowest. On the other hand, in the L setting, the Audi A4 and Mazda 3 have the highest average IVS values, which may indicate a tendency for these vehicles to maintain a larger space even in the largest setting. Figure 4.15a and 4.15b show the trends in probability for the small and large settings of the parameter, meaning, in a given traffic flow, the set distance and distribution for each vehicle can affect the efficiency and safety in traffic flow. In the plots of density from the large (L) distance setting, one can observe individual peaks for each vehicle representing a frequency of finding a particular IVS measurement. These peaks may suggest the most normally held IVS for each car at this setting. An example is the Toyota RAV4 and Tesla Model S, which had narrower peaks; hence, they have evener IVS. On the other hand, the BMW I3 and Audi E-TRON had peaks that were wider in nature. Hence, this would be pointing toward a more uneven IVS. For the small (S) setting, the density plots are obviously going to represent tighter clusters, as is the expectation for a smaller IVS. The median values will be lower for all vehicles, and the distributions will be tighter, meaning there will be less spread of IVS than compared with the L setting.

Figure 4.16 shows the IVS distributions for the vehicles involved in the campaigns held on the public roads. The distance for the campaigns is set at a minimum. Therefore, there is no data related to the large settings. However, it can be seen obviously that the IVS has a large range even though the distance setting is minimal. To be noted, there is some data recording problem that the IVS might be quite low.

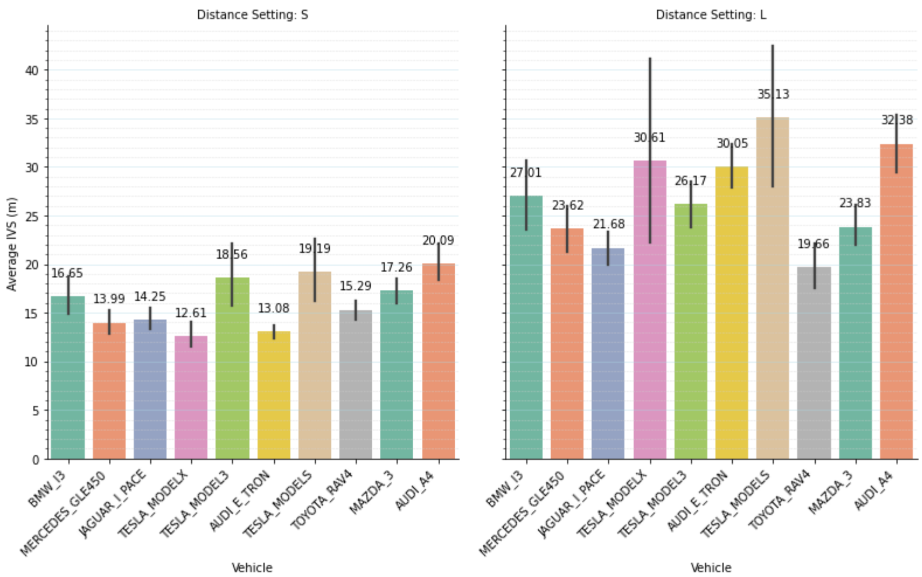
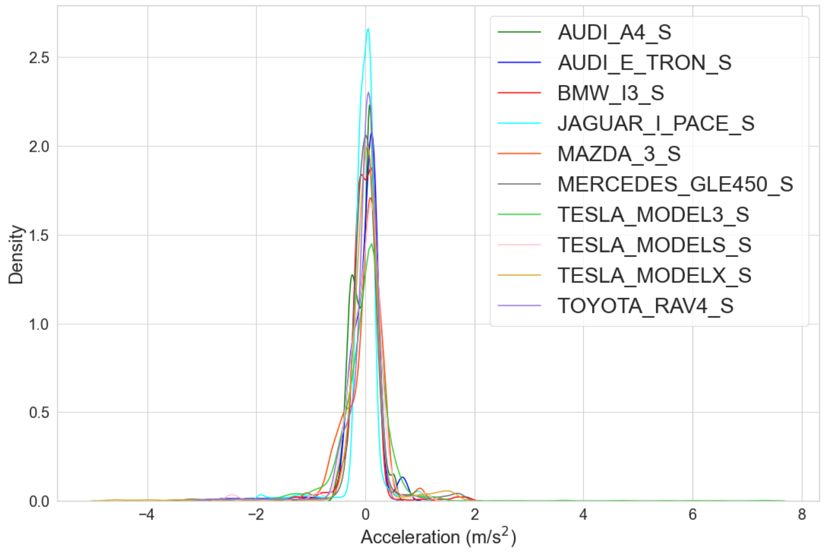
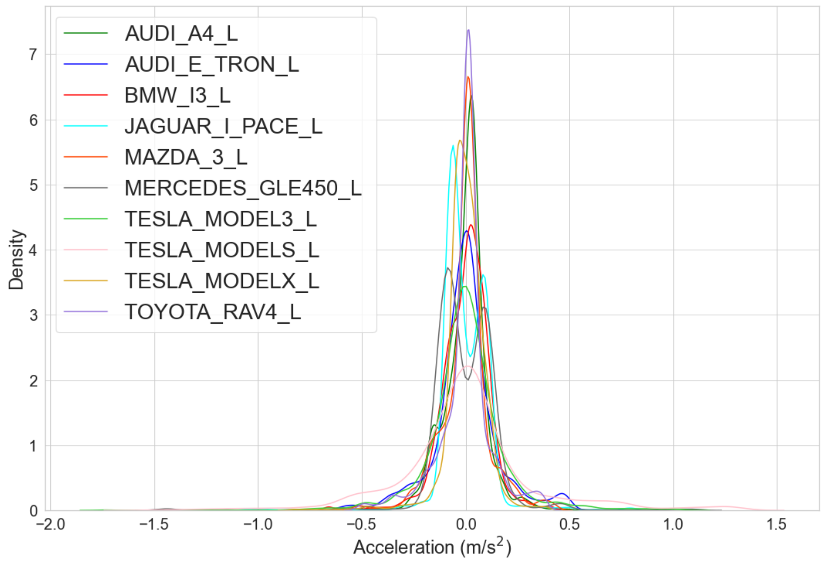


Figure 4.14: Average IVS - Zalazone Campaign



(a) Distance setting: Small



(b) Distance setting: Large

Figure 4.15: Acceleration distribution of each vehicle - ZalaZone Campaign

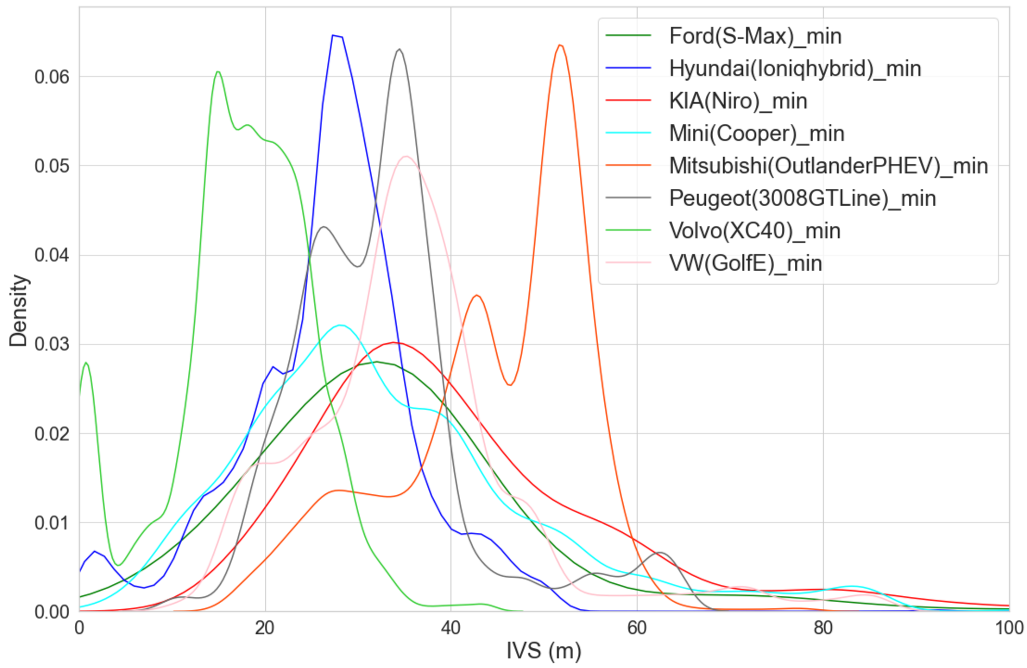


Figure 4.16: IVS distribution of each vehicle with large distance setting - Cherasco and Vicolungo Campaign

4.4.4. Time Gap

The time gap data is from the Zalazone, Cherasco, and Vicolungo Campaign in the OpenACC database as introduced in detail in section 4.1.1. For Zalazone, it is a closed environment for testing the ACC performance. Each test round was recorded in a file, and all vehicles had the same distance settings, which could be small(S), medium(M), and large(L). However, there were only two test rounds with the distance setting of the medium, and only four vehicles were involved. Therefore, in the following data analysis, the test round with a medium distance setting was removed due to the lack of data points and the vehicles involved. This research only takes the small and large distance settings into account.

Because of the purpose of the Zalazone campaign, there were some disturbances during each test round, which resulted in an unstable vehicle platoon. This instability, caused time gaps that did not align with the desired settings. Therefore, the first step of data processing is to get the desired time gap of each ACC system under stationary states. The data is filtered with the acceleration within $\pm$ 0.5 m/s^2, which could seen as stationary states. Figure 4.17 illustrates the time gap values with the highest frequency, which might indicate the desired time gap for the vehicle. It can be seen that there are significant differences between distance settings, small and large. Most of the values are below 2 seconds for the small distance setting except for MAZDA 3 and AUDI A4. On the other hand, the average time gap values are all above 2 seconds. The difference between the two distance settings for each brand is shown in Table 4.9, and there are significant differences between the distance settings. Therefore, for the simulation setup, it will be assumed that the percentage of the vehicle uses a small or large distance, and the distributions of the distance setting will be applied instead of combining the time gap setting for each vehicle. In addition, two AUDI vehicles have the largest average time gap when the distance setting is large. According to the owners' manuals of Audi E-TRON and A4, five time-interval options are available. These are 1 second, 1.3 seconds, 1.8 seconds, 2.4

seconds, and 3.6 seconds. Therefore, the findings from the empirical data fit the description and the setting of the vehicle manufacturer. It can be concluded that AUDI has a distinct setting from other vehicles in the large-distance setting. Furthermore, although the average time gap has been calculated, different situations on the road might result in different time gap changes over time within the same setting. Figure 4.18a and 4.18b show the distribution of the time gap for each vehicle under the small and large settings.

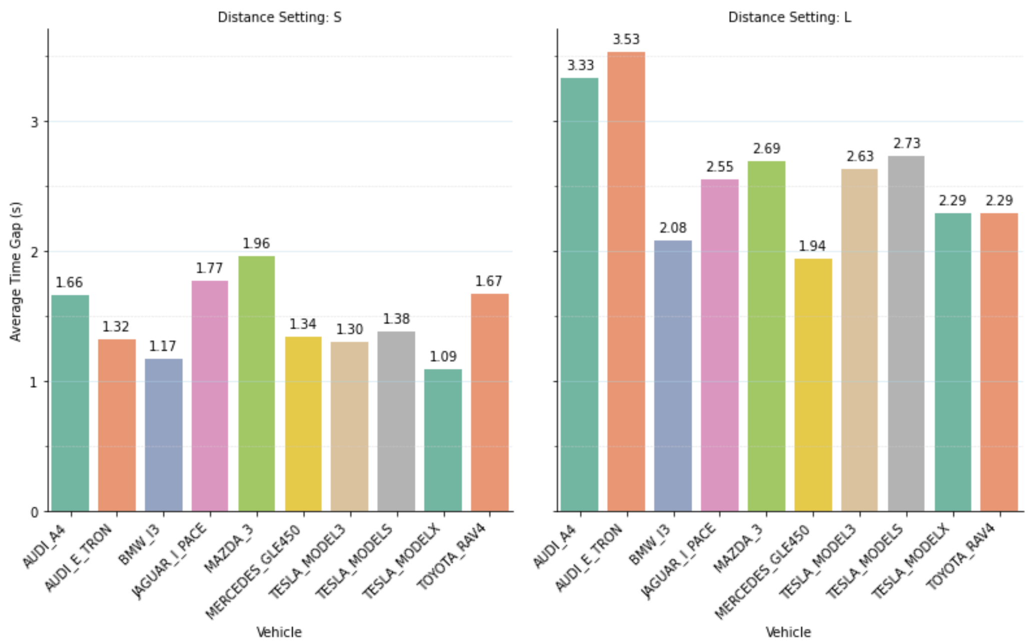
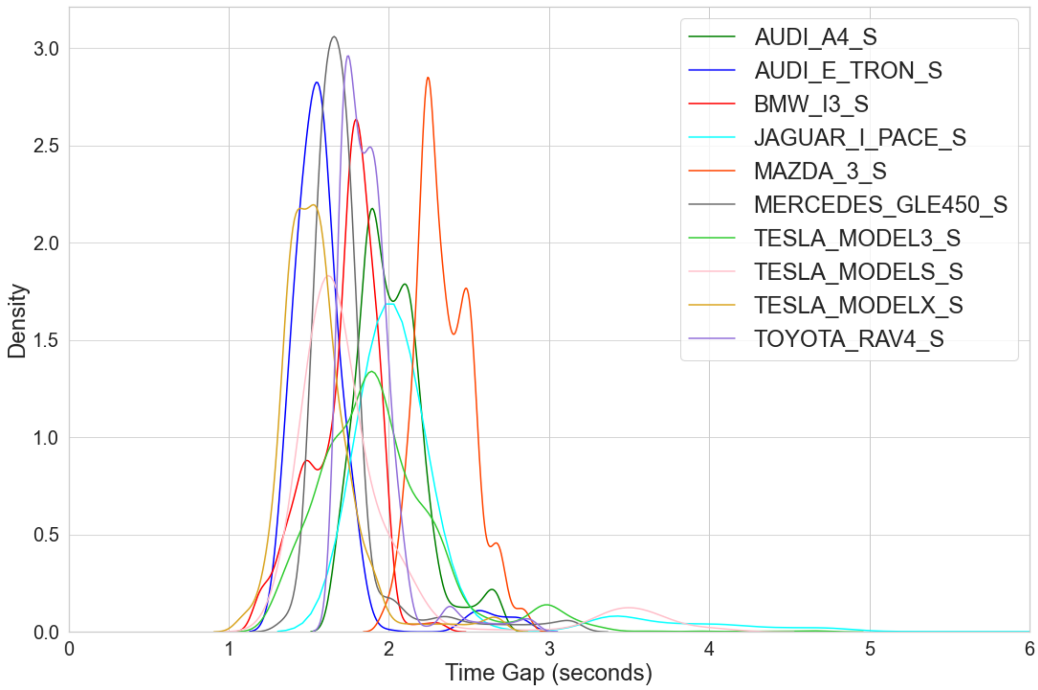


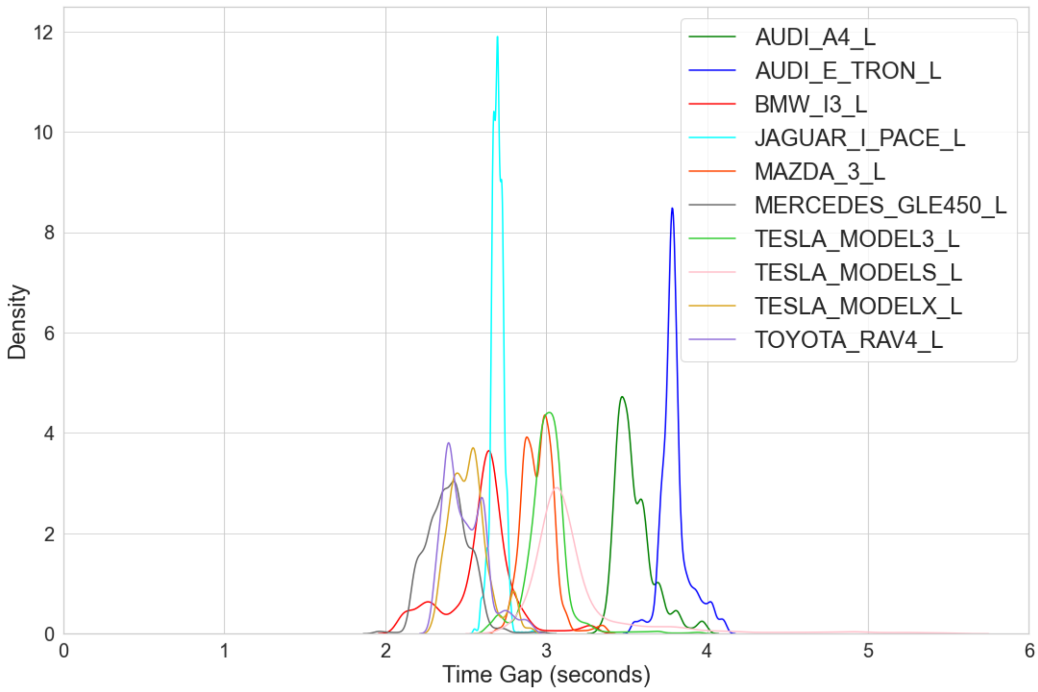
Figure 4.17: Most frequent time gap values - Zalazone Campaign

Table 4.9: Vehicles and differences between small and large distance settings

Vehicle	Difference (s)
BMW i3	0.91
MERCEDES GLE450	0.92
JAGUAR I PACE	0.83
TESLA MODEL X	1.2
TESLA MODEL 3	1.01
AUDI E TRON	2.12
TESLA MODEL S	1.19
TOYOTA RAV4	0.6
MAZDA 3	0.77
AUDI A4	1.53



(a) Distance setting: Small



(b) Distance setting: Large

Figure 4.18: Acceleration distribution of each vehicle - ZalaZone Campaign

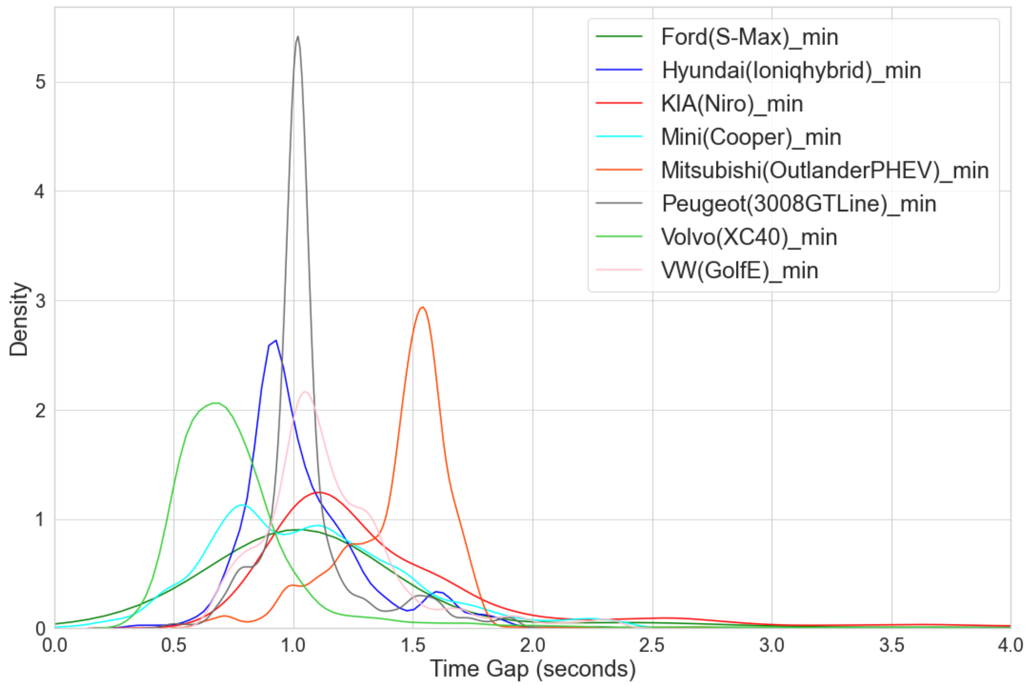


Figure 4.19: Time gap distribution of each vehicle with large distance setting -Cherasco and Vicolungo Campaign

4.4.5. Response Time

The following section is based on the results from Makridis et al., 2020b. In the paper, Makridis et al. used data from the AstaZero Campaign from OpenACC to calculate the response time of different vehicle brands in the same database as this research. Therefore, the results are applied to this research. The response time is the observable response time, which is the response that an ordinary observer would understand under stable and safe conditions. It was estimated under normal (non-critical driving conditions). For each lap, the response time for the ACC controller is calculated by the correlation between the speed difference of two sequential vehicles and the follower's acceleration. The idea is based on the assumption that when two vehicles are driven by their ACC controllers under stable car-following conditions, the ACC system of the follower keeps a constant time headway value according to the driver's desired setting. Under stationary states, both vehicles ideally have the same speed. At some point, the leader performs an action that can be either acceleration or deceleration, which creates a speed difference between the two vehicles and thus changes the time headway of the follower. Since the follower aims to keep a constant time headway, it performs a reaction at some later point in time, which is either acceleration or deceleration, respectively. The time difference between the leader's action and the follower's response is the observable response time (response time). The response time is estimated for each of the four leader-follower pairs of the car platoon.

In more detail, given the two stationary signals $\Delta v_{l-f,t}$ and $a_{f,t}$, a time delay T on the acceleration of the follower is applied and computed the cross-covariance function between these two signals as follows:

$$\sigma_{\Delta v,a_f}(T) = \frac{1}{N-1}\sum_{t=1}^{N}(\Delta v_{l-f,t} - \mu_{\Delta v})(a_{f,t-T} - \mu_a) \tag{4.1}$$

where $\mu_{\Delta v}$ and μ_a are the means of each time series and N is the number of measurements.

The Pearson correlation coefficient, which measures the linear correlation between A and B, derives from the following normalization:

$$r_{\Delta v,a_f}(T) = \frac{\sigma_{\Delta v,a_f}(T)}{\sqrt{\sigma_{\Delta v,\Delta v}(0)\sigma_{a_f,a_f}(0)}} \tag{4.2}$$

where $\sigma_{\Delta v,\Delta v}(0)$ and $\sigma_{a_f,a_f}(0)$ are the variances of each signal.

The peak frequency corresponds to the estimated delay, that is, the response time for the corresponding test lap. In other words, the response time of the controller is derived by the following:

$$\tau_{\text{delay}} = \text{argmax}(r_{\Delta v,a_f}(T)) \qquad T = \{0, 0.1, \ldots, T_{\max}\} \tag{4.3}$$

where T_{max} is the maximum response time assumed in the analysis. In the present work, it was assumed that the maximum response time would be 4s. Laps that do not involve perturbations (vehicles driving with constant speed) have low correlation and are excluded from the results. For this work, results with correlation coefficient values below 0.7 were discarded.

Figure 4.20 depicts a summary of the response time estimates for each vehicle, with individual data points representing the estimated response times over a single lap distance. The dataset includes response times over 72 laps, allocated as follows: 17 for Vehicle 1 (V1), 15 for Vehicle 2 (V2), 19 for Vehicle 3 (V3), and 21 for Vehicle 4 (V4). An additional 11 laps were excluded from the analysis due to low correlation coefficient values, which serve as a metric of reliability for the estimations. Moreover, the data indicated a trend wherein lower correlation coefficients were associated with higher response time estimates, particularly for Vehicles 1 and 2. To address this, Figure 4.20 presents the weighted response times for each vehicle, calculated as the sum of the product of each lap's response time and its corresponding correlation coefficient, normalized by the sum of the coefficients. This weighted average ensures that laps with higher correlation coefficients have a more pronounced impact on the aggregated response time measurement.

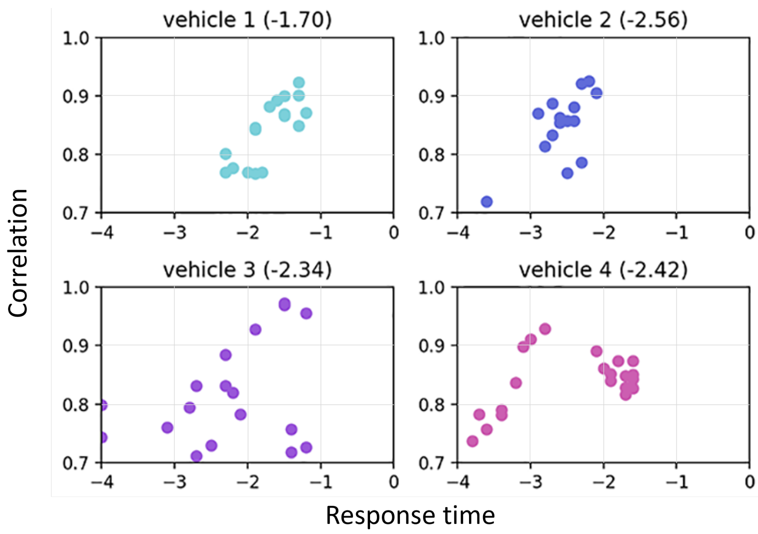


Figure 4.20: Estimated response times per vehicle per lap (Makridis et al., 2020b)

The analysis yielded weighted response times of 1.7 seconds for Vehicle 1 (V1), 2.56 seconds for Vehicle 2 (V2), 2.34 seconds for Vehicle 3 (V3), and 2.42 seconds for Vehicle 4 (V4), with V1 being identified as the Tesla Model 3the sole electric power-train vehicle included in the experiment. This observation leads to an interesting hypothesis: electric power-train vehicles may have shorter response times.

4.4.6. Standstill Distance

The standstill distance refers to the initially set minimum distance between vehicles, significantly influencing the acceleration performance and the calculation of time gaps. This parameter was estimated based on data from the AstaZero Campaign recorded in the OpenACC database. The experiments in the campaign were designed as the vehicles initiating movement from a standstill and ending in a full stop. Therefore, the data for calculating the standstill distance were derived from the final phase of each experiment. This phase involved the vehicles decelerating to a complete stop, during which the inter-vehicle space was measured at speeds lower than 3 kilometers per hour. Figure 4.21 presents the standstill distances across various vehicle brands in terms of the maximum and minimum distance settings. The average standstill distances is shown in Table 4.10. It can be assumed from the data that there is a heterogeneity in these parameters among the different brands. In addition, he data reveal a distinct difference between the maximum and minimum distance settings, with the BMW X5 being an exception to this trend. For subsequent simulations, the average values of the standstill distances, as depicted in the figure, will be utilized as input variables.

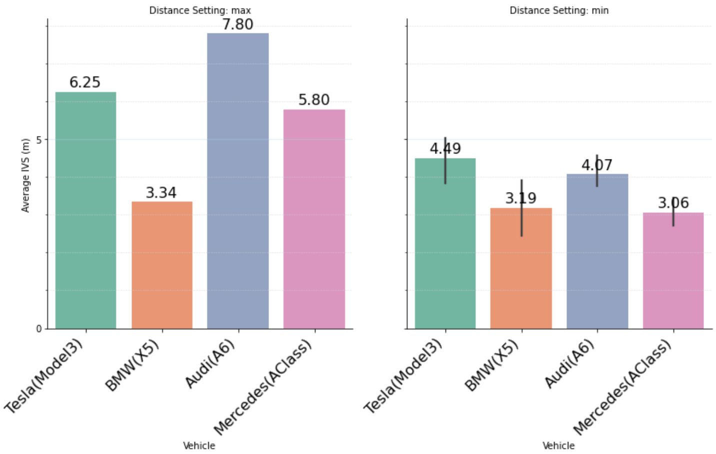


Figure 4.21: Average Standstill Distance - AstaZero Campaign

Table 4.10: Average standstill distance (m)

Vehicle	max	min
TESLA MODEL 3	6.25	4.49
BMW X5	3.34	3.19
Audi A6	7.80	4.07
Mercedes AClass	5.80	3.05

4.4.7. String Stability

From the empirical data, the string instabilities of the ACC systems were observed in the empirical data. Figure 4.22 shows the speed profile of the fourth test runs in Zalazone Campaign, Dynamic Part, from the OpenACC database. It can be seen that there is are noticeable response time for ACC systems to initiate deceleration, as mentioned in section 4.4.5. The response time results in the delay, which necessitates a more significant deceleration to maintain the desired distance setting, which is subsequently followed by an overshoot as the system compensates for the excessive deceleration. In addition, these instabilities are propagated to vehicles positioned further back in the platoon. The legend indicates the vehicles in the sequence of their positions within the platoon. Figure 4.23 illustrates the statistical analysis of vehicle speed from the same test run. The x-axis represents the vehicle brands and models in sequence, corresponding to their positions in the platoon. It can then be observed that the later positions in the platoon performed larger standard deviations, providing clear evidence of string instabilities, particularly for the vehicles positioned after the 5th spot. These instabilities were observed in all test parts. In this subsection, only the results from Dynamic Part 4 are presented as examples. However, the position of the vehicles is not the same for all the test runs in the campaign and there might be only two or three test runs where the same vehicle sequence is repeated. Therefore, it is hard to determine the level of the string instabilities in each vehicle due to the lack of data.

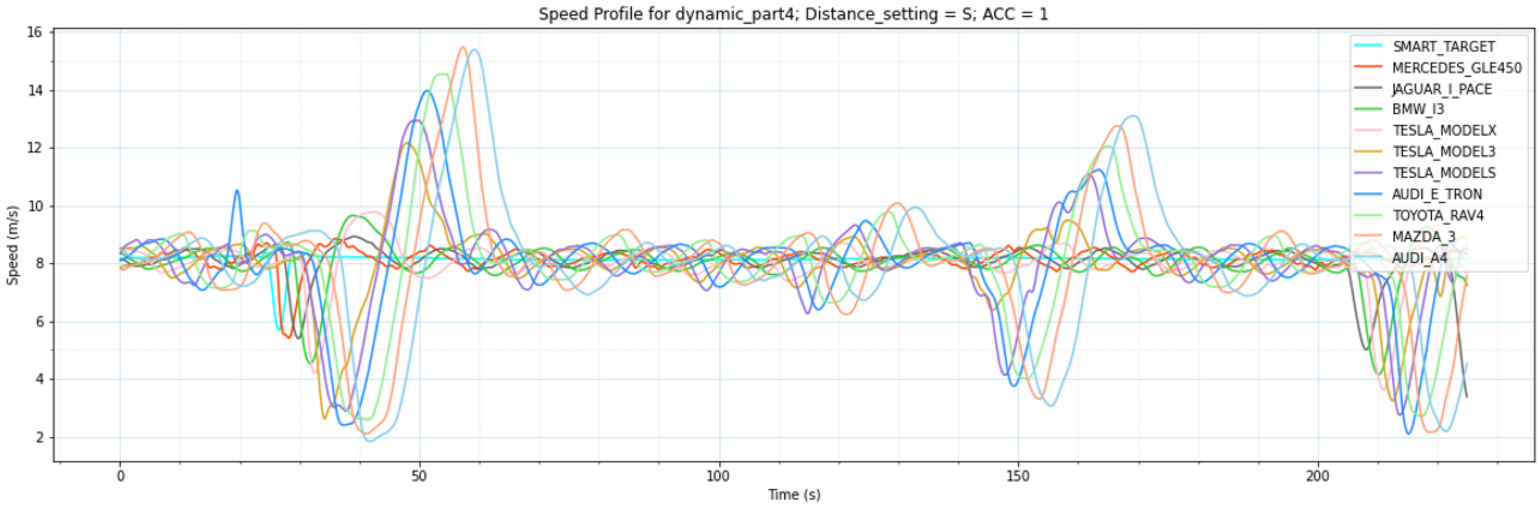


Figure 4.22: Speed Profile - Dynamic Part 4

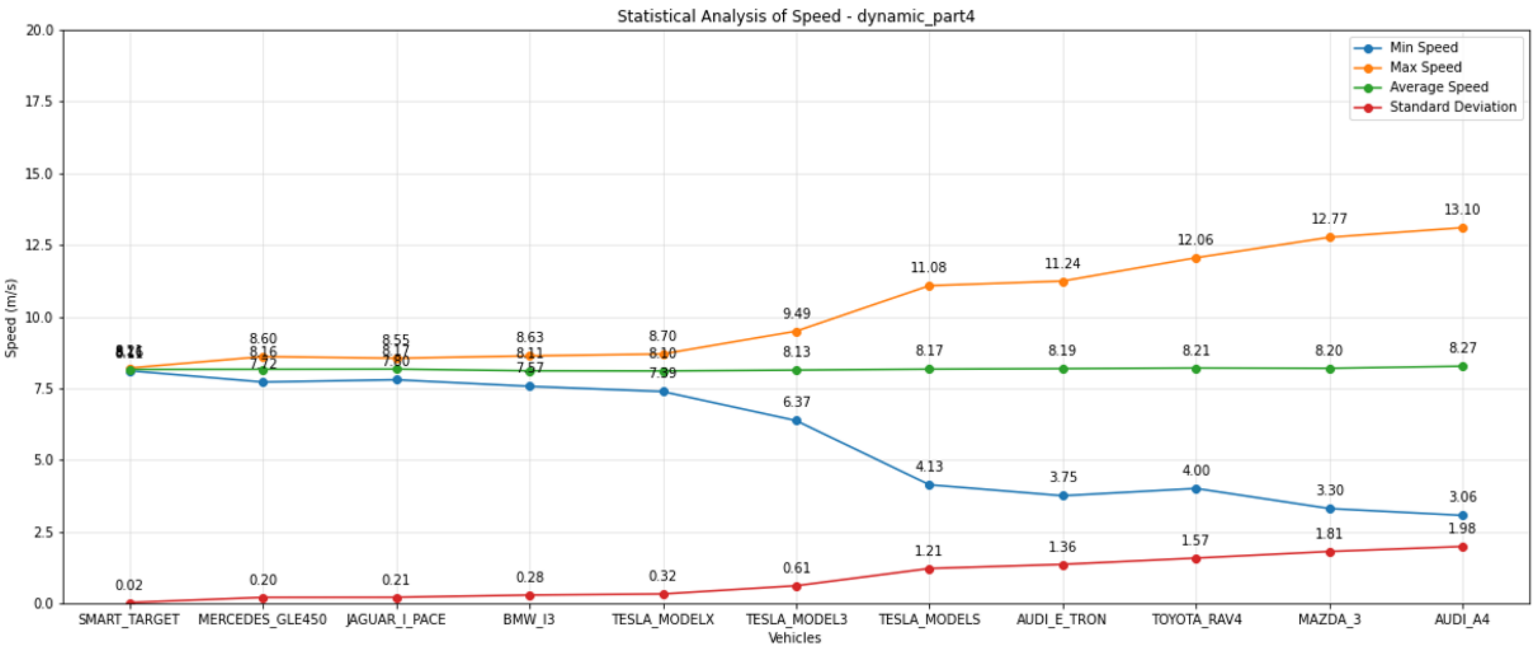


Figure 4.23: Statistical Analysis of Speed - Dynamic Part 4

4.5. Market Share

Figure 4.24 shows the passenger car sales in the Netherlands in 2023. It is used to assume the market penetration rates of different brands on the highway. If the vehicle is mentioned in the figure, but there is no information from the database, it will not be used in the simulation. For the "Others," which has a percentage of 32.5%, the vehicles in the dataset that are not mentioned in the figure will be used. For example, Tesla, JAGUAR, Audi, and Mercedes.

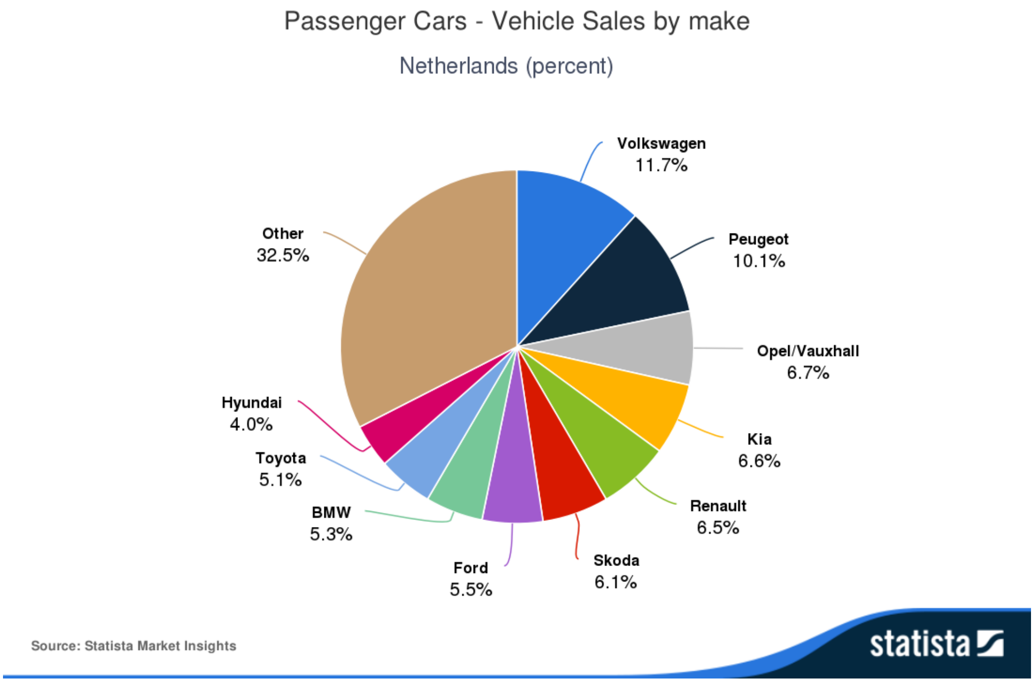


Figure 4.24: Market penetration rates of passenger cars in the Netherlands(Statista, 2024)

4.6. Summary of the ACC Characteristics

This section summarizes the ACC characteristics from the databases. Due to the data availability, there are some assumptions made. The following subsections explain how the assumptions are made. In the end, the table of the summary is presented.

Market Share

If vehicles are included in the statistical results for market share, they are assigned their respective share from these statistics. If not, their market share is assumed to be 5%, except for Tesla. Since Tesla exclusively manufactures electric vehicles, its market share is assumed to be equivalent to the total market share of the electric vehicle segment, according to the statistics. The sum of the market shares listed in the table does not add up to 100% , indicating that the vehicles in the database do not comprehensively represent all vehicle types. Therefore, the remaining market share is categorized as 'others' and is represented using the TNO ACC V1 model.

Acceleration Capabilities

Maximum deceleration might be impossible because of the safety concerns when conducting the experiments. Therefore, the assumptions are made as follows:

- The maximum deceleration rate for a vehicle's ACC system is defined by the vehicle's highest deceleration rate if it is less than -3.5 m/s^2. These values are rounded to the first decimal place. For example, a deceleration rate of -4.06 m/s^2 would be rounded to -4.0. It is considered that manufacturers do not set maximum deceleration rates to specific decimal points but use approximate values like 0 or 0.5.
- If it is larger than -3.5 m/s^2 from empirical data on the vehicle, it shall be regarded that the ACC system has a maximum deceleration rate of -3.5 m/s^2, according to ISO 15622 standard regulations.

The maximum deceleration rate for ACC systems does not represent the maximum deceleration rate of the vehicle. It can be said that if the ACC systems judge there will be a deceleration larger than the accelerating capabilities of the systems itself, it requests the driver to take over control (Volvo, 2018). In the literature, most ACC studies have adopted constant values for maximum simplicity, e.g., 2.0m/s^2 and -6 m/s^2 are commonly chosen as the maximum acceleration/deceleration values, probably because they are the physical bounds of a regular vehicle in all states (Wang et al., 2020). As for the acceleration capabilities for the vehicles themselves,

Inter-vehicle Space (IVS) and Time Gap

Since the campaigns were conducted on public roads using the OpenACC database, only minimum distance settings were used, and comprehensive data on larger distance settings was lacking. Further details were obtained from the owners' manuals. Some vehicles use time-distance-based settings, but specifics on inter-vehicle space are not provided. Others might indicate various levels of distance settings without precise values; in such cases, assumptions are made based on similar vehicles with the same level of settings (e.g., 4 levels of distance setting). For Peugeot and Mitsubishi, which feature 3-level distance settings without specified values, assumptions are based on ISO15622, which mandates at least one-time gap setting in the range of 1.5 to 2.2 seconds for speeds exceeding 8 m/s (International Organization for Standardization, 2018).

Response Time

The response time data is based on findings from Makridis et al., 2020a, which utilized the AstaZero Campaign from the OpenACC database. The research noted that the vehicle with an electric powertrain, V1, displayed notably faster response times than other vehicles. Although it's not definitively clear whether the powertrain type directly affects response times, it's assumed there might be a connection. Therefore, vehicles sharing the same type of powertrain are presumed to have similar response times. The table shows the vehicles categorized as three types of powertrains: electric, gasoline, and diesel.

Standstill Distance

The standstill distance data are sourced exclusively from the AstaZero Campaign in the OpenACC database, as this was the only experiment designed to include scenarios that ended at a full stop. This dataset is based on the same assumptions as the "Response time" data, both of which are derived from the same campaign.

4.6.1. Final Input Table

Table 4.12 presents a summary of the characteristics of various ACC systems discussed in this chapter, highlighting the differences between them. However, not all characteristics could be incorporated into the simulations due to several limitations, such as the lack of relevant ACC settings in the external driver model or insufficient data to accurately represent these differences. The table below lists the ACC system characteristics that were excluded from the simulations, along with the reasons for their exclusion.

Table 4.11: Summary of ACC Characteristics and Reasons for Exclusion from Simulations

ACC Characteristics	Reason
IVS	The inter-vehicle distance may vary depending on the speed of the vehicles. Therefore, only the time gap, which accounts for these speed differences, is used in the simulation.
Response time	There is no relevant setting about the response time in the external driver model utilized in VISSIM.
String stability	There is no relevant setting about the string stability in the external driver model utilized in VISSIM. In addition, the data is insufficient to highlight the differences among various ACC systems.

The characteristics that are considered in the simulations are highlighted in yellow in the first row. The values from Table 4.12 are used as the basis for the inputs in these simulations. A note below the table clarifies the meanings of the different colored text used.

Table 4.12: Summary of ACC systems' characteristics from the empirical data and owners manuals

Vehicle Brand	Market share(%)	Model	Acceleration (m/s^2) (max/ min)	Inter-vehicle space (m) (S/ L)	Time gap (s) (S/ L)	Response time (s)	Standstill distance (m) (min/ max)	Min Set Speed for ACC (km/hr)	Speed required to activate ACC (km/hr)	ACC speed range (km/hr)
Hyundai	4.0	Ioniq Hybrid	2.00/ -3.50	26.88/ 52.43	1.00/ 2.5	2.42 (gasoline)	3.05/ 5.80	30	30/ 10	30-190/ 10-190
Volvo	4.0	XC40	2.00/ -3.50	8.98/ 55	1.53/ 3.00	2.34 (diesel)	3.19/ 3.34	30	15/ 0	15-200/ 0-200
Volkswagen	11.7	Golf E	2.00/ -3.50	35.78/ 55	1.15/ 3.00	1.7 (e)	4.49/ 6.25	30	30/ 10	30-150/ 0-150
Peugeot	10.1	3008 GTLine	2.00/ -4.00	32.68/ 52.43	1.06/ 2.20	2.34 (diesel)	3.19/ 3.34	30	30/ 10	30-180/ 10-180
Kia	6.6	Niro	2.10/ -4.00	46.65/ 52.5	1.48/ 2.51	2.42 (gasoline)	3.05/ 5.80	30	30/ 0	10-160/ 0-160
Ford	5.5	S-Max	3.00/ -4.00	48.60/ 52.43	1.61/ 2.50	2.34 (diesel)	3.19/ 3.34	30	30/ 10	30-190/ 10-190
Mitsubishi	4.0	Outlander PHEV	4.00/ -4.00	44.51/ 50	1.44/ 2.20	2.42 (gasoline)	3.05/ 5.80	40	40/ 10	30-180/ 10-180
BMW	5.3	**I3**	2.00/ -3.50	16.65/ 27.01	1.17/ 2.08	2.34 (diesel)	3.19/ 3.34	30	30/ 0	30-180 / 0-180
		X5	2.50/ -3.50	21.62/ 46.67	1.14/ 2.51	2.34 (diesel)	3.19/ 3.34	30	30/ 0	30-180 / 0-180
		530i	3.00/ -5.00	17.03/ 51.66	1.20/ 2.50	2.34 (diesel)	3.19/ 3.34	30	30/ 0	30-180 / 0-180
Toyota	5.1	**RAV4**	2.00/ --3.50	15.29/ 19.66	1.67/ 2.29	2.42 (gasoline)	3.05/ 5.80	30	30/ 30	30-190/ 30-190
Tesla	7.6	**Model X**	2.00/ -5.00	12.61/ 30.61	1.09/ 2.29	1.7 (e)	4.49/ 6.25	30	30/ 0 (if a preceding vehicle is within 1.5m)	30-150/ 0-150
		Model S	2.00/ -3.50	19.19/ 35.13	1.38/ 2.73	1.7 (e)	4.49/ 6.25	30	30/ 0 (if a preceding vehicle is within 1.5m)	30-150/ 0-150
		Model 3	2.00/ -3.50	22.40/ 45.72	1.23/ 2.53	1.7 (e)	4.49/ 6.25	30	30/ 0 (if a preceding vehicle is within 1.5m)	30-150/ 0-150
Audi	4.0	**A4**	2.00/ -3.50	16.46/ 32.38	1.66/ 3.33	2.42 (gasoline)	3.05/ 5.80	30	30/ 0 (if the vehicle is not stationary for more than 3 minutes)	30-150/ 0-150
		A6	2.50/ -4.00	22.91/ 66.16	1.17/ 3.54	2.56 (diesel)	4.07/ 7.80	30	30/ 0 (if the vehicle is not stationary for more than 3 minutes)	30-150/ 0-150
		A8	2.00/ -3.50	20.09/ 32.38	0.721/ 3.55	2.56 (diesel)	4.07/ 7.80	30	30/ 0 (if the vehicle is not stationary for more than 3 minutes)	30-150/ 0-150
		E TRON	2.00/ -3.50	12.60/ 30.05	1.32/ 3.53	1.7 (e)	4.49/ 6.25		30/ 0 (if the vehicle is not stationary for more than 3 minutes)	30-150/ 0-150
Mercedes	4.0	**GLE450**	2.00/ -3.50	13.99/ 23.62	1.34/ 1.94	2.42 (gasoline)	3.05/ 5.80	20	20/ 20	20-210/ 0-210
		A Class	3.00/ -3.50	21.91/ 44.99	1.16/ 2.41	2.42 (gasoline)	3.05/ 5.80	20	20/ 20	20-160/ 0-160
JAGUAR	4.0	**I PACE S**	2.00/ -3.50	14.25/ 21.68	1.77/ 2.55	1.7 (e)	4.49/ 6.25	32	32/ 0	32-200/ 0-200
Mazda	4.0	**3**	2.00/ -3.50	17.26/23.83	1.96/ 2.89	2.42 (gasoline)	3.05/ 5.80	30	30/ 0	30-145/ 0-145

Yellow highlighted texts: The characteristics that can be set in the simulation.
Light blue texts: The data on vehicles is from the Cherasco Campaign in the OpenACC database.
Green texts: The data on vehicles is from the Vicolungo Campaign in the OpenACC database.
Bold texts: The data on vehicles is from the ZalaZone Campaign Dynamic part in the OpenACC database.
Dark orange texts: The data on vehicles is from the AstaZero Campaign in the OpenACC database.
Dark blue text: The vehicle is from the SAE L2 database.
Red text: The assumptions are made for the values.
Underlined text: The data is sourced directly from the owner's manual

5 Simulation Results

In this chapter, the results of the first nine simulation scenarios are analyzed, with each indicator for assessment discussed in its own subsection. The chapter begins with section 6.1, which focuses on traffic flow efficiency, followed by an examination of vehicle network performance in section 5.2, and concludes with an analysis of traffic safety in section 5.3.In the end, the transition control-related outputs are present in section 5.4. The figures in this chapter use scenario names from Table 3.4 as the captions. The results are presented in terms of different indicators rather than different ACC MPRs. Furthermore, most of the results of the 50PR scenarios are not presented in this chapter due to the length of the report. Instead, they are put in Appendix C.

5.1. Traffic Flow Efficiency

5.1.1. Speed Distribution

The speed distribution of each scenario is illustrated by heatmaps. The x-axis represents the time interval in minutes, ranging from 0 to 180 minutes. The y-axis shows the loop detector positions, ranging from 1 to 35. The locations of on- and off-ramps are also plotted in the figure. On-ramps are indicated by the long dash pattern and labels beginning with 'O' (origin), and off-ramps are represented by the dotted dash pattern and labels starting with 'D' (destination), are marked. In addition, the color scale on the right side of the heatmaps indicates the average harmonic speed in kilometers per hour (km/h), with a gradient from red, indicating lower speeds 0 km/h, to blue, indicating higher speeds up to 120 km/h. The results of 50PR scenarios are not in the following section; instead, they are in Figure C.1.

Base

In the base scenario, as shown in Figure 5.1, it can be seen there is a distinct bottleneck between loop detectors 18 and 19, where is the on-ramp 6. The bottleneck occurs due to the reduced lanes after the acceleration sections due to the reduction in lanes following the acceleration sections, which are used to merge on on-ramps into the main traffic flow.

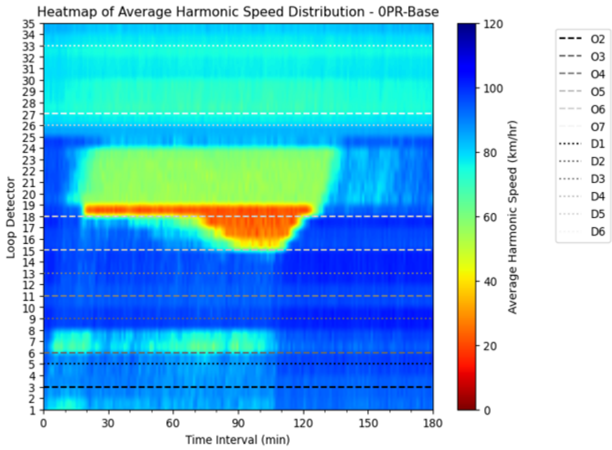


Figure 5.1: Speed Distribution Heatmap - 0PR-Base

Scenarios with 25% ACC MPRs (25PR-)

Figure 5.2 illustrates the speed distribution for 25PR scenarios under different distance settings. From left to right, the configurations are all small settings, a mix of small and large settings, each accounting for 50%, and all large settings. In addition, for enhanced comparison, the speed distribution for the 25PR-Speed-SL scenario is displayed below the figure for 25PR-All-SL. This scenario represents conditions where ACC systems are unable to follow the full-speed range with mixed distance settings, providing a clearer perspective on how these configurations affect speed distribution.

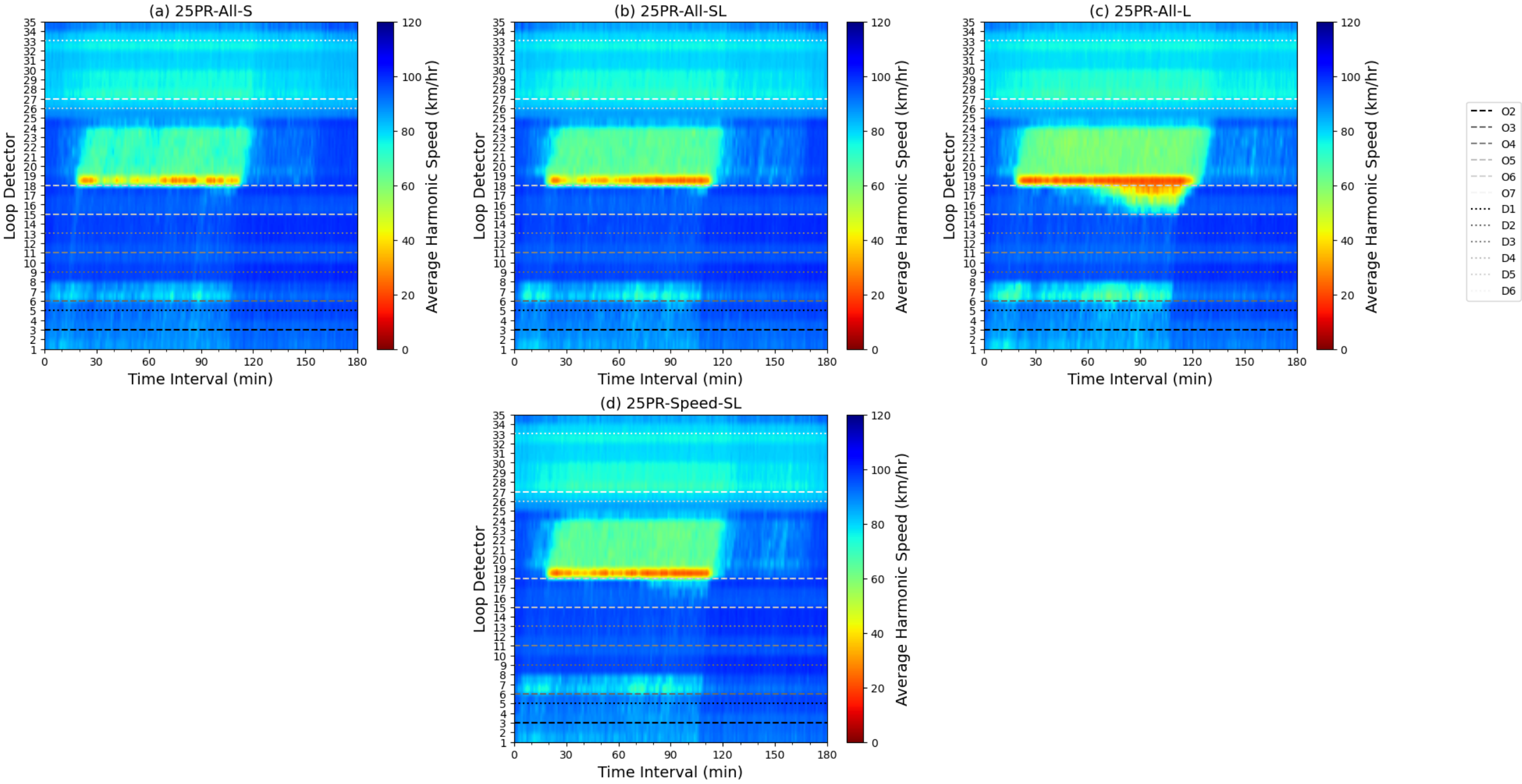


Figure 5.2: Speed Distribution Heatmap - 25PR scenarios

The figure shows that, overall, the average speed has increased. However, the degree of congestion reduction varies across the different scenarios. Among them, the scenario with only small distance settings experiences the least congestion. In contrast, the scenario where ACC vehicles use only large distance settings also reduces congestion compared to the base scenario but remains the most congested among the 25PR scenarios. For the 25PR-Speed-SL scenario, which shares the same distance settings as 25PR-All-SL, there is a slight increase in congestion, particularly between 30 and 60 minutes.

Scenarios with 75% ACC MPRs (75PR-)

Figure 5.3 illustrates the speed distribution for scenarios with 75% ACC MPRs under different distance settings. From left to right, the configurations are all small settings, a mix of small and large settings, each accounting for 50%, and all large settings. In addition, the speed distribution the scenario 75PR-Speed-SL, where the ACC systems cannot follow the full-speed range with the mix distance setting leading to transition of controls, is also present under the figure for 25PR-All-SL.

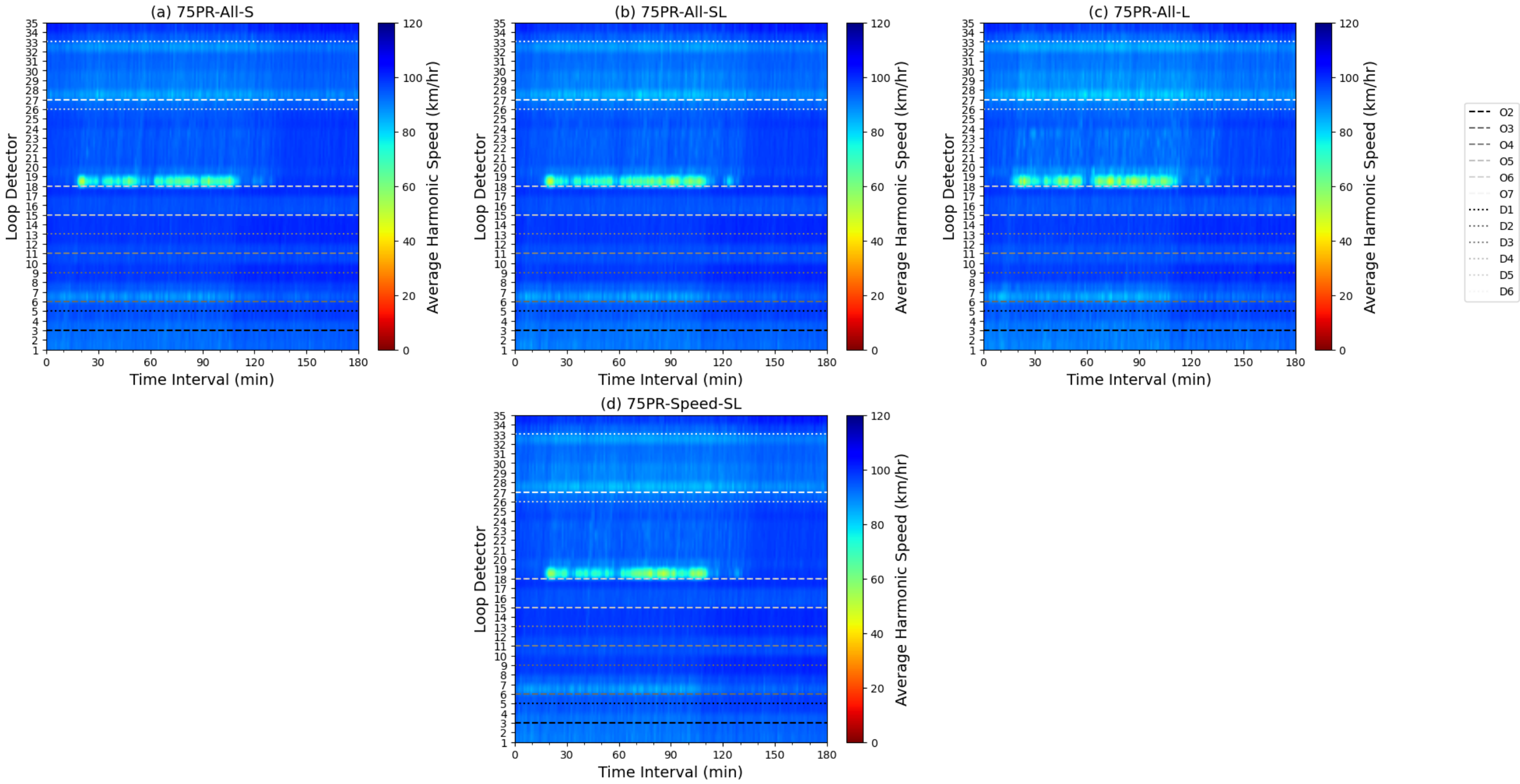


Figure 5.3: Speed Distribution Heatmap - 75PR scenarios

Figure 5.3 shows that congestion is reduced more compared to the base and 25PR scenarios. Furthermore, the congestion levels across the scenarios with 75% ACC MPRs are relatively similar, and the differences in congestion levels among the 75PR scenarios are less significant compared to the differences observed among the 25PR scenarios.

Overall, it can be observed that the congestion levels decrease after introducing vehicles equipped with the ACC systems and the transition control models compared to the base scenario, and the distance settings play a role in the final congestion pattern. The following findings are drawn by comparing the results with the base scenario, and the extent of congestion reduction is evaluated across different scenarios with the same ACC MPRs. When smaller following distances are applied, congestion is further reduced. On the other hand, when a larger number of vehicles operate with larger distance settings while ACC is active, there is a slight increase in congestion levels, particularly distinct at lower MPRs of ACC. In scenarios where ACC systems are unable to manage full-speed following, congestion levels are higher compared to scenarios utilizing a mix of minimum speeds for ACC systems, even when a combination of small and large distance settings is applied. This effect is especially also more observable at lower MPRs of ACC.

5.1.2. Time Gap

Figure 5.4 shows the time gap distribution with ACC under different distance settings. The time gap distribution of scenario 25PR-Speed-SL is not in the figure because it has the same distance setting as 25PR-All-SL. The results show that while the ACC systems attempted to maintain the desired time gap, variations in traffic dynamics resulted in deviations from the target values. This is evident from the peaks and spread of the distributions, which reflect the influence of traffic flow on maintaining consistent time gaps. In addition, it can be observed that different distance settings result in varying time gap distributions. This variation also impacts the speed distribution, as discussed in Section 5.1.1. Especially when the distance setting is the only controlled factor, scenarios with larger distance settings tend to show more congestion. This suggests that maintaining larger time gaps can lead to increased congestion levels.

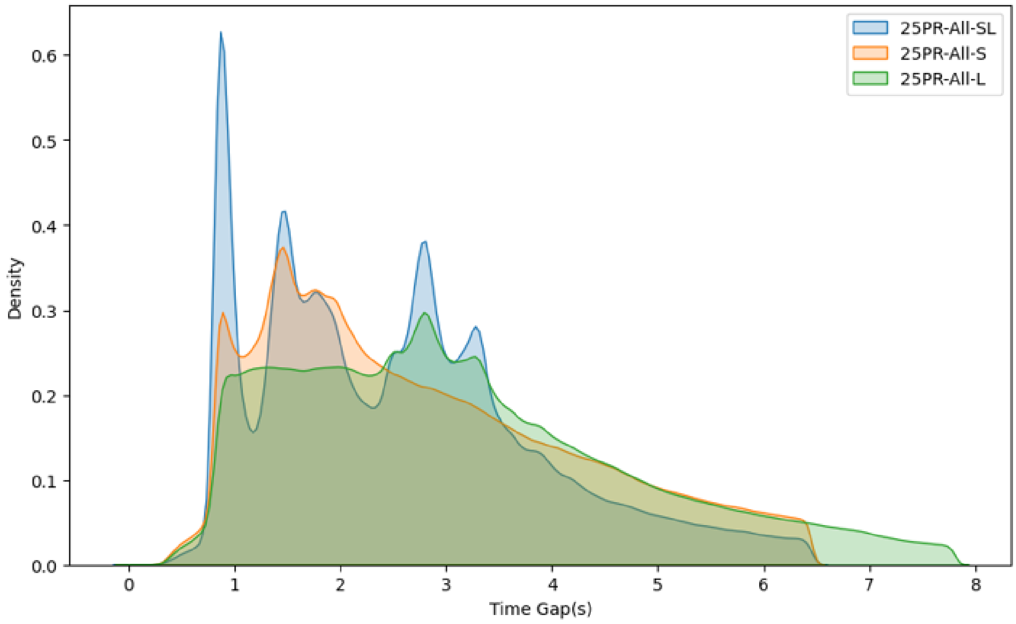


Figure 5.4: 25PR - Time gap distribution with ACC on under different distance settings

Figure 5.5 shows the same for 75PR scenarios. The scenarios compared are 75PR-All-SL, 75PR-All-S, and 75PR-All-L. Scenario 75-Speed-SL is also not in the figure due to the same distance setting as 75PR-All-SL. It can be observed that in these high ACC penetration scenarios, there is a significant peak in the time gap values of around 1 second, although the desired time gap input follows the distribution from Chapter 4, as shown in Figure 5.6. This suggests that even though the ACC systems aim to maintain a desired time gap, the actual time gaps frequently cluster around 1 second. This indicates that the ACC systems are actively regulating the vehicle spacing, though traffic dynamics might still cause deviations from the desired time gap. Figure 5.6 provides a comparison between the 0PR-Base scenario and the 75PR-All-SL scenario, alongside the desired input time gap distribution and the actual vehicle-applied time gap in the simulation. The desired input time gap, represented by the green bar, refers to the distribution derived from the data analysis results and is used as the input distribution function for the time gap. The actual time gap applied to vehicles in the simulation refers to the time gaps assigned to ACC vehicles during the vehicle generation process, as described in section 3.3.1. It is evident that in the 75PR-All-SL scenario, the time gap values around 1 second are more frequent compared to the base scenario. Despite the consistent input of the desired time gap, the real-time application of the ACC systems results in a distinct distribution pattern. The shorter time gap can also lead to higher capacity and less congestion, which can be supported by the heatmap in section 5.1.1.

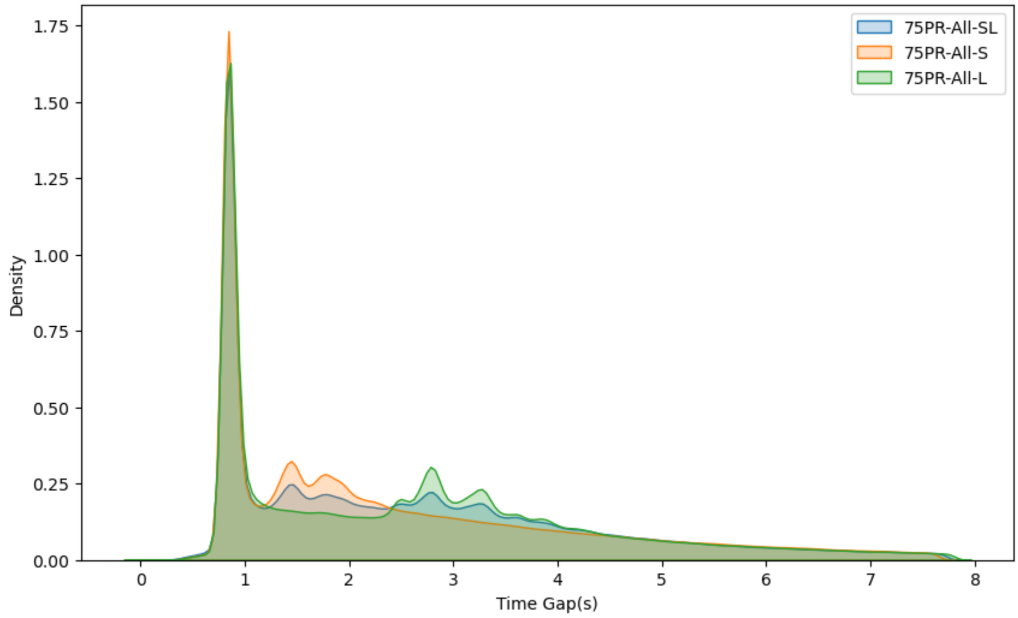


Figure 5.5: 75PR- Time gap distribution with ACC on under different distance settings

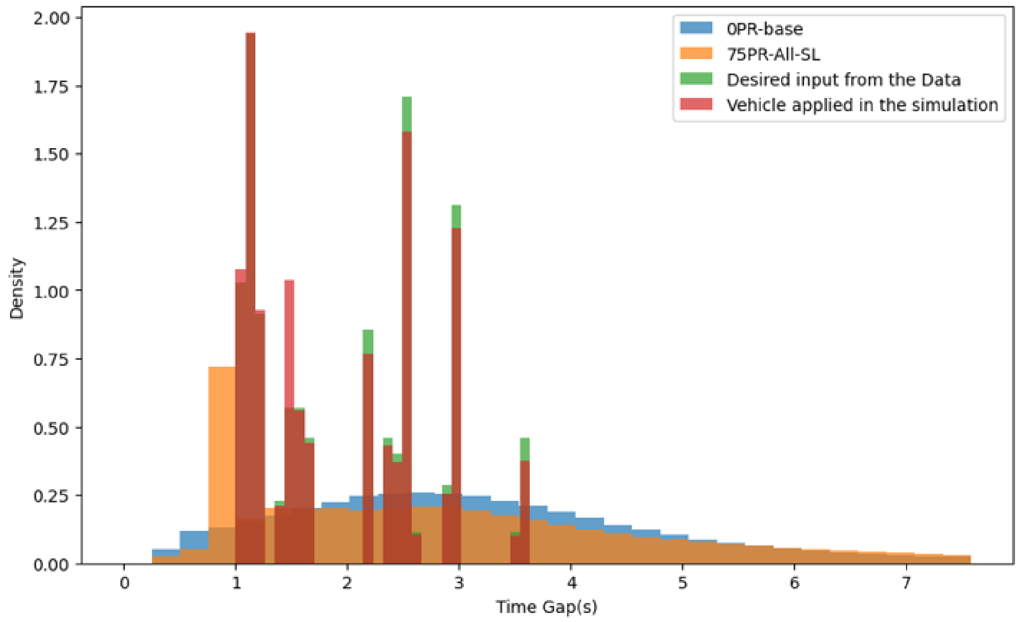
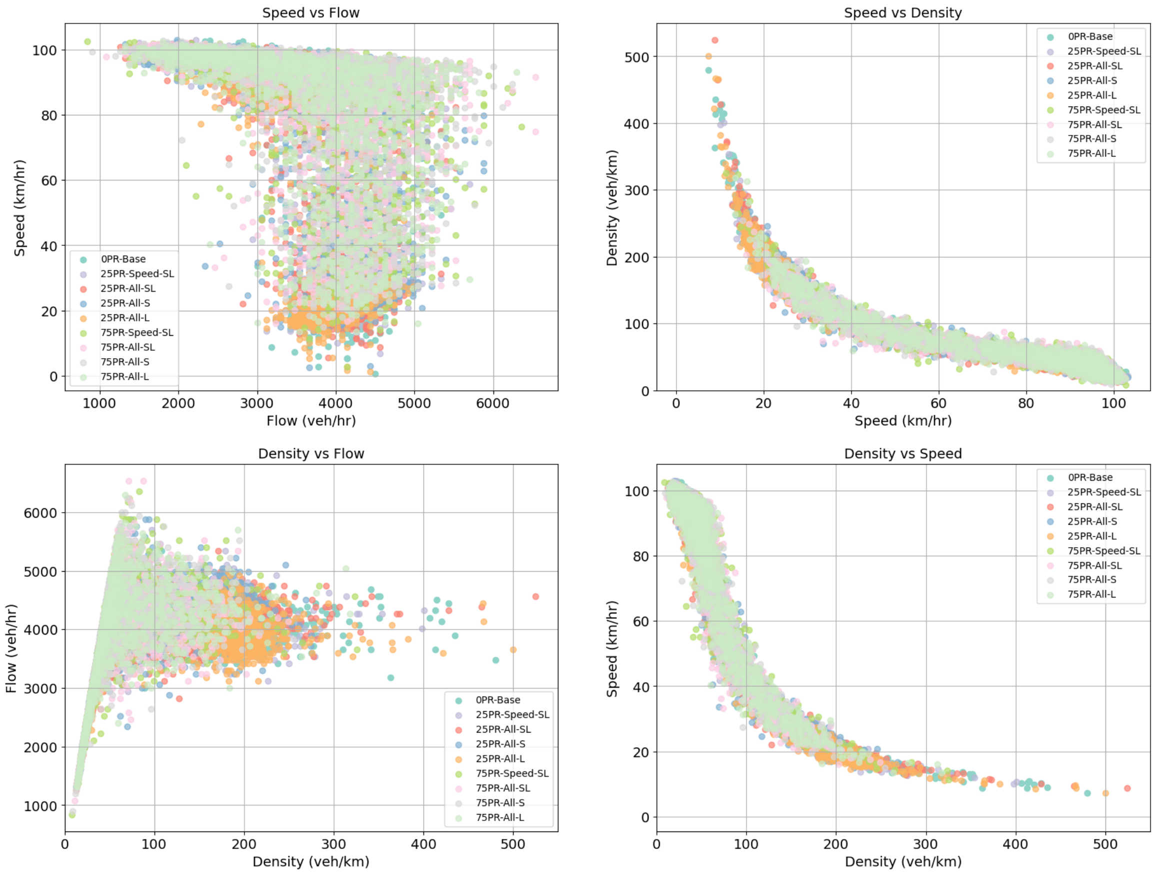


Figure 5.6: Input desired time gap and the actual time gap assigned to the ACC vehicles in Scenario 75PR-All-SL

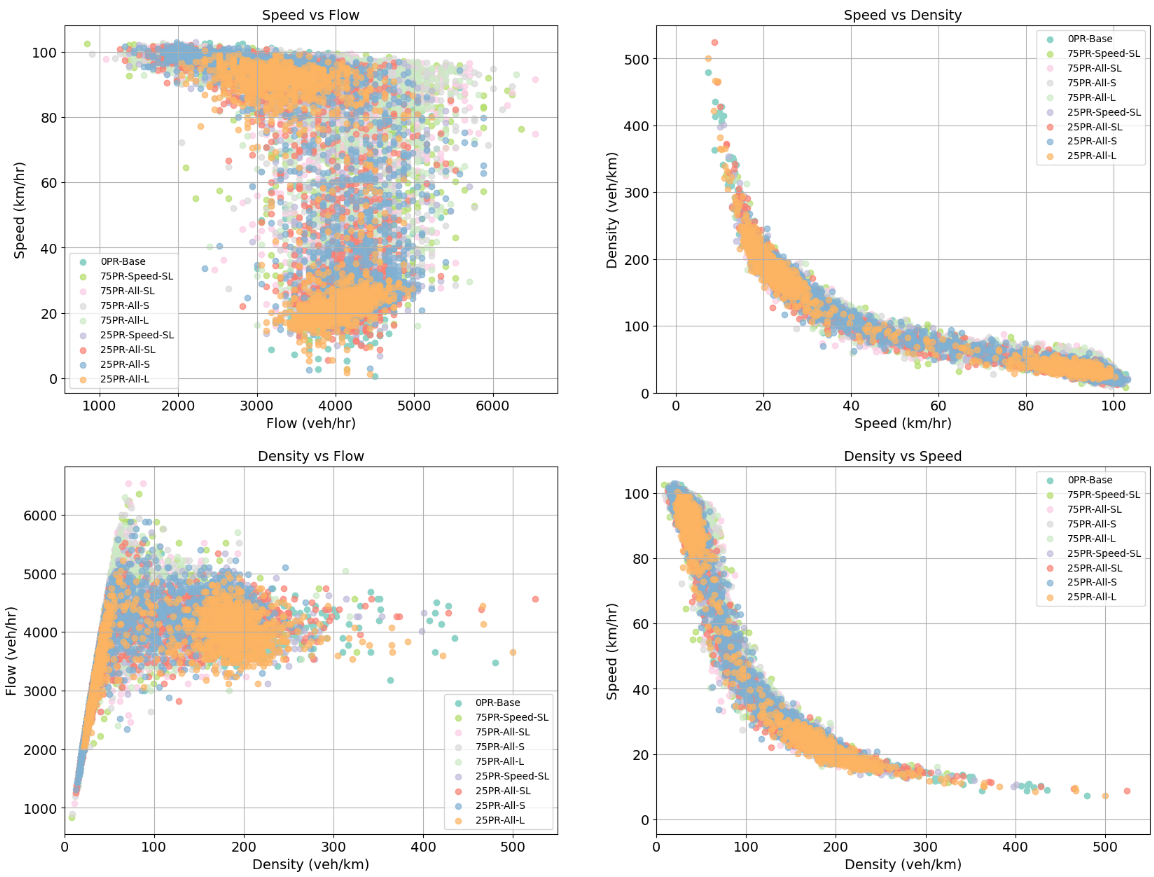
5.1.3. Fundamental Diagrams

Figure 5.7a and 5.7b display a series of scatter plots and density plots that compare different traffic scenarios based on three key metrics: speed, flow, and density. The data for these fundamental diagrams are collected from Loop Detector 19, where a bottleneck is generated due to a reduction in the number of lanes from four to three. Although both figures use the same dataset, they present the data in different sequences to highlight different aspects of the scenarios. In Figure 5.7a, the data points for the 75PR scenarios are positioned in the foreground. On the other hand, in Figure 5.7b, the 25PR scenarios are brought to the front, allowing the data points to remain visible. Examining these two figures together provides a more comprehensive understanding of the relationships between the key metrics for different ACC market penetration scenarios. The main report only put these two figures with all scenarios plotted. For the individual figures plot for each scenario, they are put in appendix D.

It can be observed that as ACC MPRs increase, the road capacity, represented by traffic flow, tends to increase. This means that roads can accommodate more vehicles per hour with higher ACC penetration. In addition, for a given level of flow, traffic density is lower when ACC MPRs are higher, indicating more efficient use of road space. This relationship is further supported by the speed distribution data, which shows that congestion levels decrease as ACC MPRs increase. It is worth noting that the threshold for maximum flow is 6,000 vehicles per hour. In 75PR scenarios, the flow peaks exceed this threshold, indicating superior capacity and efficiency. In contrast, the peaks for the 2PR scenarios and the 0PR-base scenario are below 6,000 vehicles per hour, indicating the limitations of lower ACC penetration in handling higher traffic volumes. This data clearly illustrates the effectiveness of ACC systems with transition control models in improving overall traffic performance and reducing congestion at higher penetration levels, which also aligns with the findings from other indicators.



(a) 25PR+75PR



(b) 75PR+25PR

Figure 5.7: Fundamental diagrams for all scenarios at the bottleneck

5.2. Vehicle Network Performance

The results of the 50PR scenarios for vehicle network performance are presented here using bar charts, which provide a clear visual representation of how ACC MPRs influence traffic efficiency. Figure 5.8 displays two key indicators recorded directly from VISSIM: average delay and total travel time. The blue bars represent the average delay, which consistently decreases as ACC market penetration increases. In the 0PR-Base scenario, the average delay is 95.14 seconds. When the ACC MPR is 25% in the 25PR-All-S scenario, the delay reduces to 54.57 seconds, showing a distinct improvement of 43% compared to the 0PR-Base scenario. As ACC penetration increases further, the reduction becomes even more significant. In the 50PR-All-S scenario, the delay drops to 37.97 seconds, reflecting a 60% decrease from the 0PR-Base scenario. Finally, in the 75PR-All-S scenario, the delay reaches its lowest value of 32.70 seconds, marking a 65% reduction. This downward trend in delay across the scenarios highlights how increasing the penetration of ACC systems with transition control models leads to smoother and more efficient traffic flow.

Moreover, similar improvements are observed in the total travel time, represented by the orange bars. In the 0PR-Base scenario, the total travel time is 8.36 million seconds. With 25% ACC penetration in the 25PR-All-S scenario, total travel time decreases to 7.19 million seconds, indicating a 14% reduction. As ACC MPR increases, the improvements become more substantial. In the 50PR-All-S scenario, the total travel time drops to 6.60 million seconds, a 21% decrease. Finally, in the 75PR-All-S scenario, total travel time further reduces to 6.38 million seconds, resulting in a 24% improvement compared to the 0PR-Base scenario.

Other scenarios follow similar trends. For instance, in the 25PR-All-L scenario, which models a larger vehicle distance setting, the average delay is 82.97 seconds, and the total travel time is 7.86 million seconds. This scenario shows improvement, but at a slower rate compared to the smaller distance settings, indicating that tighter vehicle spacing enhances the effectiveness of ACC systems. As ACC penetration reaches 75% in the 75PR-All-L scenario, the average delay drops to 37.92 seconds, and total travel time decreases to 6.38 million seconds, similar to the improvements seen in smaller distance settings. In scenarios such as 25PR-Speed-SL, the average delay is 64.46 seconds, and the total travel time is 7.46 million seconds. At 75% penetration in the 75PR-Speed-SL scenario, these values reduce to 35.10 seconds and 6.76 million seconds, respectively.

Overall, it can be observed that both average delay and total travel time are significantly reduced after introducing ACC systems with the transition control model. Across all vehicle settings, as the ACC MPRs increase, the reductions in average delay and total travel time become more distinct. This trend clearly indicates that higher ACC MPRs contribute to more efficient traffic flow and reduced congestion, reinforcing the finding from the speed distribution analysis discussed in Section 5.1.1. The results show that ACC systems not only improve individual vehicle behavior but also enhance overall traffic network performance, especially at higher ACC MPRs.

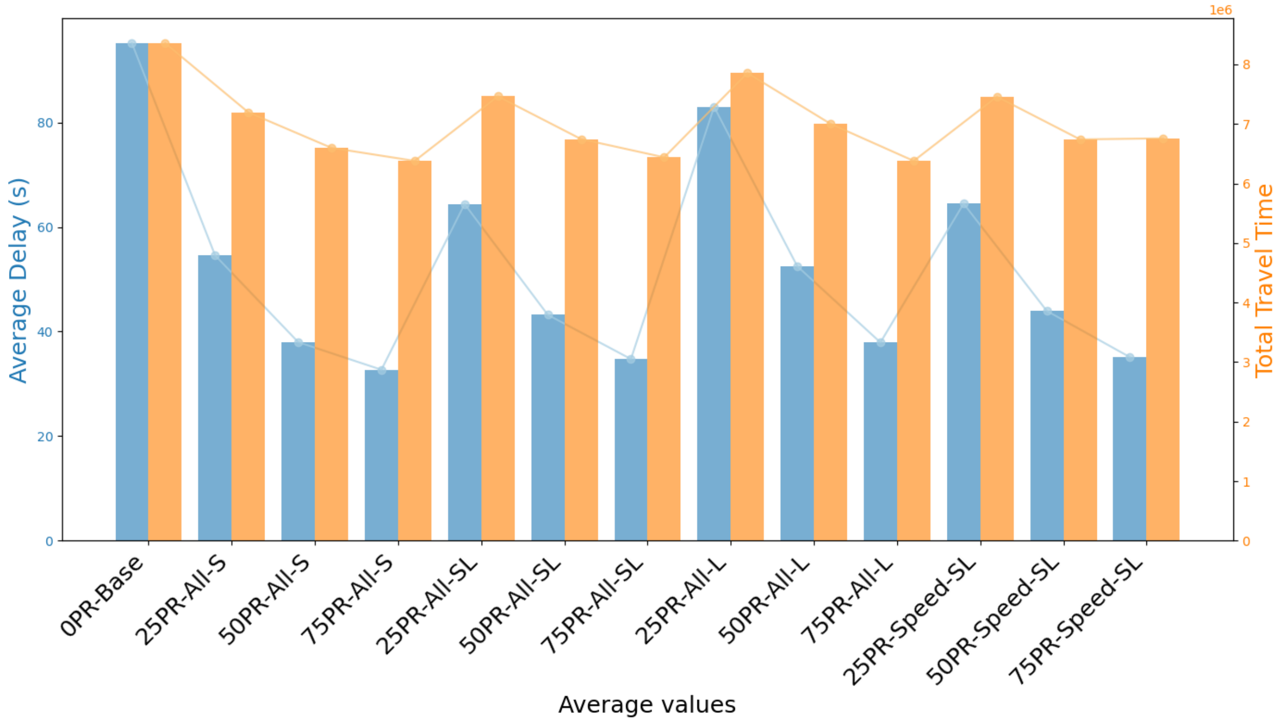


Figure 5.8: Vehicle network performance indicators

Figure 5.9 presents a comparative analysis of vehicle network performance indicators across different ACC market penetration rates (MPRs) using three subfigures for each MPR: 25%, 50%, and 75%. Each subfigure uses the same x-axis and y-axis scales, along with a consistent grid, providing a clear view of performance across different scenarios.

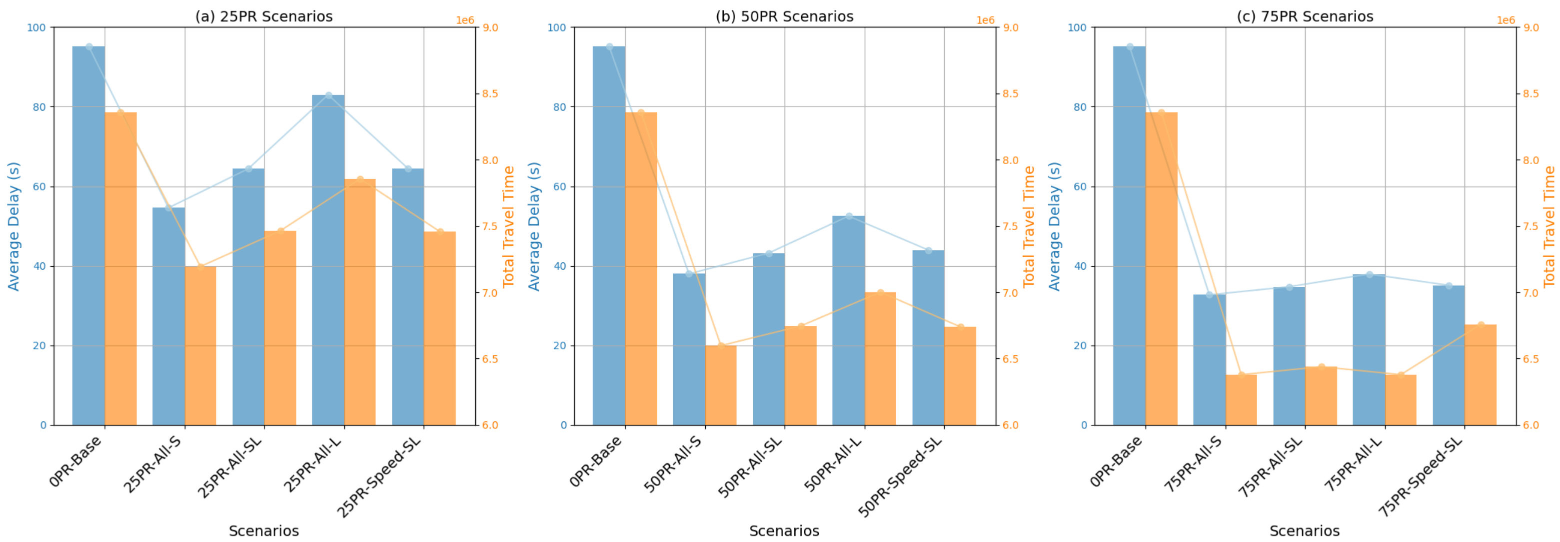


Figure 5.9: Vehicle network performance indicators in terms of different ACC MPRs

5.3. Traffic Safety

5.3.1. Time-to-collision (TTC)

The TTC values analysis is considered the only TTC value below 5 seconds. It can be observed that the introduction of ACC systems has an impact on TTC values, which lead to longer and safer than the corresponding base scenario (0PR-Base). As is shown in Figure 5.10, the TTC values for all percentiles are the lowest when vehicles are human-driven. This tendency is more distinct at lower percentiles. Moreover, when distance settings are mixed, incorporating both small and large distance settings, TTC values tend to decrease, especially for the 25PR scenarios. This may be attributed to the more heterogeneous traffic flow created by mixed-distance settings. From the perspective of the ACC MPRs, only at the 10th percentile do the 75PR scenarios demonstrate significantly higher TTC values. The results for 50PR scenarios are shown in Figure C.2.

In addition, it is worth noting that a small distance setting alone may also have a slight advantage in terms of safety, as it tends to keep a bit longer TTC values compared to other settings. The reason could be that the small distance setting leads to less congestion, as discussed in Section 5.1.1, and the traffic flow is more homogeneous. By allowing vehicles to operate closer together without compromising safety, this setting can lead to smoother traffic flow and less congestion. Overall, the small distance setting not only contributes to increased safety through extended TTC values but also reduces traffic congestion.

Table 5.1: Overall TTC (consider only the values smaller than 5)

Percentile	0PR-Base	25PR-All-SL	25PR-All-S	25PR-All-L	25PR-Speed-SL	75PR-All-SL	75PR-All-S	75PR-All-L	75PR-Speed-SL
10	0.87	1.32	1.56	1.47	1.31	1.60	1.64	1.61	1.62
25	1.62	2.14	2.36	2.30	2.19	2.32	2.40	2.29	2.34
50	2.88	3.18	3.36	3.33	3.28	3.27	3.34	3.26	3.30
75	3.99	4.12	4.20	4.19	4.17	4.15	4.18	4.14	4.16
90	4.61	4.66	4.68	4.68	4.67	4.67	4.67	4.66	4.67

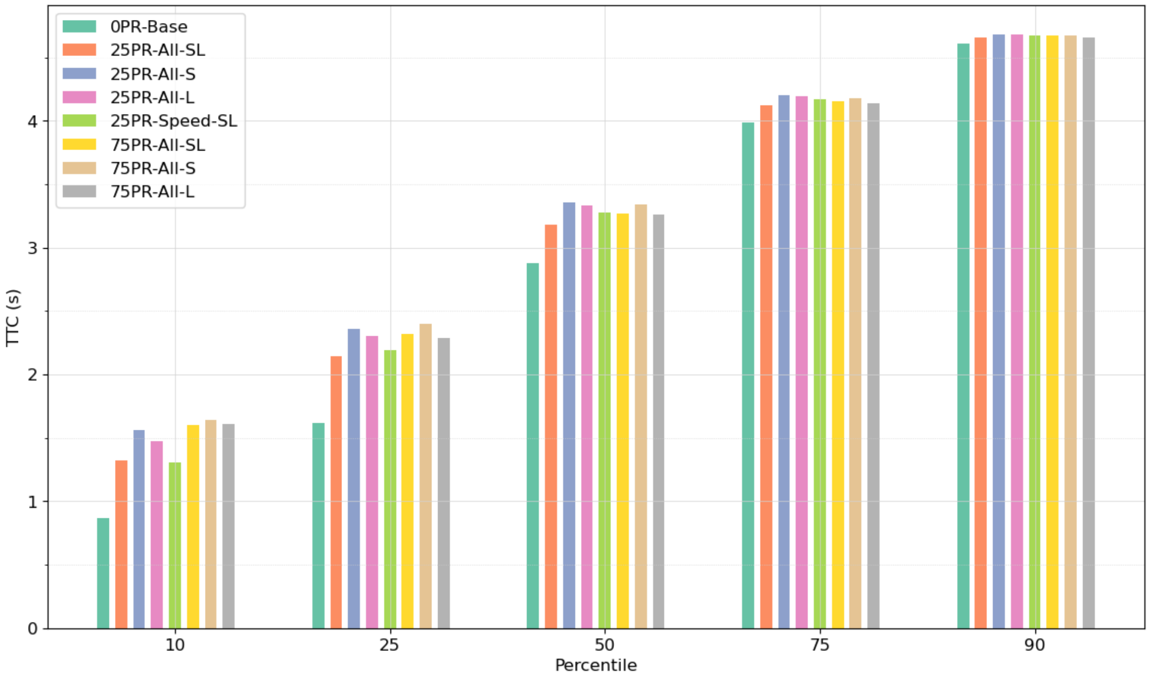


Figure 5.10: Overall Time-to-collision

5.3.2. Acceleration

In section 2.4.2, it is mentioned that the American Association of State Highway and Transportation Officials sets a deceleration threshold of -3.6. Figure 5.11 shows a histogram of acceleration values divided into two subfigures using this threshold as a separator, while those also included 50PR scenarios are shown in C.3. Because the frequency of accelerations below -3.6 is very low, these values are plotted separately for clarity. It is important to note that the y-axis tickers for the two subfigures are not the same. In subfigure (a), the y-axis has a maximum value of 0.0040, while in subfigure (b), it reaches 3.0. The histogram shows that most acceleration behaviors fall within a safe and stable range, with the majority of acceleration values between -2 and 2.

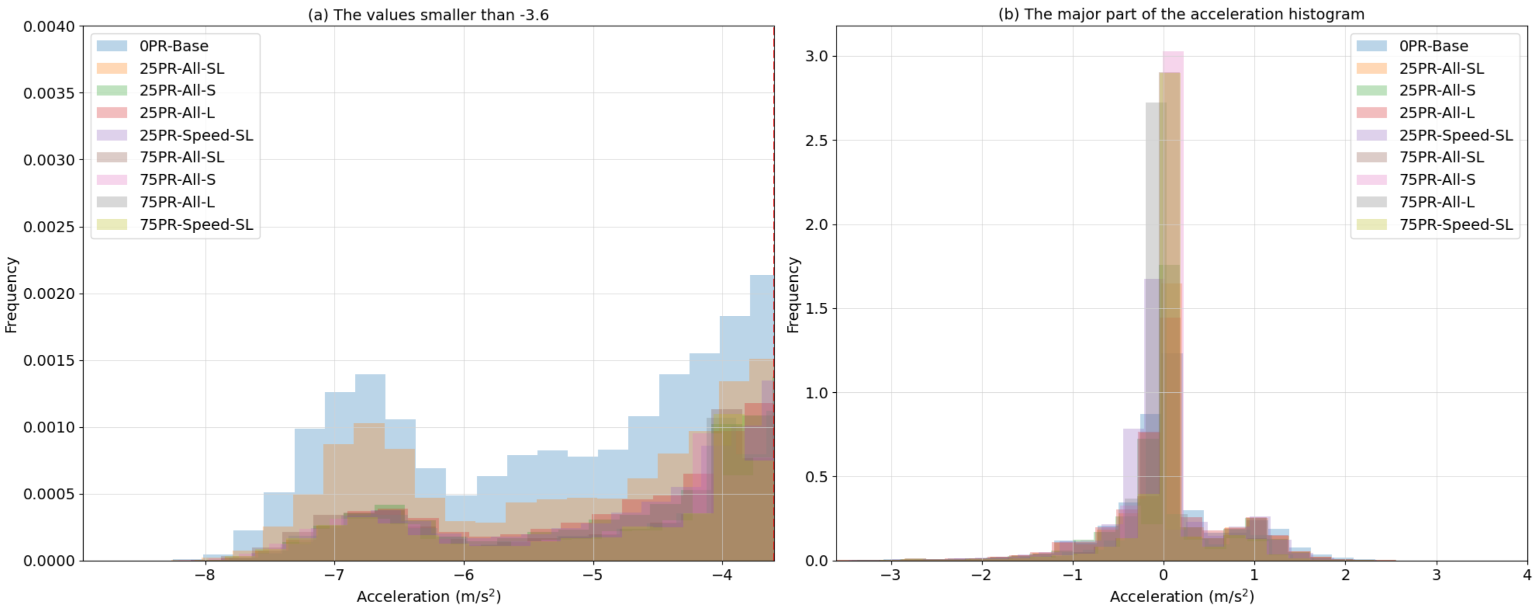


Figure 5.11: Acceleration Histogram

However, there are still some critical deceleration behaviors, as shown in Figure 6.12(a). Figure 5.12 illustrates the number of points smaller than the threshold. As for the 50PR scenarios, it is shown in Figure C.4. It can be seen that the base scenarios had the highest number of such points. With the implementation of ACC systems with the transition control model, the deceleration becomes more stable, and the number of points below the threshold is significantly reduced. In addition, it can be observed that the number of critical deceleration rates is lower in scenarios that include only small distance settings under the same ACC MPRs. This could explain the TTC results in Section 5.3.1, where scenarios with only small distance settings show slightly larger TTC values.

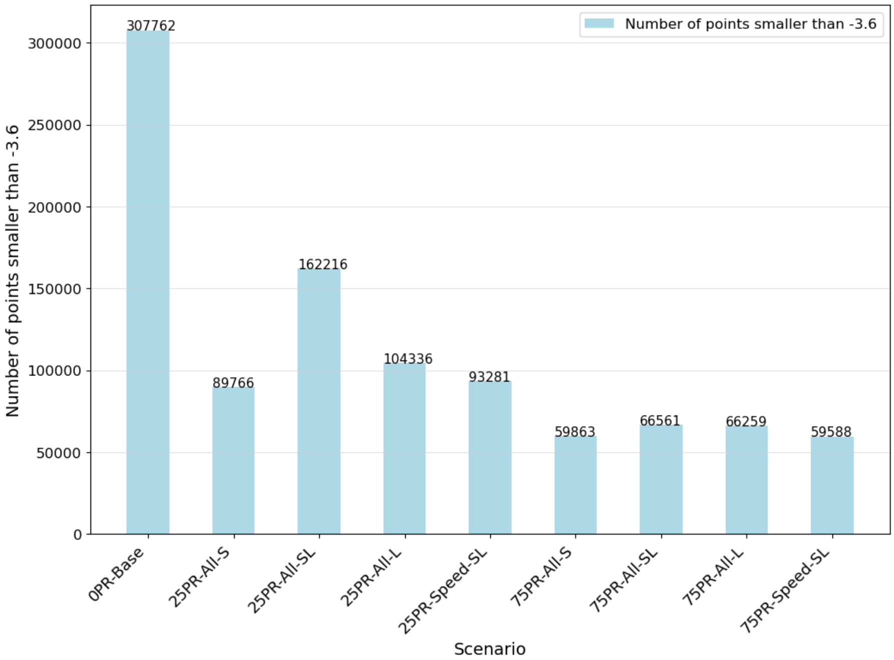


Figure 5.12: The number of acceleration points smaller than the threshold (-3.6 m/s^2) for each scenario

5.4. Transition Control-related Output

5.4.1. Number of Transition Control Types

There are four different scenarios under both 25% and 75% ACC MPRs, and the simulation seed for each scenario was ten. There are three outputs about the transition control types, which are DIDC, DIAC, and AIDC, across ten runs. Table 5.2 and 5.3 present the number of transition types for 25PR and 75PR scenarios, respectively. Table C.1 shows the results for 50PR scenarios. In the table within the following sections, each cell contains two values. The first value, located before the slash, represents the total number. The second value, located after the slash, represents the value per kilometer traveled, indicating the value per kilometer traveled across the entire simulation, including all drivers, rather than being limited to a single driver. For example, in Table 5.2, the cell for DIDC of 25PR-All-SL reads "41306 / 1.48," which means that 41306 is the total number and 1.48 is the value per kilometer traveled.

Table 5.2: Number of transition controls of different types - 25PR Scenarios

Transition type (Total number/ number per km)	25PR-All-SL	25PR-All-S	25PR-All-L	25PR-Speed-SL
DIDC	41306/ 1.48	45353/ 1.64	41575/ 1.48	42195/ 1.50
DIAC	40183/ 1.44	43511/ 1.60	41814/ 1.48	41672/ 1.48
AIDC	1340/ 0.08	1302/ 0.04	1505/ 0.04	1619/ 0.06
Time of ACC activated	87.49%	89.05%	86.14%	87.01%

Table 5.3: Number of transition controls of different types - 75PR Scenarios

Transition type (Total number/ number per km)	75PR-All-SL	75PR-All-S	75PR-All-L	75PR-Speed-SL
DIDC	108883/ 4.34	106254/ 4.37	112408/ 4.37	110730/ 4.45
DIAC	102427/ 4.08	99673/ 4.10	106623/ 4.15	104687/ 4.21
AIDC	2304/ 0.09	2093/ 0.09	2838/ 0.11	2114/ 0.08
Time of ACC activated	91.16%	91.43%	90.72%	90.95%

In the 25PR scenarios, the DIDC values range from 41,306 to 45,353 total, with per kilometer values between 1.48 and 1.64. This indicates a moderate frequency of driver-initiated deceleration events. DIAC values are relatively consistent across different conditions, ranging from 40,183 to 43,511 total, with per-kilometer values between 1.44 and 1.60. On the other hand, AIDC values are significantly lower, indicating fewer instances of ACC-initiated deceleration, with totals ranging from 1,302 to 1,619 and per kilometer values between 0.04 and 0.08. The time of ACC activation varies slightly but remains around 87-89%, showing consistent engagement of the ACC systems in these scenarios. In the 75PR scenarios, the number of transition events is significantly higher, which aligns with the increased presence of ACC vehicles expected to be around three times more than in the 25PR scenarios. DIDC values range from 106,254 to 112,408 total, with per-kilometer values between 3.336 and 4.373. This indicates a higher frequency of driver-initiated deceleration events compared to 25PR scenarios. DIAC values also increase, ranging from 99,673 to 106,623 total, with per kilometer values between 3.154 and 4.147.

The number of transition controls per kilometer is roughly the same for the scenarios within the same ACC MPRs, indicating that the distance setting is not the primary factor influencing transition controls. In the 25PR scenarios, the number of transition controls for 25PR-All-S is slightly higher than in other 25PR scenarios, possibly due to more time being available for the ACC system to activate.

5.4.2. Number of Transition Control Causes

Table 5.4 and 5.5 present the number of transition causes for 25PR and 75PR scenarios, respectively. As for the 50PR scenarios, the results are shown in Table C.2. The causes include approaching a lower-speed leader, meeting the ACC deceleration threshold, hitting the lower speed bound, forward collision warning (FCW), lane changes, and driver decision activation.

Table 5.4: Number of transition control causes - 25 PR Scenarios

Transition Causes (Total number/ number per km)	25PR-All-SL	25PR-All-S	25PR-All-L	25PR-Speed-SL
Approach Lower Speed Leader	811/ 0.028	619/ 0.024	377/ 0.012	512/ 0.012
*AccDecelThreshold	823/ 0.028	699/ 0.024	735/ 0.024	713/ 0.024
Lower Speed Bound	1114/ 0.036	760/ 0.028	4305/ 0.152	5535/ 0.196
**FCW	19389/ 0.688	20420/ 0.744	20370/ 0.516	20396/ 0.724
Lane Change	39316/ 1.400	43023/ 1.568	40289/ 1.416	40280/ 1.432
Driver Decision Activate	40183/ 1.428	43511/ 1.584	41575/ 1.464	41672/ 1.480

*AccDecelThreshold: ACC systems meet the minimum deceleration rate of the operational design domain.
**FCW: Forward collision warning.

Table 5.5: Number of transition control causes - 75PR Scenarios

Transition Causes (Total number/ number per km)	75PR-All-SL	75PR-All-S	75PR-All-L	75PR-Speed-SL
Approach Lower Speed Leader	3638/ 0.082	3780/ 0.156	3602/ 0.140	3613/ 0.145
AccDecelThreshold	3812/ 0.085	4409/ 0.181	3959/ 0.154	3649/0.200
Lower Speed Bound	1283/ 0.029	1032/ 0.042	1891/ 0.074	3353/ 0.135
FCW	33188/ 0.744	32196/ 1.325	38847/ 1.511	35776/ 1.437
Lane Change	100151/ 2.245	97142/ 3.998	104540/ 4.066	102149/ 4.104
Driver Decision Activate	102427/ 2.296	99673/ 4.102	106623/ 4.147	104387/ 4.194

In the 25PR scenarios, lane changes, and driver decision activation are the most frequent transition causes, with values indicating a high occurrence rate. Forward collision warnings (FCW) are also prevalent. Other causes, such as meeting the ACC deceleration threshold or the lower speed bound, are less frequent but still noteworthy. For instance, the total number of lane change transitions ranges from 39,316 to 43,023, with values per kilometer traveled between 1.400 and 1.568. On the other hand, driver decision activation ranges from 40,183 to 43,511 in total, with per-kilometer values from 1.428 to 1.584. In the 75PR scenarios, the frequency of lane changes and driver decision activation increases significantly compared to the 25PR scenarios. Given that ACC vehicles in the 75PR scenarios should be around three times more than in the 25PR scenarios, this increase is expected. The data show that these transition causes have higher values, indicating more frequent occurrences in higher market penetration rate scenarios. For example, lane changes in the 75PR scenarios range from 97,142 to 104,540, with per-kilometer values between 3.078 and 4.066. Driver decision activation ranges from 99,673 to 106,623, with per-kilometer values from 3.145 to 4.147. Besides, FCW occurrences remain substantial. The ACC deceleration threshold and lower speed bound transitions also show higher values, which suggest more frequent transitions in scenarios with higher ACC penetration rates.

5.4.3. Location of Transition Controls

Table 5.6 shows the percentage of transition control around on and off-ramps and the bottleneck for the 25PR and 75PR scenarios. The area around on- and off-ramps is defined by the number of lane changes due to the on- or off-ramps. For the off-ramps, the area of interest starts at the point where the additional lane for exiting traffic begins and extends to the start of the off-ramp, represented by points A to B in Figure 5.13. For the on-ramps, the area begins at the point where the ramp merges into the highway and continues until the lane drop ends, returning the highway to its normal number of lanes, as shown by points C to D in the same figure.

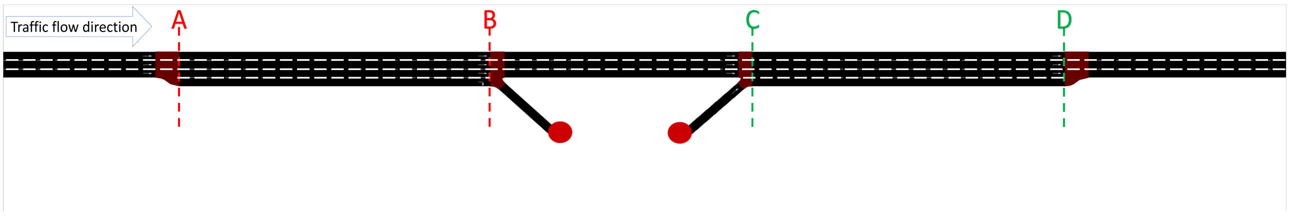


Figure 5.13: Schematic illustration defining the area around on- and off-ramps

As for the 50PR scenarios, the results are shown in Table C.3 and C.4. The bottleneck is recognized as the road section between loop detectors 18 and 19 from the speed distribution heatmap in section 5.1.1. The bottleneck is also a part of the area around on-ramp 6.

Table 5.6: Percentage (%) of transition control around ramps and the bottleneck

Scenario	Around Ramps	Around Bottleneck
25PR-All-SL	50.69	33.48
25PR-All-S	52.14	34.96
25PR-All-L	56.85	35.54
25PR-Speed-SL	55.31	38.52
75PR-All-SL	54.87	26.42
75PR-All-S	55.42	26.36
75PR-All-L	54.03	27.09
75PR-Speed-SL	54.28	27.59

Table 5.7: Percentage(%) of transition control causes around the bottleneck

Scenario	Lane Change	Lower Speed Bound	FCW
25PR-All-SL	23.2	83.6	65.9
25PR-All-S	25.9	97.1	66.1
25PR-All-L	22.9	93.3	68.4
25PR-Speed-SL	22.9	94.1	68.4
75PR-All-SL	23.5	91	67.9
75PR-All-S	23.3	94.6	74.7
75PR-All-L	24.8	92.1	60.5
75PR-Speed-SL	24.8	88.5	69.6

For all scenarios, over 50% of transition control occurred around on- and off-ramps. The data indicate that in the 25PR scenarios, the percentage of transition controls around ramps ranges from 50.69% to 56.85%, with the highest percentage observed in the 25PR-All-L scenario. Around bottlenecks, the percentages are slightly lower, ranging from 33.48% to 38.52%, with the 25PR-Speed-SL scenario showing the highest percentage. In the 75PR scenarios, the percentage of transition controls around ramps is relatively consistent, ranging from 54.03% to 55.42%. The 75PR-All-S scenario has the highest percentage. Transition controls around bottlenecks in the 75PR scenarios are lower than those in the 25PR scenarios, ranging from 26.36% to 27.59%. The 75PR-Speed-SL scenario shows the highest percentage in this category. It can also be seen in Table 5.4 that lane change is the main reason for deactivating the ACC systems. It is expected that there will be more lane change behaviors around ramps due to the entrance and exit of the highway.

6 Discussion

The results of this study provide insights into the impact of transition control mechanisms in ACC systems across various automotive brands on traffic flow efficiency and road safety. This chapter delves deeper into the results, comparing them with previous research. Section 6.2 explored the various settings of ACC systems in this research. Section 6.1 delved into the implications of the results with previous research. In the end, the limitations of the research and proposed recommendations for future research are also addressed in sections 6.3 and 6.4.

6.1. Discussion about the Results

6.1.1. Traffic Flow Efficiency

In this subsection, the following indicators are discussed: average speed, traffic flow, traffic density, total travel time, and average delays. The introduction of ACC systems with transition control models can improve traffic flow efficiency. The analysis of speed distribution across different scenarios reveals significant insights into how varying MPRs of ACC systems influence traffic dynamics. In the base scenario (0PR-Base), without ACC vehicles, a bottleneck forms near on-ramp 6, causing reduced speeds and increased congestion. The introduction of ACC vehicles, especially at higher MPRs, improves traffic flow significantly. This improvement is more distinct in scenarios with smaller distance settings (25PR-All-S and 75PR-All-S) compared to those with larger distance settings. This is based on the assumption that drivers are attentive and engaged in the driving process, as only the take-over time is considered in the simulation for drivers' responses. It was concluded that there are two factors that could influence the congestion level: time gap settings and the ACC MPRs. This finding indicates that ACC, when widely adopted, can reduce traffic congestion and enhance flow stability. However, scenarios, where ACC systems cannot follow the full-speed range (e.g., 25PR-Speed-SL and 75PR-Speed-SL), show less improvement in congestion reduction, indicating the critical role of ACC system capabilities in maintaining traffic flow. Furthermore, the speed distribution analysis indicates that the introduction of ACC vehicles leads to more homogeneous speed patterns across different lanes, reducing the occurrence of sudden braking and accelerating events that typically contribute to traffic instability.

From the fundamental diagrams, it is also evident that as the ACC MPRs increase, the capacity also increases. This is demonstrated by the peaks of the flow in each figure. In addition, within the same ACC MPRs, a higher number of small distance settings results in greater capacity. This observation supports the conclusion that both ACC MPRs and distance settings are significant factors influencing congestion levels.

Regarding vehicle network performance, the vehicle network performance metrics, such as average delay and total travel time, further support the findings from the speed distribution analysis. Introducing ACC systems with transition control models leads to reduced delays and travel times, particularly as the MPR increases. For instance, the average delay in the 0PR-Base scenario is 95.14 seconds, which decreases to 32.70 seconds in the 75PR-All-S scenario, resulting in a reduction of approximately 65%. Similarly, total travel time decreases from 8.36 million seconds in the 0PR-Base scenario to 6.38 million seconds in the 75PR-All-S scenario, demonstrating the positive impact of higher ACC penetration rates on traffic flow efficiency. The scenario analysis indicates that higher ACC MPRs contribute to more efficient traffic flow, emphasizing the potential benefits of ACC adoption for overall traffic performance. Furthermore, in scenarios with higher MPRs of ACC vehicles (75PR-All-S and 75PR-All-L), there is a marked reduction in the average delay per vehicle and the total travel time across the network. These metrics are critical indicators of traffic efficiency, as they reflect the extent to which traffic congestion is reduced. The reduced travel times imply that vehicles can maintain higher average speeds, and the lower delays indicate fewer interruptions in traffic flow. Moreover, the performance improvements observed in scenarios with small-distance settings underscore the need for ACC systems to be capable of safely maintaining shorter following distances.

These findings align with previous research that also indicates the importance of distance settings and speed adaptability in traffic flow that shorter distance settings can lead to higher capacity and less congestion (Liu et al., 2018; Makridis et al., 2019). Research from Yu et al. (2021) and He et al. (2019) also pointed out that ACC reduces congestion and smooths traffic flow under optimal conditions, such as high penetration of ACC vehicles, controlled or homogeneous traffic environments, and steady traffic speeds.

However, divergence from other research has also been identified. Some studies have reported neutral or negative impacts of ACC on traffic flow, particularly in mixed-traffic environments, such as urban areas and highways with low ACC MPRs where the interactions of ACC vehicles and human-driven vehicles arise. For example, He et al. (2019), as mentioned in the previous section, also indicated that while ACC can improve flow efficiency under certain conditions, traffic instabilities may arise when ACC vehicles interact with human-driven vehicles. These instabilities often result from discrepancies in driving behavior, such as sudden lane changes or manual disengagement of ACC, which can disrupt the consistent operation of ACC systems and reduce their effectiveness. The divergence between the findings of this study and others may be attributed to methodological differences, such as the focus on ACC system variations across different brands and models rather than on driver-related behaviors or mixed-traffic dynamics. For instance, this research examines the aspects of ACC systems, while other studies may place greater emphasis on driver behavior, human-vehicle interactions, or traffic conditions in mixed environments.

6.1.2. Traffic Safety

The TTC analysis provides insights into the safety implications of different ACC systems with transition control models. One key finding is that the introduction of ACC systems generally leads to an overall increase in TTC values, indicating improved safety margins compared to the base scenario (0PR-Base), which involves only human-driven vehicles. This effect is more observable at the lower percentiles of TTC values, indicating the potential risks associated with manual driving in situations where the likelihood of collisions is higher.

Another interesting observation from the results is the impact of different distance settings on TTC values. Scenarios with mixed-distance settings, combining both small and large distances, tend to exhibit lower TTC values, particularly when ACC MPRs are low. Interestingly, scenarios with only small distance settings display slightly higher TTC values compared to those with only large distances or mixed settings under the same ACC MPRs. This counter-intuitive result can be attributed to the assumption of the simulation that human drivers react almost perfectly, which fails to fully capture the diversity and variability of real-world driving behaviors. Under this assumption, the consistent small distance settings applied by ACC systems may contribute to smoother and more predictable traffic flow, reducing the likelihood of sudden braking and leading to higher TTC values. Furthermore, it is also important to consider the time gap settings of human drivers, as human-driven vehicles constitute the majority in scenarios with low ACC MPRs. The 50th percentile time gap for human drivers is 1.69 seconds, meaning that half of the drivers maintain a time gap of 1.69 seconds or less between their vehicle and the one in front. In comparison, the largest time gap within the small distance settings among different ACC systems is 1.97 seconds. This indicates that the time gap maintained by half of the human drivers falls within the range of the small distance settings used by ACC systems. Overall, these findings suggest that in the controlled environment of the simulation, the uniformity provided by small distance settings may enhance traffic stability, even though it challenges the common expectation that longer distances are safer.

However, these findings do not align with those reported in previous research. Qin et al. (2019) identified unstable ACC vehicles as a significant factor contributing to negative safety outcomes. Her study, which analyzed both cooperative adaptive cruise control (CACC) and ACC systems, demonstrated that fully CACC-equipped traffic flows can significantly mitigate rear-end crash risks compared to traffic scenarios dominated by manually driven vehicles. The simulations conducted in that research indicated that the instability of ACC vehicles within mixed traffic flows was a primary driver of adverse safety results. In contrast, this research did not account for string stability effects nor the speed drops after a transition control, which could be some key reasons for the divergence in findings. The absence of string stability considerations means that potential oscillations and irregularities in vehicle-following behavior, especially in mixed scenarios with both ACC and human-driven vehicles, were not accounted for. This limitation may explain why the current results suggest safety benefits in scenarios where previous research indicated risks. It also underscores the importance of including string stability analysis in future studies to gain a more comprehensive understanding of ACC systems' impact on traffic safety.

Research by Li et al. (2017) has shown that ACC systems can significantly enhance safety when designed with appropriate parameters, such as larger time gaps, shorter time delays, and higher maximum emergency deceleration rates. However, their study focused on time gaps of 0.6, 1.1, and 1.6 seconds, which only overlap with the small distance settings used in this research. While the time gaps of 1.1 and 1.6 seconds align with the small distance settings in the simulations, this research also includes scenarios with larger distance settings involving time gap values larger than 2 seconds, a range not covered in their work. Although the 0.6-second time gap from their study was not an intended parameter here, it occasionally occurred during the simulations due to the traffic dynamics. Moreover, this research does not include relevant settings for response time, which is conceptually similar to time delay and, therefore, assumes nearly zero time delays. In addition, the maximum deceleration rates differ between the studies: Li et al. (2017) set the maximum deceleration rates at -4.8 m/s^2 for human-driven vehicles and -2.8, -3.8, or -4.8 m/s^2 for ACC vehicles, whereas this research uses a maximum deceleration rate of -6 m/s^2 for both vehicle types. Despite these methodological differences, the findings from this research generally align with the key factors identified by Li et al. (2017) that contribute to enhanced safety. However, it remains uncertain how the effects observed in their study would translate to scenarios with time gaps larger than 1.6 seconds, as this was the upper limit tested in their experiments.

Building on the speed distribution analysis from previous sections, scenarios with smaller distance settings show a more obvious reduction in congestion. In addition, the acceleration results indicate that these scenarios have less critical deceleration behavior compared to those with only large distance settings or mixed distance settings, particularly at low ACC MPRs. From the perspective of ACC MPRs, the analysis also reveals that MPRs of ACC systems do not uniformly lead to longer TTC values across all percentiles. Only at the 10th percentile do the 75PR scenarios demonstrate significantly higher TTC values. This suggests that while higher MPRs can enhance safety in more congested scenarios, their impact diminishes as traffic stabilizes. Above the 50th percentile, TTC values converge across different scenarios.

Overall, the TTC analysis indicates that small distance settings tend to enhance road safety. However, the simulation does not account for string instability, making ACC vehicles more predictable and avoiding the occurrence of instability, which is often cited as a main cause of negative safety outcomes. In addition, the more uniform the distance settings in the scenarios, the higher the TTC values observed at the lower percentiles.

The acceleration behavior demonstrates that a higher frequency of critical deceleration behaviors occurs in scenarios with a larger proportion of human-driven vehicles. As the percentage of ACC vehicles increases, these critical deceleration behaviors significantly decrease, indicating improved traffic stability and reduced congestion potential. This indicates the positive impact of automated vehicles in enhancing traffic flow and safety by mitigating unpredictable slowdowns characteristic of human driving behavior. Integrating more ACC vehicles into the traffic system could be essential for optimizing overall traffic efficiency and safety, aligning with the research from Yu and Wang (2022) that the ACC system can conduct acceleration and deceleration in a more efficient manner.

6.1.3. Transition Control-related Output

The transition control-related results from the simulations present how ACC systems adapt to varying traffic conditions. DIDC (driver deactivates the system) refers to instances where the driver proactively initiates the transition and resumes control after deactivating the ACC system. This approach is often preemptive, allowing drivers to take control of anticipated complex situations with full awareness. In contrast, AIDC (system disengages due to operational limitations) occurs when the system itself triggers the transition due to operational constraints, requiring the driver to regain control. This reactive approach poses higher safety risks because it relies on the driver's response time to address the situation.

The initial expectation when designing the scenarios is that considering only one distance setting, especially small distance settings, could lead to more challenging lane-change behaviors and increased congestion and result in more transition controls. However, the results reveal that varying the distance settings alone does not significantly impact the number of transition controls. Each scenario has roughly the same number of transition controls for each type when compared at the same ACC MPR level, whether at 25% or 75% ACC MPR. Furthermore, it was observed that the occurrence of AIDC is extremely low, averaging approximately 0.05 events per kilometer across all vehicles rather than per driver. Although the human drivers' reaction times have already been taken into account, this low frequency of AIDC does not significantly impact traffic flow. Initially, it was hypothesized that the transition type of AIDC could negatively affect traffic flow efficiency and safety due to drivers' potential lack of awareness during the takeover control, posing a risk. However, simulation results indicate that the implementation of ACC systems with transition control models generally enhances both traffic flow efficiency and safety, even though the simulations only considered take-over time and assumed ideal human driving behaviors without accounting for string stability in ACC systems.

On the aspect of the location of transition control, the results present how transition controls are distributed around on and off ramps as well as at bottlenecks. This examination illustrates the variance and congruence in scenarios featuring different rates of ACC adaptation (25PR and 75PR), suggesting a stable distribution of transition control events around ramps while indicating a slight decrease in bottleneck-related events as ACC MPRs. It can be concluded that the ramps and the bottleneck are important zones in which ACC systems frequently require manual interventions. The main causes of the bottleneck, such as lower bound speed limits and FCW, show consistent trends across varying scenarios.

6.1.4. Conclusion

The findings from this research indicate that transition control mechanisms can potentially enhance both traffic flow efficiency and safety on highway networks, where traffic conditions are typically less complex and more predictable than in urban environments. The smoother and more consistent nature of highway traffic, which is generally characterized by higher speeds and fewer interruptions, seems to amplify the benefits of ACC systems, particularly in reducing the complexities associated with frequent stops, starts, lane changes, and other unpredictable behaviors that are common on urban roads. These results suggest that, when integrated with transition control strategies, ACC systems have the potential to improve highway traffic flow. This research underscores the adaptability of ACC systems to highway driving conditions and highlights their capacity to make benefits in such scenarios.

However, it is important to note that these conclusions are based on certain assumptions about the behavior of both human drivers and ACC systems. The simulations did not consider the effects of string stability within ACC systems, nor did they fully capture the range of human driving behaviors, such as aggressive or defensive driving styles, or potential reactions following a transition of control, like sudden speed reductions. The model primarily focused on dynamic factors like time headway and driver take-over time, while other variations in driver behavior were not fully represented. Consequently, while the results are promising, they should be interpreted with caution, and further research is needed to explore the broader implications of these findings in more diverse and realistic driving conditions.

6.2. Variability in Setting the ACC Model

This research examines the impact of transition control in various adaptive cruise control (ACC) systems on traffic flow efficiency and safety. While 22 vehicle models were recorded and analyzed from empirical data, incorporating each model individually into the simulation would have added significant complexity. Integrating distinct ACC characteristics and market shares for every vehicle model would reduce the flexibility and scalability of the external driver model in VISSIM. To address this issue, random distributions were applied to key ACC characteristics such as time gaps and minimum and maximum acceleration rather than relying on static values. This approach more accurately reflects real-world variability, providing a dynamic representation of vehicle behavior and traffic flow, and results in a more realistic simulation of traffic conditions.

However, a limitation of this method is the potential for generating combinations of ACC characteristics that may not exist in the real world. Despite this, the approach is deemed acceptable for the purposes of this research, as the primary objective is to simulate a wide range of vehicle behaviors across different ACC systems rather than strictly mimicking specific models available in the market. Furthermore, most vehicles provide four- to five-distance settings for drivers, meaning that some minimum time gaps observed in the empirical data may correspond to intermediate settings rather than the true minimum setting. This ensures that variability is maintained while still representing feasible driving scenarios.

Regarding acceleration capabilities, several assumptions were made in this study. Due to safety concerns, the empirical data may not capture the actual maximum or minimum acceleration values. These assumptions are guided by ISO 15622, the international standard for ACC systems, to ensure consistency in modeling and analysis. It is also important to note that vehicle owners' manuals do not provide specific information about acceleration capabilities, which further necessitates these assumptions.

In summary, while using random distributions for ACC characteristics introduces some potential inaccuracies, this approach enables a more flexible and comprehensive representation of vehicle behavior in mixed-traffic environments. By incorporating these variables into the simulation, the impact of ACC systems on traffic efficiency and safety can be accurately examined while acknowledging the limitations in representing specific real-world vehicle behaviors.

6.3. Limitations

While preparing and conducting the simulation, several assumptions were made. The objective was to investigate the differences among various ACC systems and transition control models. Therefore, the model does not fully capture driver-related behaviors, which could be one of the main reasons for disturbances. Aggressive or defensive driving behaviors were considered outside the scope of this research. The simulation assumes that all human drivers perform nearly ideally, with the transition control model focusing specifically on the take-over time. In addition, the string stabilities of ACC vehicles are not well represented, which could influence traffic flow efficiency and safety. There is also a lack of empirical data to determine the extent of string instabilities for each ACC system, and the ACC model used in this research currently lacks relevant settings. Furthermore, the simulation considered only two distance settings: small and large. In reality, vehicles often have more distance settings available, with owners manuals typically listing four or five levels. However, this research simplified the simulation to include only general small and large settings, which may not fully capture the range of ACC system behaviors and interactions in real-world scenarios.

Regarding the transition control model, the speed drop after transition control was not considered. In addition, various car owner discussion forums report instances where ACC systems deactivate without apparent reason, even under clear weather conditions. This scenario was excluded from the simulation due to the lack of confirmed data regarding the frequency of such occurrences and the variability in probabilities among different car brands. Moreover, the simulation did not account for motorcycles, which are permitted on Dutch highways. This omission could limit the applicability of the findings, as ACC systems might struggle to detect and respond to motorcycles due to their smaller size and distinct movement patterns. Despite these potential challenges, accurately defining the interactions between ACC systems and motorcycles is complex, and the proportion of motorcycles on highways is relatively low. Thus, while their exclusion is a limitation, it may not significantly impact the overall conclusions regarding ACC system performance. The simulation does not consider weather conditions described in the manuals that could affect the accuracy of ACC systems and lead to AIDC transition control. This oversight is noteworthy, especially given that adverse weather conditions such as heavy rain, fog, snow, and wind are common in the Netherlands.

The simulation network in this research is based on a highway in the Netherlands. Highways typically feature more straightforward traffic flow patterns compared to urban roads, which are characterized by more complex and dynamic traffic conditions. On highways, vehicles generally move at higher speeds with fewer interruptions, leading to a more predictable flow. This environment can be more conducive to the ODD of ACC systems, which are designed to maintain speed and safe following distances in relatively stable conditions. In contrast, urban roads present a much more challenging environment for ACC systems due to their dynamic and unpredictable nature. Urban settings involve frequent stops and starts, diverse road users (such as pedestrians, cyclists, and public transport vehicles), complex intersections, and varying speed limits, all of which can push ACC systems beyond their designed ODD.

In terms of indicator selection, both TTC and DRAC are surrogate safety indicators with inherent limitations, as they serve as proxies for real crashes rather than direct measures of actual crash events. This can lead to discrepancies between surrogate measures (e.g., near misses, hard braking) and actual crash occurrences. In addition, not every near-miss results in a crash, and some crashes may occur without any prior warning based on these surrogates. Many surrogate safety analyses are based on traffic simulations, which may not perfectly replicate real-world driving behavior and conditions. The accuracy of surrogate measures can be compromised if the simulation models fail to capture the full complexity of human behavior and environmental factors.

6.4. Future Research Recommendations

This section outlines several recommendations for future research aimed at addressing the limitations identified in this research. The recommendations are divided into two key areas: improving simulation models and expanding empirical data collection. Enhancing simulations with a broader range of driver behaviors and road environments, alongside the integration of real-world data, will allow for more robust and accurate assessments of ACC systems and transition control models. By addressing both simulation improvements and data collection challenges, future research can contribute to the development of more reliable and comprehensive ACC systems and transition control models for diverse traffic scenarios.

6.4.1. Simulation

Given that the driving behaviors of human drivers are not fully captured in this study, future research could benefit from incorporating a broader range of human driving behaviors. By increasing the diversity of simulated behaviors, such as varying levels of aggression and decision-making styles, future research can develop a more comprehensive understanding of how these factors interact with ACC systems. In addition, considering the string stability of each ACC system in simulations could lead to more realistic representations of ACC behavior. This expanded approach would enable more robust and accurate simulations, leading to better predictions of ACC system performance in diverse real-world traffic dynamics.

Given the differences in road environments, future research could include simulations on networks of urban roads to provide a more comprehensive understanding of transition control models across various types of road environments. Investigating how ACC systems perform in urban settings can uncover limitations that might not be apparent on highways and can lead to the development of more robust systems capable of handling the complexities of urban traffic.

6.4.2. Empirical Data Collection

One significant area for improvement is the collection of real-world data for transition control. The data used in this research is insufficient, as it does not substantially contribute to improving the model itself. To enhance the transition control model, future research should prioritize more meticulous and extensive data collection from real-world scenarios. While the availability of a naturalistic driving database is beneficial, the quality of data recording needs improvement. For instance, although the SAE L2 database includes nine different vehicles, only the BMW vehicles provide reliable information about ACC status, resulting in the use of only a portion of the dataset. This limitation reduces the number of participants and the total mileage driven, which can affect the results. However, the fact that data from only one vehicle type was used does provide a level of consistency and comparability. Differences in ACC deactivation methods across brands could potentially influence the outcomes, and this should be considered in future research. In addition, the database only recorded the ACC status but no perspectives from the drivers' sides, which resulting the assumptions on the decision making for DIDC or the reaction after AIDC. It would be nice if there were data relevant to the reason why a driver initiates a transition control.

If the time and financial costs of naturalistic driving experiments are too high, alternative approaches could be considered. For instance, future research could explore the use of advanced driving simulators, which allow for controlled testing of various scenarios and behaviors without the extensive resources required for real-world data collection. In addition, incorporating questionnaires immediately after the experiment could capture valuable insights and perspectives from the human drivers. While these alternatives may not fully replicate the complexities of naturalistic driving, they can still offer meaningful contributions to the development and refinement of ACC systems and transition control models by integrating more human perspectives.

The use of the advanced driving simulation might also offer more comprehensive traffic safety assessments. Unlike traditional simulations, advanced simulators can allow for the inclusion of actual collision scenarios, providing more direct measures of crash risk and outcomes. This approach could help bridge the gap between surrogate measures and real-world crash data, offering a more accurate evaluation of ACC systems and transition control models. Moreover, incorporating dynamic driver behaviors and varying environmental conditions into these simulators would enhance the realism of the simulations, leading to more reliable and robust safety assessments. By expanding the range of scenarios and behaviors tested, advanced simulators could significantly improve the predictive power of traffic safety models and contribute to the development of safer ACC systems.

In addition, as more comprehensive data on transition controls becomes available and is accurately recorded, it will be possible to validate and refine the transition control model. This additional data will allow for further improvement, ensuring that the model more accurately reflects real-world scenarios and enhance its overall reliability.

7
Conclusion

This research aims to investigate the impact of transition control of ACC systems on traffic flow efficiency and safety. The characteristics of different ACC systems from different brands are taken into account to represent the real-world situations more likely. Through a series of simulation setups and analyses, several key findings and implications have been identified, and a comprehensive analysis of the impact of transition control mechanisms in ACC systems across various automotive brands on traffic flow efficiency and road safety was provided. The main research question is 'How does the efficacy of transition control mechanisms in ACC systems across different automotive brands influence traffic flow efficiency and safety?'. Each sub-question is addressed in section 7.1, with the overall conclusion provided in Section 7.2. Finally, practical recommendations are presented in Section 7.3.

7.1. Answers for the Research Questions

7.1.1. What key performance indicators are selected to assess the impact of ACC systems on traffic flow efficiency and safety?

The key performance indicators for assessing the impact of ACC systems on traffic flow efficiency and safety are crucial for both operational performance and safety margins. For traffic flow efficiency, average speed, flow, density, average delay, and total travel time are chosen as the indicators. Average speed provides insight into the fluidity of traffic, while flow measures the volume of vehicles passing a point in a given time, thus indicating road capacity. Density reflects congestion levels by indicating the number of vehicles per kilometer of road. Average delay captures the time vehicles are delayed relative to free-flow conditions, and total travel time sums the overall duration of trips. For traffic safety, Time-to-Collision (TTC), deceleration values, and time gaps are the indicators. TTC estimates the time remaining before a collision if no actions are taken to avoid that collision, thus reflecting safety margins. Deceleration values measure braking severity and potential safety risks, while time gaps refer to the temporal spacing between vehicles, indicating safe following distances. Together, these indicators provide a comprehensive assessment of how ACC systems influence traffic dynamics and safety.

7.1.2. How do ACC transition control mechanisms and characteristics vary across different automotive brands?

ACC transition control mechanisms and characteristics vary across different automotive brands. The transition mechanisms are typically categorized into three types: Driver Deactivates the System (DIDC), Driver Activates the System (DIAC), and System Disengages due to Operational Limitations (AIDC). These categories describe how control shifts between automated systems and human drivers. Based on a review of literature, empirical data analysis, and owners' manuals, several key characteristics differentiate ACC systems, including full-speed range, acceleration capabilities, inter-vehicle space (IVS), time gaps, response times, standstill distances, and string stability. Variations in these characteristics can directly influence system disengagement, as the implementation of transition control is dependent on the technology and capabilities of each ACC system.

For instance, some ACC systems will disengage when the vehicle's speed falls outside their operational range. The data from 22 ACC systems indicate that while some systems can follow vehicles down to a complete stop, others have a minimum speed threshold for maintaining vehicle following, such as 10 km/h or 30 km/h. Of these systems, five are unable to maintain vehicle following at all speeds, demonstrating the limitations in their design. Acceleration capabilities also play a critical role in system disengagement. If the acceleration or deceleration executed exceeds the system's capabilities, it may disengage to prevent unsafe conditions. The maximum deceleration values for these 22 ACC systems range from -3.5 m/s^2 to -5.0 m/s^2. For example, the ACC system of Mitsubishi Outlander PHEV can decelerate up to -5.0 m/s^2, allowing for more aggressive braking, while systems like those in the Hyundai Ioniq Hybrid and Volkswagen Golf E have a maximum deceleration of -3.5 m/s^2, potentially limiting their effectiveness in braking situations. These variations highlight the importance of understanding the specific characteristics and limitations of each ACC system to evaluate its performance under different driving conditions.

7.1.3. What are the variables and their corresponding ranges for simulating transition control in each scenario?

In simulating transition control, several critical variables must be considered to accurately model traffic dynamics. One of the primary variables is the ACC speed range. Vehicles like the Volvo XC40 with an ACC range of 0 to 200 km/h can perform full-speed follow if there is a vehicle preceding, including at a complete stop. In contrast, models such as the Mazda 3, with an ACC range of 30 to 145 km/h, cannot maintain ACC below 30 km/h, limiting their effectiveness in stop-and-go traffic, which will also result in system disengagement. Another essential variable is the acceleration capability, particularly the maximum deceleration, which can range from -3.5 m/s^2 in models like the Hyundai Ioniq Hybrid to -5.0 m/s^2 in the Mitsubishi Outlander PHEV, highlighting differences in how vehicles can respond to sudden braking situations. The inter-vehicle space (IVS) and time gap are also crucial, with the IVS ranging from 12.61 meters in the Tesla Model X to 52.43 meters in the Peugeot 3008 GTLine, indicating the varying distances vehicles maintain from others in front. Time gaps similarly vary, from as short as 1.09 seconds in the Tesla Model X to 3.00 seconds in the Volkswagen Golf E, influencing how closely vehicles follow each other. Response time is another important factor, with Tesla models exhibiting the fastest response time of 1.7 seconds, while the Audi A6 and A8 have a slower response time of 2.56 seconds. Finally, standstill distance, which impacts safety during full stops, ranges from 4.49 meters in the Volkswagen Golf E to 5.80 meters in the Mitsubishi Outlander PHEV. These variables, distributed according to market share, are critical for enhancing the realism of traffic simulations and capturing the diverse behaviors of ACC systems across different vehicle models.

These characteristics are weighted by market share to enhance the realism of simulations. For instance, to determine the maximum deceleration threshold, a list named 'ACC_max_deceleration' is created, where the deceleration values are repeated according to the market share. For example, if the Tesla Model X has a deceleration of -5.0 m/s^2 and a market share of 7.6%, the value -5.0 is repeated proportionally in the simulation list. This approach ensures that the simulated vehicle behaviors reflect real-world variability across different ACC systems.

Moreover, these ranges and thresholds are incorporated into the transition control model to manage system disengagements effectively. The system disengagement (AIDC) algorithm considers the acceleration and full speed range thresholds, which directly influence when and how the ACC systems disengage.

7.1.4. What is the expected market penetration of different brands?

The expected market penetration of different automotive brands in the context of ACC systems is informed by statistical data, particularly from studies like those focused on the Netherlands (Statista, 2024). Market penetration of various brands is considered to reflect their prevalence within the vehicle population. This information is important for simulating realistic traffic conditions with a mix of vehicle brands and their respective characteristics. The simulations assume a heterogeneous mix of brands, with the ACC systems' characteristics assigned randomly based on their market share.

7.1.5. What are the implications of transition controls on traffic flow and safety?

The implications of transition controls on traffic flow and safety are profound, significantly affecting both operational efficiency and traffic safety. Transition controls, especially in scenarios with varying levels of Adaptive Cruise Control (ACC) market penetration rates (MPRs), demonstrate a clear impact on traffic dynamics. This study considered three levels of ACC MPRs: 25%, 50%, and 75%. In this context, a low ACC MPR refers to 25%, while a high ACC MPR refers to 75%. The findings indicate that both low and high MPRs of ACC vehicles contribute to enhancing traffic flow by reducing congestion. However, the impact is more pronounced at higher MPRs, where congestion levels and affected areas are significantly reduced, leading to lower average delays and shorter total travel times. This suggests that increasing the presence of ACC-equipped vehicles on the road can substantially improve overall traffic efficiency.

On the other hand, transition controls also introduce safety challenges, particularly during scenarios where the system disengages due to operational limitations (AIDC), requiring human drivers to promptly take over control. Although these AIDC events carry inherent risks, the study found that their low frequency means that overall traffic safety is not significantly compromised. Additionally, transition controls are observed to occur more frequently around critical traffic zones such as on-ramps, off-ramps, and bottlenecks. This emphasizes the need for robust and reliable systems to maintain safety and efficiency in these areas. Overall, the integration of ACC systems with transition control mechanisms shows considerable potential to enhance both traffic flow efficiency and safety, especially in highway settings where traffic conditions tend to be more predictable and stable.

7.2. Overall Conclusion

This research has investigated the impact of different ACC systems on traffic flow efficiency and road safety, focusing on the transition control between automated driving systems and human drivers. By analyzing the characteristics of ACC systems from various automotive brands and utilizing both empirical data and traffic simulations, it was demonstrated that increased ACC market penetration rates (MPRs) generally enhance traffic flow efficiency and safety, particularly in controlled highway environments. The simulations indicated that scenarios with higher ACC penetration led to smoother traffic flow, reduced congestion, and lower risks of collisions, particularly when ACC vehicles were set to smaller following distances. However, the study also highlighted the challenges posed by the transition control process, where the brief delay required for human drivers to take over from automated systems can lead to potential safety risks, especially in complex and high-speed situations.

The research also indicated the need for further recommendation of ACC systems and their integration into more driving conditions. The limitations identified, such as the exclusion of certain vehicle types and weather conditions, suggest that real-world applications might differ from the simulated scenarios. Future research should expand on these findings by incorporating a broader range of vehicle types, including motorcycles and varying weather conditions, to assess the robustness of ACC systems under more diverse circumstances. Furthermore, understanding driver behavior during transition control remains crucial for improving the seamless integration of ACC systems into existing traffic networks. These insights are important for policymakers and automotive engineers as they work towards enhancing the safety and efficiency of automated driving technologies on public roads.

7.3. Practical Recommendation

The findings of this research provide insights that could benefit key stakeholders involved in traffic management and vehicle operation, including road users, road operators, policymakers, and original equipment manufacturers (OEMs). By implementing these recommendations, each group might play a critical role in maximizing the benefits of ACC systems.

For road users, it is recommended to use the small distance settings on ACC systems primarily when driving on highways, but only if they are fully conscious of the road conditions and are not experiencing any fatigue. These small distance settings are designed to improve traffic flow and reduce congestion in predictable environments like highways. However, using them requires the driver to pay attention to their surroundings and be in a state of alertness, as these settings reduce the buffer time available to react to sudden changes in traffic. Driving while tired can significantly impair a driver's ability to respond quickly, which is particularly risky when following vehicles closely. Therefore, it is crucial that drivers only engage these small distance settings when they are fully awake, alert, and capable of taking over manual control if necessary.

The findings are also valuable for road operators, as they can inform policies on the deployment of automated vehicles, which can result in the impact of ACC vehicles on traffic efficiency and safety. The simulation results suggest that higher MPRs of ACC-equipped vehicles can significantly improve traffic flow and reduce congestion, particularly on highways. A key recommendation, therefore, is to promote the wider adoption of ACC systems among drivers, particularly for highway use. Road operators and policymakers could collaborate to design incentives that encourage the purchase and use of ACC-equipped vehicles. These could include tax rebates, toll discounts, reduced insurance premiums, or direct financial incentives to offset the cost of purchasing vehicles with ACC capabilities. In addition, it is recommended that future driving education programs incorporate training on the use of ACC systems and make potential drivers aware of their limitations. This could be integrated into driving schools, such as those governed by CBR, to ensure new drivers understand how to safely and effectively use ACC, particularly when managing small distance settings and recognizing when manual intervention may be required.

To improve the accuracy and applicability of future simulations, original equipment manufacturers (OEMs) and vehicle manufacturers could incorporate more realistic driver behavior models into the simulations. This includes accounting for a wider range of driving behaviors, such as aggressive, defensive and distracted driving patterns, which are common in mixed-traffic environments. By including these variables, simulations can better reflect the interactions between ACC vehicles and human drivers, providing a more comprehensive understanding of how ACC systems perform under varied conditions. This would allow for the refinement of ACC algorithms to handle these real-world scenarios more effectively and lead to safer and more reliable systems on the road. In addition, as mentioned in the discussion, various car owner forums report instances where ACC systems unexpectedly deactivate, even in clear weather conditions. To address this, vehicle manufacturers could gather feedback from users, analyze the likelihood of these occurrences, and identify the underlying causes. This would help improve ACC systems and reduce such incidents.

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A

Scientific Paper

In Appendix A, two sets of page numbers are present. The upper numbers, starting from 120, correspond to the pagination of the entire research document. The bottom numbers, beginning with 1, indicate the page numbers specific to the scientific paper itself.

The Impact of Transition Control in Different Adaptive Cruise Control Systems on Traffic Flow Efficiency and Road Safety

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***Abstract*—This study examines the impact of Adaptive Cruise Control (ACC) systems on traffic flow efficiency and road safety, with a particular emphasis on transition control between automated and manual driving. Empirical data from the OpenACC database and the SAE Level 2 naturalistic driving study were analyzed to capture key ACC characteristics, which were then used in simulations to reflect the variability among different ACC systems. Simulations were conducted on a section of the Dutch A13 highway, with ACC market penetration rates (MPRs) set at 25% and 75%. The ACC and transition control models were integrated as external driver models in PTV VISSIM, under the assumption of nearly ideal human driver responses, excluding potential response delays and the string instability typically associated with ACC systems.**

The results indicate that ACC systems with transition control models significantly enhance traffic flow efficiency and safety, particularly at higher MPRs. The introduction of ACC vehicles reduced congestion and increased time-to-collision (TTC) values, reflecting improved traffic safety. However, the study highlights limitations, including simplified human driving behaviors and the exclusion of string stability effects. Future research should focus on more complex driving scenarios, such as urban environments, and enhance data collection methods to further understand ACC system performance in diverse traffic conditions.

***Index Terms*—Automated vehicle, Adaptive Cruise Control (ACC), Transition of control, Traffic simulation, Empirical data**

I. Introduction

The development of autonomous vehicles (AVs) is becoming increasingly crucial for improving transportation safety and efficiency [1]. As technology advances, automated vehicles are progressively integrating into road networks, offering the potential to reduce accidents and enhance traffic flow. Currently, automation systems classified as SAE Level 1 and Level 2 are widely deployed on public roads. Adaptive Cruise Control (ACC), a Level 1 automation system, is designed to maintain a set speed and a specified distance from a lead vehicle, providing convenience to drivers [2], [4], [5]. Despite these advancements, human drivers remain central to vehicle operation, as highlighted by SAE's classification of automated vehicles. ACC systems are driver-assist technologies, which still require constant supervision from the driver to ensure safe operation [6].

As AV technology evolves, particularly at SAE Levels 1 and 2, these systems are increasingly integrated into existing road infrastructures, bringing both safety and traffic flow implications that require careful management. ACC systems can enhance safety by reducing accidents caused by human errors such as distraction or fatigue [1]. However, safety risks arise during transition control, the switch between automated and manual driving, especially when the system disengages due to operational constraints, requiring the driver to quickly regain control [7], [8]. This transition, which typically takes 3 to 5 seconds, can lead to accidents, particularly in complex or high-speed environments, if drivers are not fully prepared [9].

Early ACC systems were limited to medium-to-high speeds and significantly influenced driving behavior by automating speed control [4], [10], [11]. While these systems demonstrated clear benefits, their studies were often constrained to specific, controlled contexts, leaving a gap in understanding their performance under diverse real-world conditions. Recent advancements have introduced full-range ACC systems capable of operating in dense, low-speed traffic, thus expanding the Operational Design Domain (ODD) [4]. Despite these advances, ACC systems still require human intervention under certain conditions outside the defined ODD, emphasizing the need to understand the impact of transitions between automated and manual control [9].

These transitions can be categorized into three types: Driver Deactivates the System (DIDC), Driver Activates the System (DIAC), and System Disengages due to Operational Limitations (AIDC) [8]. Each type presents unique challenges that can impact traffic flow and safety, particularly in scenarios involving complex maneuvers such as highway merging [7], [12]. Studies indicate that ACC is predominantly used in low-to-medium traffic densities on highways, where it helps maintain safe following distances [13]. However, transition controls can disrupt traffic flow, as drivers may require time to reactivate control, potentially causing delays and increasing the risk of accidents.

This research addresses a critical gap in understanding how the transition controls between automated and manual driving impact traffic By examining ACC systems from multiple vehicle brands, this research provides novel insights into how varying ACC characteristics influence traffic dynamics during transition control, where previous research uses one single value for each ACC setting in the simulation.

In the next section, related literature on ACC systems and transition control is reviewed. Section III explains the methodology used for analyzing both real-world and simulated scenarios involving various ACC systems. Section IV presents the findings of the data analysis and the simulation results. Section V discusses the implications for traffic safety and efficiency based on the results. Finally, Section VI concludes the research, addresses the limitations, and provides suggestions for future research.

II. Literature Review

The development of autonomous vehicles (AVs) represents a significant evolution in transportation, particularly as these vehicles begin to integrate into existing road networks. According to the SAE J3016 standard, driving automation is classified from Level 0 to Level 5, where humans maintain primary control in Levels 0 to 2 [6]. As AV technology advances, particularly at Levels 1 and 2, the challenges associated with transition control, the process of switching between automated and manual driving, become increasingly important. This transition, often triggered during system failures, typically requires drivers to regain control within 3 to 5 seconds, a critical period that can significantly impact traffic flow and safety [7], [8], [17].

Drivers' decisions to activate or deactivate ACC systems are influenced by psychological factors such as safety perception, workload, and trust in automation. Cognitive psychological theories suggest that responsibility, dynamics, and efficiency play crucial roles in how drivers interact with these systems [17]–[19]. Reduced workload due to ACC can lead to decreased situational awareness, critical for timely responses during transitions [20], [21]. Prolonged use may cause driver disengagement, increasing safety risks during manual intervention [22]. In complex driving situations or when drivers feel unsafe, they are more likely to deactivate automation and assume manual control [13], [23], [24].

System disengagement, particularly Automated System-Initiated Driver Control (AIDC), typically occurs due to sensor failures or when the system exceeds its operational limits in safety-critical situations [7], [8], [23]. Drivers must quickly reacquire control, a process heavily influenced by their situational awareness and the complexity of their environment. Lower situational awareness or distraction can delay response times, increasing accident risks during transitions [7], [25], [26]. Engaging in non-driving tasks further impairs response times, underscoring the need for systems that support drivers effectively during these critical moments [27].

ACC systems also have broader implications for traffic flow efficiency and safety. Passive transitions, such as AIDC, can lead to traffic instability, especially in mixed traffic environments with varying automation levels [28]. Familiarity with automation can decrease situational awareness and trust in the system, leading to longer takeover times and heightened safety risks during transitions [2], [3], [7], [22]. These dynamics underscore the need to balance safety and efficiency in increasingly automated traffic environments.

Traffic flow and safety are assessed using various indicators, such as traffic flow rate, density, and average speed, for efficiency, and Time-to-Collision (TTC) and Deceleration Rate to Avoid Crash (DRAC) for safety [29]–[33]. These metrics help gauge potential collisions or near-miss events, especially where crash data is limited.

ACC systems vary significantly across different vehicle brands, affecting traffic dynamics. Studies reveal differences in key performance characteristics, including response time, time headway, and string stability among ACC systems from various manufacturers [4], [15], [34]–[36]. For instance, some ACC systems are more stable at high speeds, while others perform better at low speeds. Understanding these differences is crucial for evaluating the overall impact of ACC systems on traffic flow and safety.

III. Methodology

The core method of this research involves data processing and running simulations in VISSIM. Before conducting these simulations, several preparatory steps are taken to configure the simulation settings to achieve the research objectives. The first step is the analysis of two databases, the OpenACC database and the SAE L2 database, which contain output data from field experiments with different commercial brands and vehicles. This analysis provides the necessary input parameters for the ACC vehicles within the simulation, allowing them to represent vehicle dynamics more realistic. Once the input parameters are defined, the simulation is run according to the settings. The VISSIM simulation results are then analyzed using vehicle trajectory data and predefined indicators that evaluate traffic efficiency and safety.

A. Data Process

Two empirical databases are used for the data process. The first one is the OpenACC database, which is an open source from [38]. There are four campaigns from the OpenACC database. Two of the tests were conducted on public roads during non-peak hours to minimize interference from other road users, while the other two took place in controlled test environments. These experiments were designed to evaluate the performance of various ACC systems from different experimental designs. The other one is the SAE L2 database from TNO. There are two types of outputs expected from the data analysis. The first one is the transition control-related data, and the second one is the differences in characteristics of ACC systems.

1) The Transition Control Moment: The transition control is identified by a parameter known as "driver" in the OpenACC database or "acc_state_enum" in the SAE L2 database, which differs from the preceding time step. Therefore, transition control can be classified into two categories: human to ACC and ACC to human. Based solely on the numeric data, whether the transition control from ACC to human is AIDC or DIDC cannot be judged. In the following context, the distribution is based on the transition control from ACC to human since this research would like to discuss the characteristics of the different ACC systems. During some cases, especially stop-and-go scenarios, the time gap values are extremely large because of the very low-speed values, so these data will also be filtered out as they do not represent the actual time gap setting. The data is filtered as the following steps:

1) Finding the two rows with different values in column "driver" or "acc_state_enum." Each pair is seen as a transition control moment.
2) Keeping the first rows, representing the moment just before a transition control.
3) Filtering the speed value is larger than 2 m/s, and the time gap value is between 0 and 5 seconds.
4) Filtering by the column value of "ACC" or "ACTIVE" means there will be a transition control from ACC to Human.
5) Extracting the data for further analysis.

After filtering the data, the time gap and Time-to-Collision (TTC) were analyzed to determine whether transition controls could be the decision based on safety concerns, considering the drivers' perspective. If deemed relevant, the resulting time gap or TTC distributions could be modeled and incorporated into the simulation.

2) The Characteristics of Different ACC Systems: Since the OpenACC database comprises a series of campaigns with varied experimental designs aimed at testing the performance of ACC systems, the characteristics of these systems are collected from each campaign based on the objectives and information requirements. In addition, it is important to note that the OpenACC database does not include information on acceleration values or time gaps. Therefore, these two variables were calculated based on the other recorded information. Eq. 1 is the formula for calculating acceleration based on the speed difference. $a_i(t)$ means the acceleration value of vehicle i at time t. The data is recorded at 10Hz, so the time difference is 0.1 seconds to get the acceleration values for each step except the first time step. Eq. 2 represents how the time gap is calculated. Because no inter-vehicle space (IVS) is recorded for the first vehicle, d_i means the inter-vehicle space between vehicle i and vehicle $i+1$. For example, d_1 refers to the inter-vehicle space between vehicle 1 and vehicle 2. The time gap is defined as the time difference between the rear of a vehicle and the front of its follower and $\tau_i(t)$ means the time gap value of vehicle i at time t [39]. Both acceleration and time gap are calculated based on the vehicle speed v, measured in meters per second.

$$a_i(t) = \frac{v_i(t) - v_i(t-1)}{\Delta t} \tag{1}$$

$$\tau_i(t) = \frac{d_i(t)}{v_{i+1}(t)} \tag{2}$$

Table I summarizes the different characteristics of ACC systems recorded in the OpenACC database. Each characteristic has been sourced from various campaigns, designed to evaluate particular aspects of ACC performance. The table lists these characteristics along with the respective campaigns or sources from which the data was collected.

TABLE I: ACC characteristics and the data sources

ACC Characteristics	Source
Full speed range	1. Owners' Manuals
Acceleration capabilities	1. Campaign Zalazone 2. Campaign Cherasco 3. Campaign Viclungo
Inter-vehicle space	1. Campaign Zalazone 2. Campaign Cherasco 3. Campaign Viclungo
Time gap	1. Campaign Zalazone 2. Campaign Cherasco 3. Campaign Viclungo
Response time	1. Campaign AstaZero
Standstill distance	1. Campaign AstaZero
String stability	1. Campaign AstaZero 2. Campaign Zalazone

B. Traffic Simulator

In this research, simulations are conducted using VISSIM, a leading traffic simulation software tool renowned for its microscopic-scale traffic pattern reproduction. The ACC model is integrated into VISSIM to enhance simulation capabilities VISSIM. This includes the implementation of the transition control model, which will be explained in detail in the following subsections. For human-driven vehicles, VISSIM applies the psycho-physical perception model developed by [40], [42]. This model is based on the concept that a driver of a faster-moving vehicle begins to decelerate upon reaching their perception threshold relative to a slower-moving vehicle. Due to the inability to accurately gauge the slower vehicle's speed, the faster vehicle's speed decreases below that of the slower vehicle until the driver reaches another perception threshold and begins to accelerate slightly. This results in a pattern of slight, steady acceleration and deceleration. The model accounts for varying driver behaviors through distribution functions of speed and distance behavior [40].

For the lane-change model, VISSIM distinguishes between two types of lane changes: necessary and free. Necessary lane changes are triggered by vehicle routes, dynamic path assignments, or the COM interface, with the deceleration depending on the emergency stop distance. Free lane changes occur when more space is available or when maintaining a desired speed, ensuring that safety distances are respected between vehicles. A default lane change takes 3 seconds, and while "aggressiveness" cannot be altered, the safety distance can be adjusted in the car-following model parameters. Both lane change types must respect the minimum clearance. For overtaking, vehicles consider their maximum speed and lane change behavior, preventing heavy goods vehicles (HGVs) from overtaking on gradients where they cannot reach their desired speed [40].

The ACC and transition control models are implemented in VISSIM through an "External Driver Model DLL Interface" rather than being built into the software itself [43]. This interface allows users to replace VISSIM's default driving behavior with custom models. During simulations, VISSIM calls the DLL code to update the vehicle's dynamics, such as acceleration and lane changes, based on the external model's calculations. For this research, the external driver model is applied only to ACC vehicles, while human-driven vehicles use VISSIM's built-in model.

The ACC controller model used in this research was developed by TNO and was originally designed for a Tier 1 supplier, and is therefore confidential. It has been simplified and adapted for use in a micro-simulation model. The basic operating principle is that the controllers simultaneously calculate the desired acceleration of the vehicle. The model contains three main functions and several auxiliary ones. The main functions are Cruise Control (CC), Adaptive Cruise Control (ACC), and Gap Closing (GC). These three functions are distinct "modes" for managing the vehicle, with only one active at a time. In the absence of objects within 120 meters in front of the vehicle, the CC mode maintains a user-set speed. When an object enters this range, the ACC mode activates, adjusting speed to maintain a set time headway. The third mode, GC, is used to smoothly close the gap with the new predecessor, such as merging vehicles, in a way that enhances driving comfort. The ACC controller uses inputs such as the vehicle's speed and the distance, speed, and acceleration of the object in front to determine the desired acceleration. It should be noted that there is no setting related to the response time; therefore, string instability is not captured in this model. The formulas for calculating the acceleration are as follows:

$$a_{CC}(t) = k_v \cdot (v_{set} - v_x) \quad \text{if } d_0 > 120 \tag{3}$$

where $a_{CC}(t)$ is the acceleration under CC mode at time t (m/s^2), k_v is the speed gain in the CC controller (s^{-1}), v_{set} is the desired set speed of the vehicle, v_x is the current speed of the vehicle (m/s), and d_0 is the distance to object ahead (m).

$$\begin{aligned} a_{ACC}(t) = & K_{ACC} \times (K_{dx}(d_x - d_{x_{max}}) + K_{dv} \times \Delta v(t) \\ & + K_{ACC_{ff}} \times a_{object}(t) \end{aligned} \tag{4}$$

where $a_{ACC}(t)$ is the acceleration under ACC mode at time t (m/s^2), K_{ACC} is the overall gain of the ACC controller, K_{dx} is the gain on distance error in the ACC controller (s^{-1}), d_x is the inter-vehicle space between the ego vehicle and the object vehicle (m), $d_{x_{max}}$ is the required maximum headway for the calculation of cruising setpoint (m), K_{dv} is the gain on speed error in the ACC controller (s^{-1}), $\Delta v(t)$ is the speed difference between the ego vehicle and the object vehicle (m/s), $K_{ACC_{ff}}$ is the gain on the feedforward, and a_{objec} is the acceleration of the object vehicle at time t (m/s^2).

$$a_{GC}(t) = -kp_{GC} \cdot (\Delta v(t) - v_{threshold}) \tag{5}$$

where $a_{GC}(t)$ is the acceleration under GC mode at time t (m/s^2), kp_{GC} is the gain for gap closing control (s^{-1}), $\Delta v(t)$ is the speed difference between the ego vehicle and the object vehicle at time t (m/s), and $v_{threshold}$ is the approach velocity threshold (m/s).

All acceleration formulas are subject to the inherent limitations of the ACC vehicles. Therefore, after determining the mode and the corresponding acceleration values, the final acceleration value is $a_{following}$. The following equation is then used to constrain the acceleration performance.

$$a_{min} \leq a_{following}(t) \leq a_{Max} \tag{6}$$

where a_{min} is the minimum allowed acceleration (deceleration or braking limit), and a_{Max} is the maximum allowed acceleration.

For the transition control model, the model's final decision results in one of four outcomes: DIDC, DIAC, AIDC, or no transition. These four outcomes are represented as boolean variables, and all are initially set to $False$. If the respective conditions are met, the corresponding variable will be set to $True$. The decision process consists of three layers. The first layer is the system's mandatory decision, which can also be understood as the conditions of ODD. The outcome of this layer determines whether an AIDC will occur. The second layer involves the driver's decisions, which are divided into two categories: mandatory and discretionary. The mandatory decisions include actions such as lane changes or responding to slower vehicles ahead, which are essential for the driver to execute. For instance, if the driver intends to exit the highway, they must change to the rightmost lane to leave the highway. Discretionary decisions, on the other hand, involve the driver choosing to activate the ACC system with a 50% probability.

Finally, the third layer is the final decision layer. In this layer, the priorities are ranked: DIDC takes the highest priority, followed by AIDC, and then DIAC. If none of the transition control conditions are met, the outcome will be no transition control.

C. Simulation Setup

To investigate the impacts of the transition control of ACC vehicles on traffic flow and explore the interaction between different vehicle brands' MPRs, the simulation will introduce the vehicles equipped with ACC systems from different brands with their MRPs. According to the Dutch government, the A13 highway, as shown in Figure 1, in the Netherlands is one of the busiest highways in the Netherlands [44], [45]. Therefore, it is chosen as the simulation network. The corridor is 17 km long with 5 on-ramps and 6 off-ramps from the Hauge to Rotterdam. In the opposite direction, from Rotterdam to The Hague, there are 9 on-ramps and 6 off-ramps. It is a dual-carriageway with three lanes in each direction.

Figure 2 provides a schematic of the highway infrastructure along the A13, starting from Den Haag and extending to the first exit in Rijswijk. In this diagram, ’O1’ and ’O3’ are entry points onto the freeway, matching the locations shown in Figure 1. The exit points are labeled ’D1’ and ’D0’, where ’D1’ corresponds to the same exit depicted in Figure 1, and ’D0’ represents exits for other segments of the highway, not a specific existing in the figure. Because the merging maneuvers are significant in traffic flow, the anticipated network design will incorporate segments for on-ramp and off-ramp traffic (labeled as D1 and D0, respectively). Simultaneously, the network will maintain vehicles’ input and output at the highway’s original points (labeled as O1 and D1), ensuring a comprehensive representation of vehicular movement and interactions. The simulation is scheduled to operate from 7 AM to 10 AM, spanning both the morning peak and off-peak hours. This time frame will facilitate an examination of free-flowing traffic conditions as well as congestion recovery strategies. The research will then analyze the impact on high-density and low-density traffic flow, providing a comprehensive understanding of various traffic dynamics. D4 and O6 are the entrance and exit for the highway rest area.

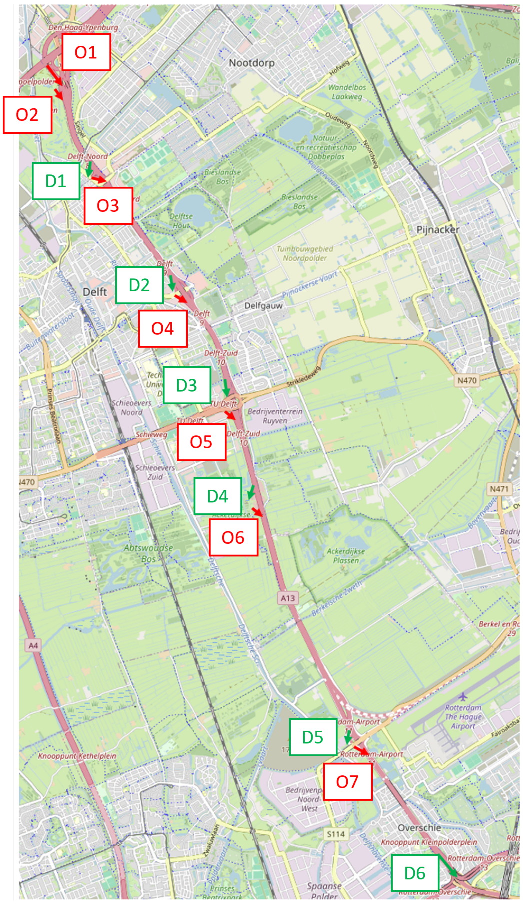

Fig. 1: A13 Highway (based on OpenStreetMap [46])

TABLE II: The location of the highway in kilometers

Origin/ Exit	Location along the highway
O1	0
D1	6
D2	7.5
D3	9.6
D4	11.6
D5	15.0
D6	17.8

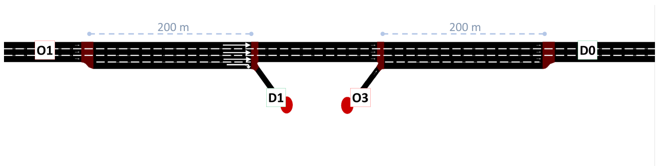

Fig. 2: A13 Schematic Diagram

1) Simulation Seed for Each Scenario: The simulation seed is configured to run each scenario ten times. This repetition accounts for the inherent randomness in vehicle behaviors. Firstly, the heterogeneity of human-driven vehicles is considered, incorporating variations in speed distribution and acceleration behavior to achieve more realistic results. Secondly, the random distribution of vehicle generation, informed by the results shown in Table IV regarding small and large distance settings, is also considered. Consequently, each scenario is executed ten times to obtain an average with a more comprehensive result.

2) ACC Market Penetration Rates (MPRs): The ACC market penetration rates (MPRs) are considered at 0%, 25%, 50%, and 75%. A scenario with 100% ACC vehicles is discarded, as it is relatively unrealistic in real-world conditions.

3) Number of Brands and Corresponding Distance Setting Percentages: The vehicles with ACC systems are assigned the values of the characteristics from Table IV. In this method, vehicle characteristics are assigned randomly from a distribution, resulting in anonymous vehicles with characteristics derived from various brands. The approach involves creating lists for each characteristic, where the weight of each value’s appearance corresponds to its market share. During the simulation, a uniform distribution is used to randomly select a value from each list to assign to the vehicle’s characteristics, thereby increasing the heterogeneity of the simulation. For instance, a vehicle might possess the time gap value of a Tesla and the acceleration capabilities of a Hyundai based on distribution data. Although the database contains only 22 models, this method allows for a broader representation of real-world variability. Figure 3 shows an example of the random distribution built from the data analysis, which is used as an input for the simulations.

1) All Distance Settings: Includes a mix of distance settings.
2) Small Distance Setting Only: Focuses on scenarios where vehicles only have small distance distances, potentially leading to more challenging lane-change behaviors and increased congestion. The distance setting

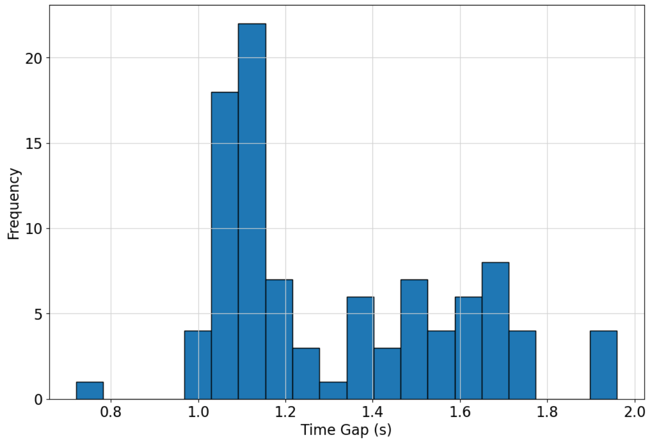

Fig. 3: Random Distribution for Time Gap - Small Setting

is considered a significant factor that might influence transition control. It is assumed that smaller distance settings could complicate lane-change maneuvers, resulting in more congested traffic patterns.

3) Large Distance Setting Only: Considers scenarios where vehicles only use large following distance settings. The large time gap might influence the capacity of the road, and in contrast to the small distance setting, there might be more space for the vehicles to make the lane changes.
4) Min speed is not zero: Vehicles that cannot follow the full-speed range will deactivate when their velocity is below certain thresholds. It may cause more congested traffic flow if the average travel speed is low or there are many stop-and-go situations.

If scenarios are not clearly defined for the distance setting, such as specifying only small distance settings, the distance settings will be equally distributed between small and large settings, which is 50% for each distance setting.

4) Truck MPRs: The choice of truck MPRs for highway traffic simulation is based on the specific traffic composition observed in the Netherlands. According to [47], the Netherlands experiences high traffic intensity due to its dense population and significant freight traffic. In this context, cars constitute 78% of the total traffic on Dutch roads, while freight transportation, primarily by trucks, accounts for 6%. Given this distribution, setting the truck MPRs at 6% can reflect the real-world conditions of Dutch highways. This realistic representation ensures that the simulation outputs are both relevant and reliable for planning and analysis purposes. The value is fixed for every scenario since the trucks are not the main focus of the research.

5) Human Driver's Reaction Time: In automated driving research, it is important to take the driver's reaction time for a takeover control of the vehicle into account [7], [48]. In this research, this is not the main research point. There is already research investigating this question. Therefore, the setting of the driver's reaction time used the results from [7], [48].

After AIDC

The mean and standard deviation values are chosen based on the findings of [48], which provide a series of scenarios for assessing driver performance. The values of mean and standard deviation for the reaction time are chosen from the results of scenarios where only no visual non-driving tasks (NDT) are involved. The mean value is 2.49, and the standard deviation is 1.12, which can be visualized in Figure 4 in log-norm distribution.

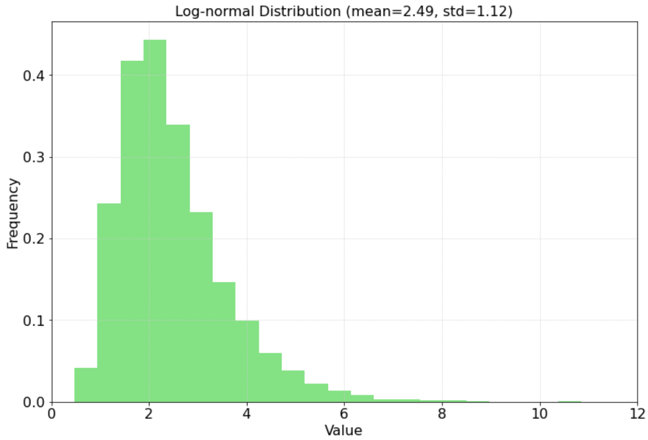

Fig. 4: Driver's reaction time under visual non-driving task

After DIDC

For the DIDC transition control, it is assumed that the driver initiates the transition control. This means the driver should already be aware of the driving situation and is usually prepared to take over control afterward [49]. Therefore, the reaction time for it is 0 seconds.

D. Time Gap of Human Drivers

The dataset containing real-world traffic information, which included time gap recordings, was applied to analyze time gap distribution patterns. By calculating the percentiles of the time gap values in this empirical dataset, the cumulative distribution function (CDF) can be plotted. This is one of the input formats for the VISSIM to set the distribution. Therefore, by incorporating these percentile values, the VISSIM simulation was able to represent the traffic dynamic more realistic.

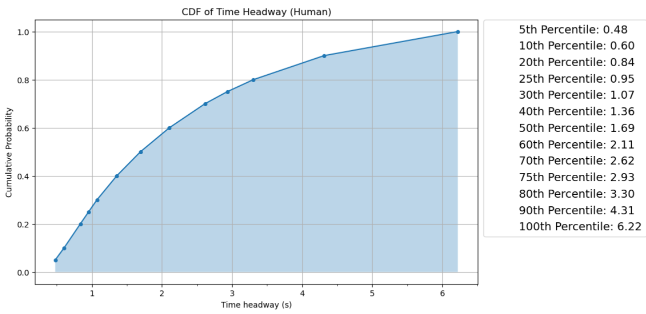

Fig. 5: Cumulative Distribution Function for Time Gap

E. Desired Speed

There are two different speed limits on the network, which are 100 kilometers per hour and 80 kilometers per hour. Therefore, there are two different desired speed distributions. The distributions are based on real-world traffic data from the same network. The speed values are taken from a free-flow situation between 6 AM and 7 AM before any congestion occurs.

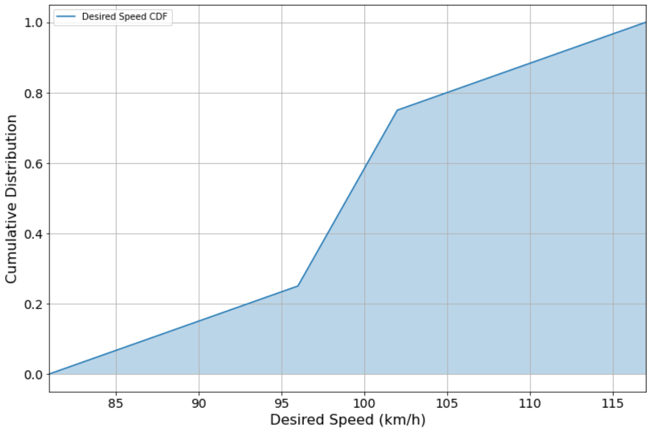

Fig. 6: Desired Speed CDF - 100 km/hr

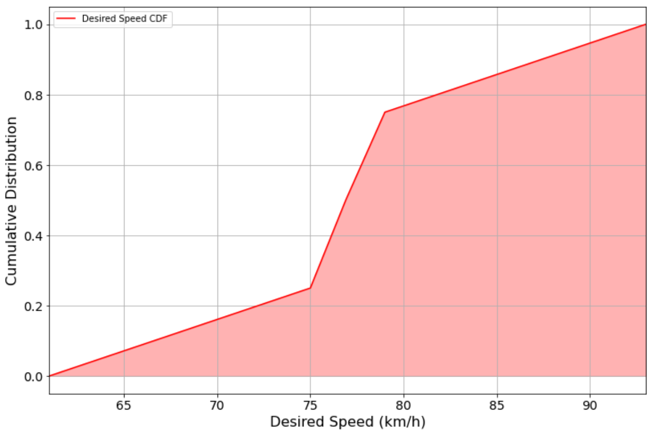

Fig. 7: Desired Speed CDF - 80 km/hr

TABLE III: Simulation Scenario Number

Scenario NO.	Name*	ACC MPRs	Vehicles involved
1 (base)	0PR-Base	0%	All human-driven vehicles
2	25PR-All-SL	25%	All in random distributions
3	25PR-All-S	25%	All in random distributions with small distance setting only
4	25PR-All-L	25%	All in random distributions with large distance setting only
5	25PR-Speed-SL	25%	All vehicles that cannot follow for full speed
6	75PR-All-SL	75%	All in random distributions
7	75PR-All-S	75%	All in random distributions with small distance setting only
8	75PR-All-L	75%	All in random distributions with large distance setting only
9	75PR-Speed-SL	75%	All vehicles that cannot follow for full speed

*The principle of the names:
the percentage of ACC - the vehicle involved - the distance setting applied

IV. Results

In this section, the results of data analysis for the various ACC characteristics are present. Furthermore, the results of the nine simulation scenarios are analyzed, with each indicator for assessment discussed in its own subsection. The chapter begins with Section 6.1, which focuses on traffic flow efficiency, followed by an examination of vehicle network performance, and concludes with an analysis of traffic safety. In addition, the figures in this chapter use scenario names from Table III as the captions. The results are presented in terms of different indicators rather than different ACC MPRs.

A. Data Analysis

1) OpenACC Database: The OpenACC database is from a series of car-following experiments involving vehicles with Adaptive Cruise Control systems (ACC). The objective of the OpenACC Database is to provide data about ACC behavior to the scientific community to understand better the properties of ACC vehicles and how their widespread use may influence traffic dynamics to anticipate possible related problems. It is an open-access database of car-following experiments involving 28 vehicles, 22 equipped with state-of-the-art commercial ACC systems. Experiments were carried out in the framework of four test campaigns. The campaigns have been designed to study, among others, vehicle dynamics in real-world conditions, the behavior of ACC systems, and car-following patterns [37].

2) TNO Database - SAE L2 Naturalistic Driving Study: Naturalistic driving data of 9 vehicles of different brands, where 20 volunteers drove for one month without ADAS and two months with ADAS. CAN-bus, MobilEye, GPS, and internal/external video are recorded. The goal was to analyze how drivers use ACC and LKS systems in naturalistic circumstances and how this changes their behavior. Data is map matched on a snapshot of the OpenStreetMap (OSM) network, resampled to 10Hz for ease of analysis, and a link is made to the NDW data to determine the traffic characteristics (speed and intensity) the vehicle was driving in. The most accessible way to work with the data is using the MySQL database (see resources for connection information). It contains the data itself but also a description of tables and columns. Although the experiment utilized both ACC and LKS, only data from ACC systems will be used in this research.

3) Various ACC Characteristics: The differences in ACC characteristics are shown in Table IV. These results are from the data analysis of the OpenACC database and SAE L2 database. The results are used as input for the simulation to represent the variety of vehicles in the real world.

B. Speed Distribution

The speed distribution of each scenario is illustrated by heatmaps. The x-axis represents the time interval in minutes, ranging from 0 to 180 minutes. The y-axis shows the loop detector positions, ranging from 1 to 35. The locations of on- and off-ramps are also plotted in the figure. On-ramps, indicated by the long dash pattern and labels beginning with 'O' (origin), and off-ramps, represented by the dotted dash pattern and labels starting with 'D' (destination), are marked. In addition, the color scale on the right side of the heatmaps indicates the average harmonic speed in kilometers per hour (km/h), with a gradient from red, indicating lower speeds 0 km/h, to blue, indicating higher speeds up to 120 km/h.

1) Base: In the base scenario, as shown in Figure 8, it can be seen there is a distinct bottleneck between loop detectors 18 and 19, where is the on-ramp 6. The bottleneck occurs due to the reduced lanes after the acceleration sections due to the reduction in lanes following the acceleration sections, which are used to merge on-ramps into the main traffic flow.

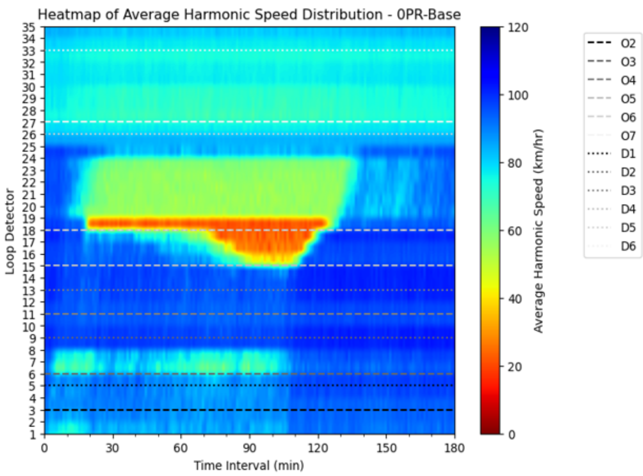

Fig. 8: 0PR-Base

2) Scenarios with 25% ACC MPRs (25PR-): Figure 9 illustrates the speed distribution for 25PR scenarios under different distance settings. From left to right, the configurations are all small settings, a mix of small and large settings, each accounting for 50%, and all large settings. In addition, for enhanced comparison, the speed distribution for the 25PR-Speed-SL scenario is displayed below the figure for 25PR-All-SL. This scenario represents conditions where ACC systems are unable to follow the full-speed range with mixed distance settings, providing a clearer perspective on how these configurations affect speed distribution.

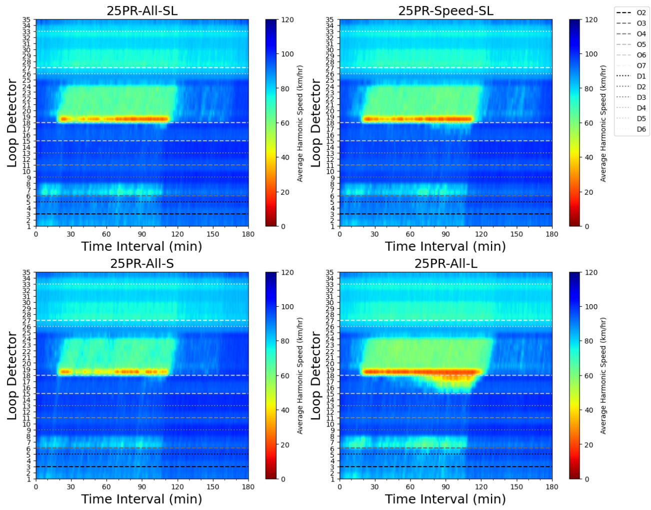

Fig. 9: 25PR scenarios

3) Scenarios with 75% ACC MPRs (25PR-): Figure 10 illustrates the speed distribution for scenarios with 75% ACC MPRs under different distance settings. From left to right, the configurations are all small settings, a mix of small and large settings, each accounting for 50%, and all large settings. In addition, the speed distribution the scenario 75PR-Speed-SL, where the ACC systems cannot follow the full-speed range with the mix distance setting, is also present under the figure for 25PR-All-SL.

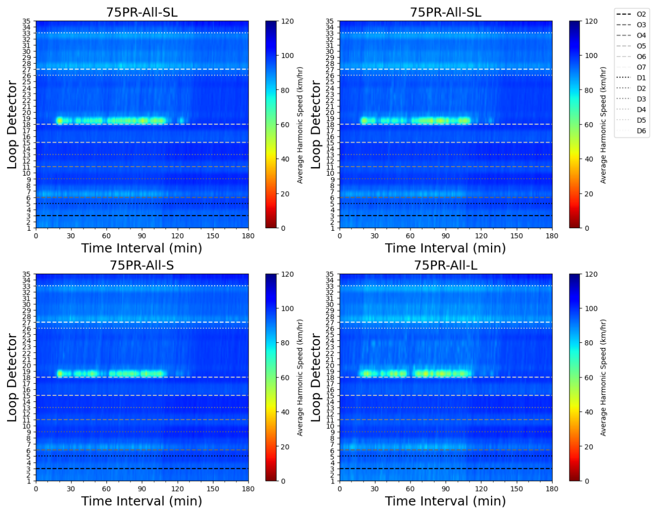

Fig. 10: 75PR scenarios

TABLE IV: Summary of ACC systems' characteristics from the empirical data and owners manuals

Vehicle Brand	Market share(%)	Model	Acceleration (m/s^2) (max/ min)	Inter-vehicle space (m) (S/ L)	Time gap (s) (S/ L)	Response time (s)	Standstill distance (m) (min/ max)	Min Set Speed for ACC (km/hr)	Speed required to activate ACC (km/hr)	ACC speed range (km/hr)
Hyundai	4.0	Ioniq Hybrid	2.00/ -3.50	26.88/ 52.43	1.00/ 2.5	2.42 (gasoline)	3.05/ 5.80	30	30/ 10	30-190/ 10-190
Volvo	4.0	XC40	2.00/ -3.50	8.98/ 55	1.53/ 3.00	2.34 (diesel)	3.19/ 3.34	30	15/ 0	15-200/ 0-200
Volkswagen	11.7	Golf E	2.00/ -3.50	35.78/ 55	1.15/ 3.00	1.7 (e)	4.49/ 6.25	30	30/ 10	30-150/ 0-150
Peugeot	10.1	3008 GTLine	2.00/ -4.00	32.68/ 52.43	1.06/ 2.20	2.34 (diesel)	3.19/ 3.34	30	30/ 10	30-180/ 10-180
Kia	6.6	Niro	2.10/ -4.00	46.65/ 52.5	1.48/ 2.51	2.42 (gasoline)	3.05/ 5.80	30	30/ 0	10-160/ 0-160
Ford	5.5	S-Max	3.00/ -4.00	48.60/ 52.43	1.61/ 2.50	2.34 (diesel)	3.19/ 3.34	30	30/ 10	30-190/ 10-190
Mitsubishi	4.0	Outlander PHEV	4.00/ -4.00	44.51/ 50	1.44/ 2.20	2.42 (gasoline)	3.05/ 5.80	40	40/ 10	30-180/ 10-180
BMW	5.3	I3	2.00/ -3.50	16.65/ 27.01	1.17/ 2.08	2.34 (diesel)	3.19/ 3.34	30	30/ 0	30-180 / 0-180
		X5	2.50/ -3.50	21.62/ 46.67	1.14/ 2.51	2.34 (diesel)	3.19/ 3.34	30	30/ 0	30-180 / 0-180
		530i	3.00/ -5.00	17.03/ 51.66	1.20/ 2.50	2.34 (diesel)	3.19/ 3.34	30	30/ 0	30-180 / 0-180
Toyota	5.1	RAV4	2.00/ --3.50	15.29/ 19.66	1.67/ 2.29	2.42 (gasoline)	3.05/ 5.80	30	30/ 30	30-190/ 30-190
Tesla	7.6	Model X	2.00/ -5.00	12.61/ 30.61	1.09/ 2.29	1.7 (e)	4.49/ 6.25	30	30/ 0 (if a preceding vehicle is within 1.5m)	30-150/ 0-150
		Model S	2.00/ -3.50	19.19/ 35.13	1.38/ 2.73	1.7 (e)	4.49/ 6.25	30	30/ 0 (if a preceding vehicle is within 1.5m)	30-150/ 0-150
		Model 3	2.00/ -3.50	22.40/ 45.72	1.23/ 2.53	1.7 (e)	4.49/ 6.25	30	30/ 0 (if a preceding vehicle is within 1.5m)	30-150/ 0-150
Audi	4.0	A4	2.00/ -3.50	16.46/ 32.38	1.66/ 3.33	2.42 (gasoline)	3.05/ 5.80	30	30/ 0 (if the vehicle is not stationary for more than 3 minutes)	30-150/ 0-150
		A6	2.50/ -4.00	22.91/ 66.16	1.17/ 3.54	2.56 (diesel)	4.07/ 7.80	30	30/ 0 (if the vehicle is not stationary for more than 3 minutes)	30-150/ 0-150
		A8	2.00/ -3.50	20.09/ 32.38	0.721/ 3.55	2.56 (diesel)	4.07/ 7.80	30	30/ 0 (if the vehicle is not stationary for more than 3 minutes)	30-150/ 0-150
		E TRON	2.00/ -3.50	12.60/ 30.05	1.32/ 3.53	1.7 (e)	4.49/ 6.25		30/ 0 (if the vehicle is not stationary for more than 3 minutes)	30-150/ 0-150
Mercedes	4.0	GLE450	2.00/ -3.50	13.99/ 23.62	1.34/ 1.94	2.42 (gasoline)	3.05/ 5.80	20	20/ 20	20-210/ 0-210
		A Class	3.00/ -3.50	21.91/ 44.99	1.16/ 2.41	2.42 (gasoline)	3.05/ 5.80	20	20/ 20	20-160/ 0-160
JAGUAR	4.0	I PACE S	2.00/ -3.50	14.25/ 21.68	1.77/ 2.55	1.7 (e)	4.49/ 6.25	32	32/ 0	32-200/ 0-200
Mazda	4.0	3	2.00/ -3.50	17.26/23.83	1.96/ 2.89	2.42 (gasoline)	3.05/ 5.80	30	30/ 0	30-145/ 0-145

Yellow highlighted texts: The characteristics that can be set in the simulation.
Light blue texts: The data on vehicles is from the Cherasco Campaign in the OpenACC database.
Green texts: The data on vehicles is from the Vicolungo Campaign in the OpenACC database.
Bold texts: The data on vehicles is from the ZalaZone Campaign Dynamic part in the OpenACC database.
Dark orange texts: The data on vehicles is from the AstaZero Campaign in the OpenACC database.
Dark blue text: The vehicle is from the SAE L2 database.
Red text: The assumptions are made for the values.
Underlined text: The data is sourced directly from the owner's manual.

It can be observed that the congestion levels decrease after introducing vehicles equipped with the ACC systems and the transition control models compared to the base scenario, and the distance settings play a role in the final congestion pattern. The following findings are drawn by comparing the results with the base scenario, and the extent of congestion reduction is evaluated across different scenarios with the same ACC MPRs. When smaller following distances are applied, congestion is further reduced. On the other hand, when a larger number of vehicles operate with larger distance settings while ACC is active, there is a slight increase in congestion levels, particularly distinct at lower MPRs of ACC. In scenarios where ACC systems are unable to manage full-speed following, congestion levels are higher compared to scenarios utilizing a mix of minimum speeds for ACC systems, even when a combination of small and large distance settings is applied. This effect is especially also more observable at lower MPRs of ACC.

C. *Fundamental Diagrams*

Figure 11 and 12 display a series of scatter plots and density plots that compare different traffic scenarios based on three key metrics: speed, flow, and density. The data for these fundamental diagrams are collected from Loop Detector 19, where a bottleneck is generated due to a reduction in the number of lanes from four to three. Although both figures use the same dataset, they present the data in different sequences to highlight different aspects of the scenarios. In Figure 11, the data points for the 75PR scenarios are positioned in the foreground. On the other hand, in Figure 12, the 25PR scenarios are brought to the front, allowing the data points to remain visible. By examining these two figures together provides a more comprehensive understanding of the relationships between the key metrics for different ACC market penetration scenarios. The main report only put these two figures with all scenarios plotted.

It can be observed that as ACC MPRs increase, the road capacity, represented by traffic flow, tends to increase. This means that roads can accommodate more vehicles per hour with higher ACC penetration. In addition, for a given level of flow, traffic density is lower when ACC MPRs are higher, indicating more efficient use of road space. This relationship is further supported by the speed distribution data, which shows that congestion levels decrease as ACC MPRs increase. It is worth noting that the threshold for maximum flow is 6,000 vehicles per hour. In 75PR scenarios, the flow peaks exceed this threshold, indicating superior capacity and efficiency. In contrast, the peaks for the 2PR scenarios and the 0PR-base scenario are below 6,000 vehicles per hour, indicating the limitations of lower ACC penetration in handling higher traffic volumes. This data clearly illustrates the effectiveness of ACC systems with transition control models in improving overall traffic performance and reducing congestion at higher penetration levels, which also aligns with the findings from other indicators.

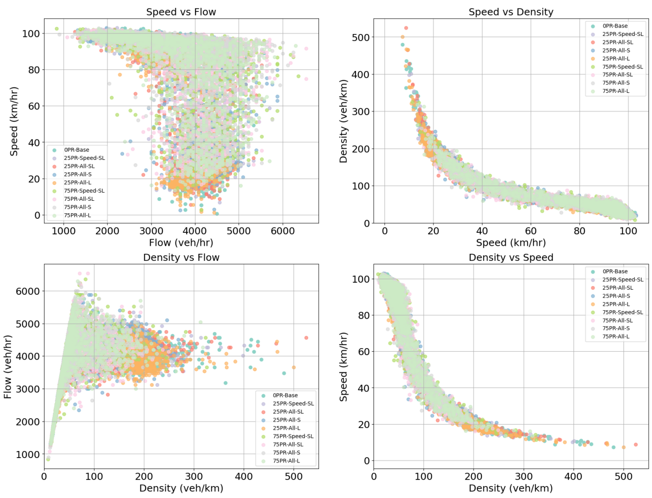

Fig. 11: Fundamental diagrams for all scenarios at the bottleneck

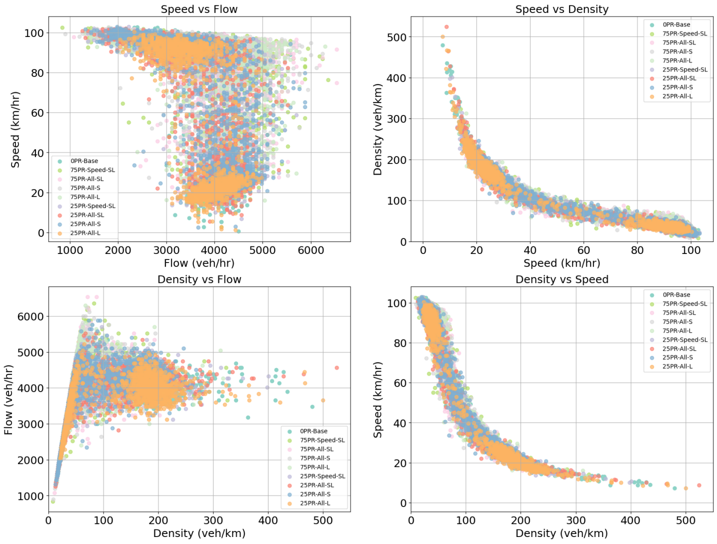

Fig. 12: Fundamental diagrams for all scenarios at the bottleneck

D. *Vehicle Network Performance*

Figure 13 displays two key indicators recorded directly from VISSIM: average delay and total travel time. The blue bars represent the average delay, which consistently decreases as ACC market penetration increases. In the 0PR-Base scenario, the average delay is 95.14 seconds. When the ACC MPR is 25% in the 25PR-All-S scenario, the delay reduces to 54.57 seconds, showing a distinct improvement of 43% compared to the 0PR-Base scenario. As ACC penetration increases further, the reduction becomes even more significant. In the 75PR-All-S scenario, the delay reaches its lowest value of 32.70 seconds, marking a 65% reduction. This downward trend in delay across the scenarios highlights how increasing the penetration of ACC systems with transition control models leads to smoother and more efficient traffic flow.

Moreover, similar improvements are observed in the total travel time, represented by the orange bars. In the 0PR-Base scenario, the total travel time is 8.36 million seconds. With 25% ACC penetration in the 25PR-All-S scenario, total travel time decreases to 7.19 million seconds, indicating a 14% reduction. As ACC MPR increases, the improvements become more substantial.In the 75PR-All-S scenario, total travel time further reduces to 6.38 million seconds, resulting in a 24% improvement compared to the 0PR-Base scenario.

Other scenarios follow similar trends. For instance, in the 25PR-All-L scenario, which models a larger vehicle distance setting, the average delay is 82.97 seconds, and the total travel time is 7.86 million seconds. This scenario shows improvement, but at a slower rate compared to the smaller distance settings, indicating that tighter vehicle spacing enhances the effectiveness of ACC systems. As ACC penetration reaches 75% in the 75PR-All-L scenario, the average delay drops to 37.92 seconds, and total travel time decreases to 6.38 million seconds, similar to the improvements seen in smaller distance settings. In scenarios such as 25PR-Speed-SL, the average delay is 64.46 seconds, and the total travel time is 7.46 million seconds. At 75% penetration in the 75PR-Speed-SL scenario, these values reduce to 35.10 seconds and 6.76 million seconds, respectively.

Overall, it can be observed that both average delay and total travel time are significantly reduced after introducing ACC systems with the transition control model. Across all vehicle settings, as the ACC MPRs increase, the reductions in average delay and total travel time become more distinct. This trend clearly indicates that higher ACC MPRs contribute to more efficient traffic flow and reduced congestion, reinforcing the finding from the speed distribution analysis discussed in Section IV-B. The results show that ACC systems not only improve individual vehicle behavior but also enhance overall traffic network performance, especially at higher ACC MPRs.

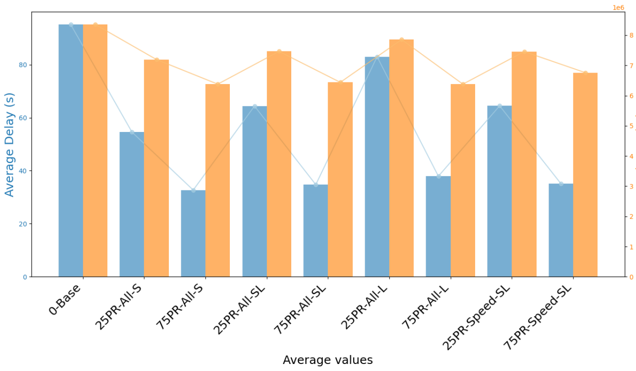

Fig. 13: Vehicle network performance indicators

E. Time-to-collision (TTC)

The TTC values analysis is considered the only TTC value below 5 seconds. It can be observed that the introduction of ACC systems has an impact on TTC values, which lead to longer and safer than the corresponding base scenario (0PR-Base). As is shown in Figure 14, the TTC values for all percentiles are the lowest when vehicles are human-driven. This tendency is more distinct at lower percentiles. Moreover, when distance settings are mixed, incorporating both small and large distance settings, TTC values tend to decrease. This may be attributed to the more heterogeneous traffic flow created by mixed-distance settings. From the perspective of the ACC MPRs, only at the 10th percentile do the 75PR scenarios demonstrate significantly higher TTC values.

In addition, it is worth noting that a small distance setting alone may also have a slight advantage in terms of safety, as it tends to keep a bit longer TTC values compared to other settings. The reason could be that the small distance setting leads to less congestion, as discussed in Section IV-B, and the traffic flow is more homogeneous. By allowing vehicles to operate closer together without compromising safety, this setting can lead to smoother traffic flow and less congestion. Overall, the small distance setting not only contributes to increased safety through extended TTC values but also reduces traffic congestion.

TABLE V: Overall TTC (consider only the values smaller than 5)

Percentile	0PR-Base	25PR-All-SL	25PR-All-S	25PR-All-L	25PR-Speed-SL	75PR-All-SL	75PR-All-S	75PR-All-L	75PR-Speed-SL
10	0.87	1.32	1.56	1.47	1.31	1.60	1.64	1.61	1.62
25	1.62	2.14	2.36	2.30	2.19	2.32	2.40	2.29	2.34
50	2.88	3.18	3.36	3.33	3.28	3.27	3.34	3.26	3.30
75	3.99	4.12	4.20	4.19	4.17	4.15	4.18	4.14	4.16
90	4.61	4.66	4.68	4.68	4.67	4.67	4.67	4.66	4.67

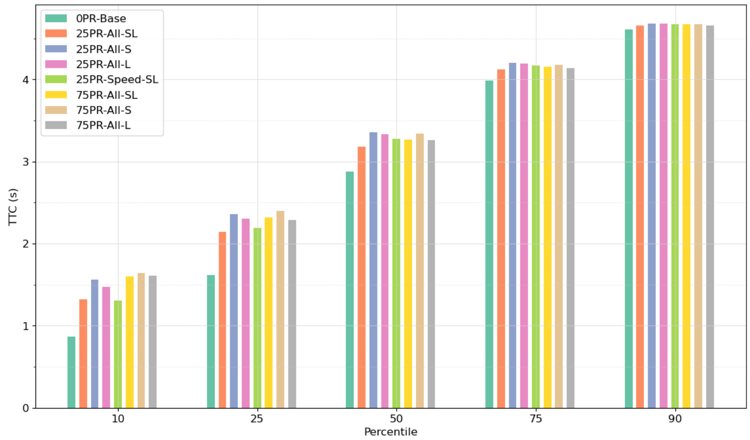

Fig. 14: Overall Time-to-collision

F. Acceleration

The American Association of State Highway and Transportation Officials sets a deceleration threshold of -3.6. Figure 15 shows a histogram of acceleration values divided into two subfigures using this threshold as a separator. Because the frequency of accelerations below -3.6 is very low, these values are plotted separately for clarity. It is important to note that the y-axis tickers for the two subfigures are not the same. In subfigure (a), the y-axis has a maximum value of 0.0040, while in subfigure (b), it reaches 3.0. The histogram shows that most acceleration behaviors fall within a safe and stable range, with the majority of acceleration values between -2 and 2.

However, there are still some critical deceleration behaviors, as shown in Figure 6.12(a). Figure 16 illustrates the number of points smaller than the threshold. It can be seen that the base scenarios had the highest number of such points. With the implementation of ACC systems with the transition control model, the deceleration becomes more stable, and the number of points below the threshold is significantly reduced. In addition, it can be observed that the number of critical deceleration rates is lower in scenarios that include only small distance settings under the same ACC MPRs. This could explain the TTC results in Section IV-E, where scenarios with only small distance settings show slightly larger TTC values.

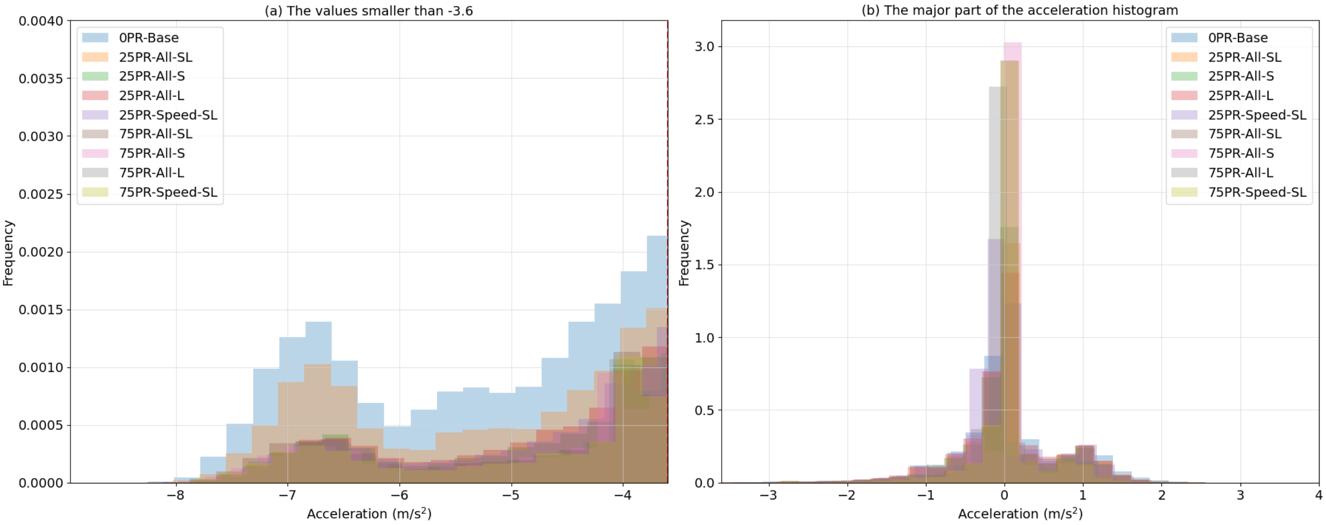

Fig. 15: Acceleration Histogram

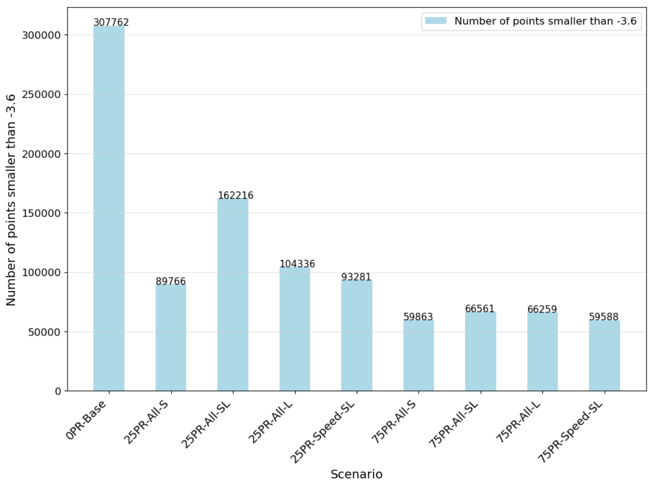

Fig. 16: The number of points smaller than the threshold for each scenario

G. Transition Control-related Output

1) Number of Transition Control Types: There are four different scenarios under both 25% and 75% ACC MPRs, and the simulation seed for each scenario was ten. There are three outputs about the transition control types, which are DIDC, DIAC, and AIDC, across ten runs. Table VI and VII present the number of transition types for 25PR and 75PR scenarios, respectively. In the table within the following sections, each cell contains two values. The first value, located before the slash, represents the total number. The second value, located after the slash, represents the value per kilometer traveled, indicating the value per kilometer traveled across the entire simulation, including all drivers, rather than being limited to a single driver. For example, in Table VI, the cell for DIDC of 25PR-All-SL reads "41306 / 1.48," which means that 41306 is the total number and 1.48 is the value per kilometer traveled.

TABLE VI: Number of transition controls of different types - 25PR Scenarios

Transition type (Total number/ number per km)	25PR-All-SL	25PR-All-S	25PR-All-L	25PR-Speed-SL
DIDC	41306/ 1.48	45353/ 1.64	41575/ 1.48	42195/ 1.50
DIAC	40183/ 1.44	43511/ 1.60	41814/ 1.48	41672/ 1.48
AIDC	1340/ 0.08	1302/ 0.04	1505/ 0.04	1619/ 0.64
Time of ACC activated	87.49%	89.05%	86.14%	87.01%

TABLE VII: Number of transition controls of different types - 75PR Scenarios

Transition type (Total number/ number per km)	75PR-All-SL	75PR-All-S	75PR-All-L	75PR-Speed-SL
DIDC	108883/ 4.34	106254/ 4.37	112408/ 4.37	110730/ 4.45
DIAC	102427/ 4.08	99673/ 4.10	106623/ 4.15	104687/ 4.21
AIDC	2304/ 0.09	2093/ 0.09	2838/ 0.11	2114/ 0.08
Time of ACC activated	91.16%	91.43%	90.72%	90.95%

In the 25PR scenarios, the DIDC values range from 41,306 to 45,353 total, with per-kilometer values between 1.48 and 1.64. This indicates a moderate frequency of driver-initiated deceleration events. DIAC values are relatively consistent across different conditions, ranging from 40,183 to 43,511 total, with per-kilometer values between 1.44 and 1.60. On the other hand, AIDC values are significantly lower, indicating fewer instances of ACC-initiated deceleration, with totals ranging from 1,302 to 1,619 and per kilometer values between 0.04 and 0.08. The time of ACC activation varies slightly but remains around 87-89%, showing consistent engagement of the ACC systems in these scenarios. In the 75PR scenarios, the number of transition events is significantly higher, which aligns with the increased presence of ACC vehicles expected to be around three times more than in the 25PR scenarios. DIDC values range from 106,254 to 112,408 total, with per-kilometer values between 3.336 and 4.373. This indicates a higher frequency of driver-initiated deceleration events compared to 25PR scenarios. DIAC values also increase, ranging from 99,673 to 106,623 total, with per kilometer values between 3.154 and 4.147.

The number of transition controls per kilometer is roughly the same for the scenarios within the same ACC MPRs, indicating that the distance setting is not the primary factor influencing transition controls. In the 25PR scenarios, the number of transition controls for 25PR-All-S is slightly higher than in other 25PR scenarios, possibly due to more time being available for the ACC system to activate.

2) Number of Transition Control Causes: Table VIII and IX present the number of transition causes for 25PR and 75PR scenarios, respectively. The causes include approaching a lower-speed leader, meeting the ACC deceleration threshold, hitting the lower speed bound, forward collision warning (FCW), lane changes, and driver decision activation.

In the 25PR scenarios, lane changes and driver decision activations are the most frequent transition causes, with values indicating a high occurrence rate. Forward collision warnings (FCW) are also prevalent. Other causes, such as meeting the ACC deceleration threshold or the lower speed bound, are less frequent but still noteworthy. For instance, the total number of lane change transitions ranges from 39,316 to 43,023, with values per kilometer traveled between 1.400 and 1.568. On the other hand, driver decision activation ranges from 40,183 to 43,511 in total, with per-kilometer values from 1.428 to 1.584. In the 75PR scenarios, the frequency of lane changes and driver decision activations increases significantly compared to the 25PR scenarios. Given that ACC vehicles in the 75PR scenarios should be around three times more than in the 25PR scenarios, this increase is expected. The data show that these transition causes have higher values, indicating more frequent occurrences in higher market penetration rate scenarios. For example, lane changes in the 75PR scenarios range from 97,142 to 104,540, with per-kilometer values between 3.078 and 4.066. Driver decision activations range from 99,673 to 106,623, with per-kilometer values from 3.145 to 4.147. Besides, FCW occurrences remain substantial. The ACC deceleration threshold and lower speed bound transitions also show higher values, which suggest more frequent transitions in scenarios with higher ACC penetration rates.

3) Location of Transition Controls: Table X shows the percentage of transition control around on and off-ramps and the bottleneck for the 25PR and 75PR scenarios. The bottleneck is recognized as the road section between loop detectors 18 and 19 from the speed distribution heatmap in section IV-B. The bottleneck is also a part of the area around on-ramp 6.

TABLE X: Percentage of transition control around ramps and the bottleneck

Scenario	Around Ramps	Around Bottleneck
25PR-All-SL	50.69	33.48
25PR-All-S	52.14	34.96
25PR-All-L	56.85	35.54
25PR-Speed-SL	55.31	38.52
75PR-All-SL	54.87	26.42
75PR-All-S	55.42	26.36
75PR-All-L	54.03	27.09
75PR-Speed-SL	54.28	27.59

TABLE XI: Percentage of transition control causes at the bottleneck

Scenario	Lane Change	Lower Speed Bound	FCW
25PR-All-SL	23.2	83.6	65.9
25PR-All-S	25.9	97.1	66.1
25PR-All-L	22.9	93.3	68.4
25PR-Speed-SL	22.9	94.1	68.4
75PR-All-SL	23.5	91	67.9
75PR-All-S	23.3	94.6	74.7
75PR-All-L	24.8	92.1	60.5
75PR-Speed-SL	24.8	88.5	69.6

For all scenarios, over 50% of transition control occurred around on and off-ramps. The data indicate that in the 25PR scenarios, the percentage of transition controls around ramps ranges from 50.69% to 56.85%, with the highest percentage observed in the 25PR-All-L scenario. Around bottlenecks, the percentages are slightly lower, ranging from 33.48% to 38.52%, with the 25PR-Speed-SL scenario showing the highest percentage. In the 75PR scenarios, the percentage of transition controls around ramps is relatively consistent, ranging from 54.03% to 55.42%. The 75PR-All-S scenario has the highest percentage. Transition controls around bottlenecks in the 75PR scenarios are lower than those in the 25PR scenarios, ranging from 26.36% to 27.59%. The 75PR-Speed-SL scenario shows the highest percentage in this category.

It can also be seen in Table VIII that lane change is the main reason for deactivating the ACC systems. It is expected that there will be more lane change behaviors around ramps due to the entrance and exit of the highway.

V. Discussion

This research explores the effects of adaptive cruise control (ACC) system variability on traffic flow efficiency and safety. Given the complexity of incorporating all 22 vehicle models into the simulation, random distributions were applied to key ACC characteristics, such as time gaps, acceleration capabilities, and ACC following speed boundaries. This method allowed for a more dynamic and realistic representation of vehicles, reflecting the variability seen in real-world traffic.

TABLE VIII: Number of transition control causes - 25 PR Scenarios

Transition Causes (Total number/ number per km)	25PR-All-SL	25PR-All-S	25PR-All-L	25PR-Speed-SL
Approach Lower Speed Leader	811/ 0.028	619/ 0.024	377/ 0.012	512/ 0.012
*AccDecelThreshold	823/ 0.028	699/ 0.024	735/ 0.024	713/ 0.024
Lower Speed Bound	1114/ 0.036	760/ 0.028	4305/ 0.152	5535/ 0.196
**FCW	19389/ 0.688	20420/ 0.744	20370/ 0.516	20396/ 0.724
Lane Change	39316/ 1.400	43023/ 1.568	40289/ 1.416	40280/ 1.432
Driver Decision Activate	40183/ 1.428	43511/ 1.584	41575/ 1.464	41672/ 1.480

*AccDecelThreshold: ACC systems meet the minimum deceleration rate of the operational design domain.
**FCW: Forward collision warning.

TABLE IX: Number of transition control causes - 75PR Scenarios

Transition Causes (Total number/ number per km)	75PR-All-SL	75PR-All-S	75PR-All-L	75PR-Speed-SL
Approach Lower Speed Leader	3638/ 0.082	3780/ 0.156	3602/ 0.140	3613/ 0.145
AccDecelThreshold	3812/ 0.085	4409/ 0.181	3959/ 0.154	3649/0.200
Lower Speed Bound	1283/ 0.029	1032/ 0.042	1891/ 0.074	3353/ 0.135
FCW	33188/ 0.744	32196/ 1.325	38847/ 1.511	35776/ 1.437
Lane Change	100151/ 2.245	97142/ 3.998	104540/ 4.066	102149/ 4.104
Driver Decision Activate	102427/ 2.296	99673/ 4.102	106623/ 4.147	104387/ 4.194

Although this approach can occasionally produce unrealistic combinations, it was considered acceptable for this research, as it prioritizes flexibility and diversity in simulating different ACC behaviors. Assumptions about acceleration, informed by ISO 15622, were necessary due to limitations in empirical data availability, particularly regarding the actual acceleration capabilities of vehicles in real-world conditions.

The findings indicate that the introduction of ACC systems, particularly at higher market penetration rates (MPRs), significantly improves traffic flow efficiency. Scenarios with smaller time gaps led to more distinct reductions in congestion, especially near bottlenecks. As MPRs increased, traffic flows became more homogeneous, resulting in fewer instances of abrupt braking and accelerating, which are typically associated with human-driven vehicles. In addition, the analysis of speed distribution showed that ACC systems could create more stable and predictable speed patterns, which helps to maintain traffic flow and reduce congestion. The results from this study are consistent with prior research, which also found that higher ACC penetration reduces traffic congestion and smooths traffic flow when optimal conditions, such as high ACC adoption and consistent traffic speeds, are met [50], [51]. Research from [52] and [53] also pointed out that ACC reduces congestion and smooths traffic flow under optimal conditions, such as high penetration of ACC vehicles, controlled or homogeneous traffic environments, and steady traffic speeds. However, it is worth noting that in scenarios where ACC systems were not capable of following the full speed range (e.g., due to speed limitations), the improvements in congestion were less pronounced. This emphasizes the importance of the ACC system's ability to adapt to different traffic dynamics.

From the traffic safety perspective, the time-to-collision (TTC) analysis revealed that ACC systems generally improve safety margins, particularly compared to scenarios where only human-driven vehicles are present. Higher ACC penetration rates resulted in increased TTC values, particularly at lower percentiles, which are typically associated with more critical traffic situations. Interestingly, scenarios with mixed distance settings, which combine small and large following distances, resulted in lower TTC values than those with more consistent settings. This counter-intuitive result can be attributed to the assumption in the simulation that human drivers react perfectly, which does not fully capture the variability of real-world driving behaviors. Despite this assumption, the more uniform small distance settings applied by ACC systems may contribute to smoother traffic flow, reducing the likelihood of sudden braking and resulting in higher TTC values.

These findings contrast with previous research that has identified potential negative safety outcomes associated with ACC in mixed traffic environments. For instance, [55] found that unstable behavior of ACC vehicles within mixed traffic could contribute to rear-end crash risks, especially in environments where both ACC-equipped and human-driven vehicles interact. In their study, the lack of string stability in ACC systems was a significant factor contributing to these risks. The current study did not account for string stability or for the potential speed drops that can occur when drivers take over control from ACC systems, which may explain the divergence in findings. Including string stability in future research could provide a more comprehensive understanding of ACC's impact on traffic safety, particularly in mixed-traffic scenarios.

Transition control-related results, which examine the switch between ACC and manual control, also provide valuable insights. The number of transition controls, both proactive (driver-initiated) and reactive (system-triggered), remained relatively consistent across scenarios with different ACC MPRs and distance settings. This suggests that the variation in ACC distance settings does not significantly influence the number of transitions. It was hypothesized that more frequent transitions would occur in scenarios with small distance settings, potentially increasing the likelihood of traffic instability. However, the simulation results did not support this hypothesis, as transition events were distributed consistently across scenarios. The low frequency of reactive transitions, where the system disengages due to operational limitations (AIDC), further indicates that ACC systems with transition control models maintain stable traffic flow. Although AIDC events are generally considered to pose higher risks due to the reliance on drivers' response times, their low occurrence, approximately 0.05 events per kilometer, suggests that they do not substantially impact overall traffic performance.

Another key insight is the distribution of transition control events near ramps and bottlenecks. The results showed that ramps and bottleneck areas are critical zones where transition controls are more likely to occur, indicating that these areas may require further attention when designing ACC systems for highway environments. Despite the initial concerns about the potential negative impact of transition controls on traffic efficiency and safety, the results suggest that, even in these critical zones, ACC systems with transition control mechanisms generally enhance traffic flow and safety, particularly on highways where traffic conditions are less complex and more predictable than in urban environments.

However, the findings of this research should be interpreted with caution. The simulations were based on several assumptions about the behavior of both human drivers and ACC systems, including near-perfect reactions from human drivers and a lack of consideration for string stability within ACC systems. These assumptions limit the ability to fully capture the variability and complexity of real-world traffic conditions, particularly the diversity in human driving behaviors, such as aggressive or defensive driving styles. Previous research, such as the study by [54], has highlighted the importance of key parameters in ACC system design, such as time gaps, time delays, and maximum deceleration rates. Their study, which focused on time gaps of 0.6 to 1.6 seconds, demonstrated the importance of longer time gaps for improving traffic safety. In contrast, this research included scenarios with larger distance settings (time gaps above 2 seconds), and while it found similar results regarding safety improvements, the absence of detailed considerations for response time and string stability may have influenced the outcomes.

In conclusion, this study demonstrates that ACC systems with transition control models can enhance both traffic flow efficiency and safety, particularly in highway environments where traffic is more predictable and less variable. However, further research is needed to address the limitations of the current study, particularly the absence of string stability analysis and the oversimplification of human driving behavior. Future studies should explore how these factors influence ACC performance in more complex and realistic traffic scenarios, such as urban environments or situations with highly mixed traffic compositions. Despite these limitations, the results suggest that ACC adoption, especially with higher MPRs, can offer significant benefits for improving traffic flow and reducing congestion.

VI. Conclusion

This research has investigated the impact of different ACC systems on traffic flow efficiency and road safety, focusing on the transition control between automated driving systems and human drivers. By analyzing the characteristics of ACC systems from various automotive brands and utilizing both empirical data and traffic simulations, it was demonstrated that increased ACC market penetration rates (MPRs) generally enhance traffic flow efficiency and safety, particularly in controlled highway environments. The simulations indicated that scenarios with higher ACC penetration led to smoother traffic flow, reduced congestion, and lower risks of collisions, particularly when ACC vehicles were set to smaller following distances. However, the study also highlighted the challenges posed by the transition control process, where the brief delay required for human drivers to take over from automated systems can lead to potential safety risks, especially in complex and high-speed situations.

The research also indicated the need for further recommendation of ACC systems and their integration into more driving conditions. The limitations identified, such as the exclusion of certain vehicle types and weather conditions, suggest that real-world applications might differ from the simulated scenarios. Future research should expand on these findings by incorporating a broader range of vehicle types, including motorcycles and varying weather conditions, to assess the robustness of ACC systems under more diverse circumstances. Furthermore, understanding driver behavior during transition control remains crucial for improving the seamless integration of ACC systems into existing traffic networks. These insights are important for policymakers and automotive engineers as they work towards enhancing the safety and efficiency of automated driving technologies on public roads.

A. Limitations

This research made several assumptions to focus on comparing different ACC systems and transition control models. Human driver behavior, such as aggressive or defensive driving, was simplified, assuming nearly ideal performance. The model also did not account for string stability in ACC vehicles, a factor that can influence traffic efficiency and safety. There is a lack of empirical data on string stability for each ACC system, and the simulation used only two distance settings (small and large), whereas real vehicles typically offer more options. This simplification might limit the accuracy in simulating real-world ACC behavior.

Additionally, the transition control model did not factor in speed drops after manual interventions. Certain real-world ACC issues, such as system deactivation under clear conditions, were excluded due to insufficient data on their frequency. The simulation also did not include motorcycles, which are present on Dutch highways, potentially affecting ACC system interactions. Furthermore, weather conditions that could impact ACC performance were not considered, despite their relevance in the Netherlands.

The highway-based simulation, while suitable for ACC systems, may not fully capture the complexities of urban road traffic, where conditions are more dynamic. Lastly, the use of surrogate safety indicators, such as TTC and DRAC, limits the analysis since these are proxies for crashes rather than direct crash data.

B. Future Research Recommendations

Future research should include more diverse human driving behaviors, such as aggressive or defensive driving, to better simulate real-world interactions with ACC systems. Incorporating string stability into simulations would provide a more accurate depiction of ACC performance. Expanding simulations to urban environments will also give a broader understanding of ACC system limitations.

In terms of data collection, more empirical data from real-world transition control events is crucial. Current datasets lack consistency and do not cover driver perspectives during transitions. Utilizing advanced driving simulators or conducting naturalistic driving studies with more detailed data collection could help refine ACC models and improve their accuracy.

C. Practical Recommendations

For road users, it is recommended to use small ACC distance settings on highways but only when fully alert. Driver training should include education on ACC system limitations. For road operators, promoting ACC adoption through incentives could improve traffic flow. Original equipment manufacturers (OEMs) should gather feedback to address unexpected ACC deactivation issues and enhance system reliability.

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B

Summary of Studies on Transition Control and System Disengagement

This appendix shows the tables of the literature review on system disengagement.

Table B.1: Summary of Studies on Transition Control and Disengagement in Automated Driving

Author (Year)	Methodology	Main Findings
Gold et al. (2013)	Participants in an advanced driving simulator followed a lead vehicle that suddenly swerved, revealing a stranded vehicle ahead, requiring them to brake and swerve to avoid a collision. Groups where vehicles were driven manually were compared with those in fully automated mode (attentive and inattentive to driving tasks).	The manual driving group performed avoidance maneuvers better than those driving in fully automated mode, regardless of attentiveness. This emphasizes the challenge of regaining full situational awareness and vehicle control, especially in emergency situations involving acute hazards.
Merat et al. (2014)	Participants in a driving simulator were asked to resume control of an automated vehicle on a motorway in two different conditions: paying attention to the roadway in fully automated mode and paying attention to the roadway in semi-automated mode.	Attentive drivers regained control in an average of 10 seconds, while less attentive drivers took 35-40 seconds. This suggests that when drivers are unaware, messages about a manual switch must be provided properly and timely, indicating that planned switches to manual should occur in low crash-risk traffic situations.

Continued on next page

Table B.1 Summary of Studies on Transition Control and Disengagement in Automated Driving

Author (Year)	Methodology	Main Findings
Vogelpohl et al. (2018)	A driving simulator experiment examined drivers' responses to Take-Over Requests (TOR) in automated driving. The study varied complexity and Non-Driving Related Tasks (NDRTs) to assess reaction times and control regaining post-TOR.	Distracted drivers could disengage automation and take control quickly after a TOR. However, their reaction to subsequent tasks was delayed, indicating a reduced situational awareness compared to manual driving. This highlights the importance of designing automated systems that aid drivers during the transition to manual control.
Varotto et al. (2020)	A driving simulator explored the transitions from full-range Adaptive Cruise Control to manual driving. Participants' reactions to Take-Over Requests were examined during and after transitions to manual control.	During the transition to manual control, drivers showed increased sensitivity to the environment, leading to larger decelerations when approaching slower vehicles. Overruling the ACC by pressing the gas pedal significantly increased speed and acceleration across all traffic conditions, particularly at high densities. These behaviors suggest a compensation strategy to adjust to the perceived risk and difficulty of the task. The study's findings indicate significant changes in driver behavior characteristics over time when deactivating or overruling the ACC. This suggests the need for human-like driving assistance systems that can adapt to a wide range of traffic situations and enhance comfort and safety.
Li et al. (2020)	A driving simulator experiment to assess the take-over performance of high crash risk (HCR) and lower crash risk (LCR) drivers in conditionally automated driving. The experiment included factors such as engagement in non-driving tasks and different time budgets for taking over control.	LCR drivers generally exhibited shorter brake reaction times than HCR drivers, indicating better take-over performance. The study also highlighted the detrimental effects of engaging in tasks while driving, which led to longer response times and reduced safety in take-over situations. Additionally, shorter time budgets negatively impacted the take-over quality and safety.

Continued on next page

Table B.1 Summary of Studies on Transition Control and Disengagement in Automated Driving

Author (Year)	Methodology	Main Findings
(Weaver and DeLucia, 2022)	A systematic literature search of 8446 articles eventually narrowed to 48 articles containing 51 experiments for a meta-analysis. They focused on variables like the time allowed for drivers to take over (time budget), engagement in non-driving related tasks, and the type of information support provided during the takeover.	Engaging in non-driving related tasks generally leads to poorer takeover performance, especially if these tasks demand resources overlapping with the driving task. In addition, the evidence suggests that shorter time budgets might impair takeover performance, though these findings were less conclusive.
Shahini and Zahabi (2022)	A systematic literature review and meta-analysis to assess the effects of different levels of automation and non-driving related tasks (NDRT) on driver performance and workload. Key databases such as Compendex, Google Scholar, Web of Science, and Scopus were utilized to identify relevant studies, which were then analyzed using statistical tools to evaluate the effects comprehensively.	Higher levels of automation generally improved driver performance by reducing workload, especially in conditions of high automation compared to manual driving. However, engagement in non-driving-related tasks tended to impact driver performance negatively, emphasizing the complexities of automated driving systems and the need for careful integration of such tasks.

C

50PR Scenarios Results

This appendix shows the results for 50PR scenarios.

C.1. Speed distribution in heatmap

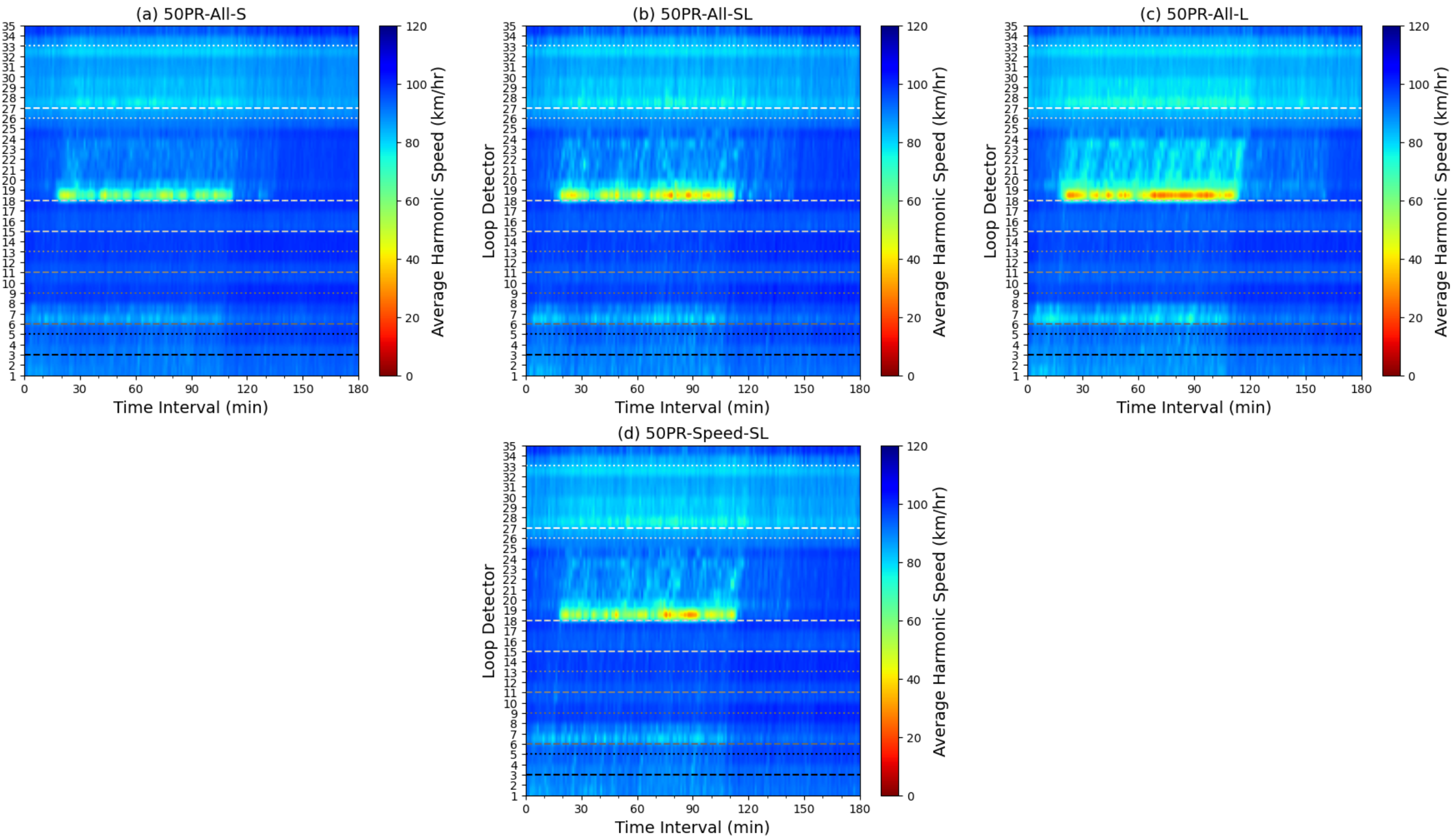

Figure C.1: 50PR scenarios

C.2. Time-to Collision (TTC)

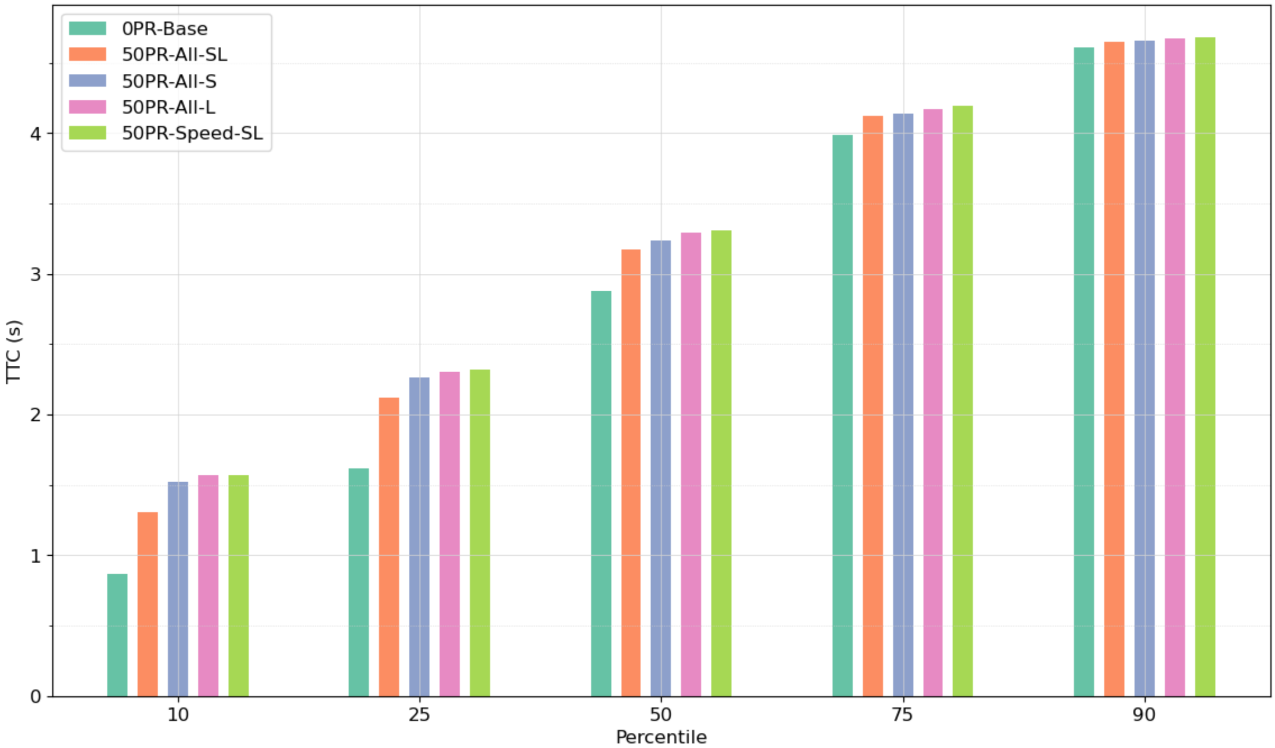

Figure C.2: Overall TTC (consider only the values smaller than 5) for 50PR scenarios

C.3. Acceleration

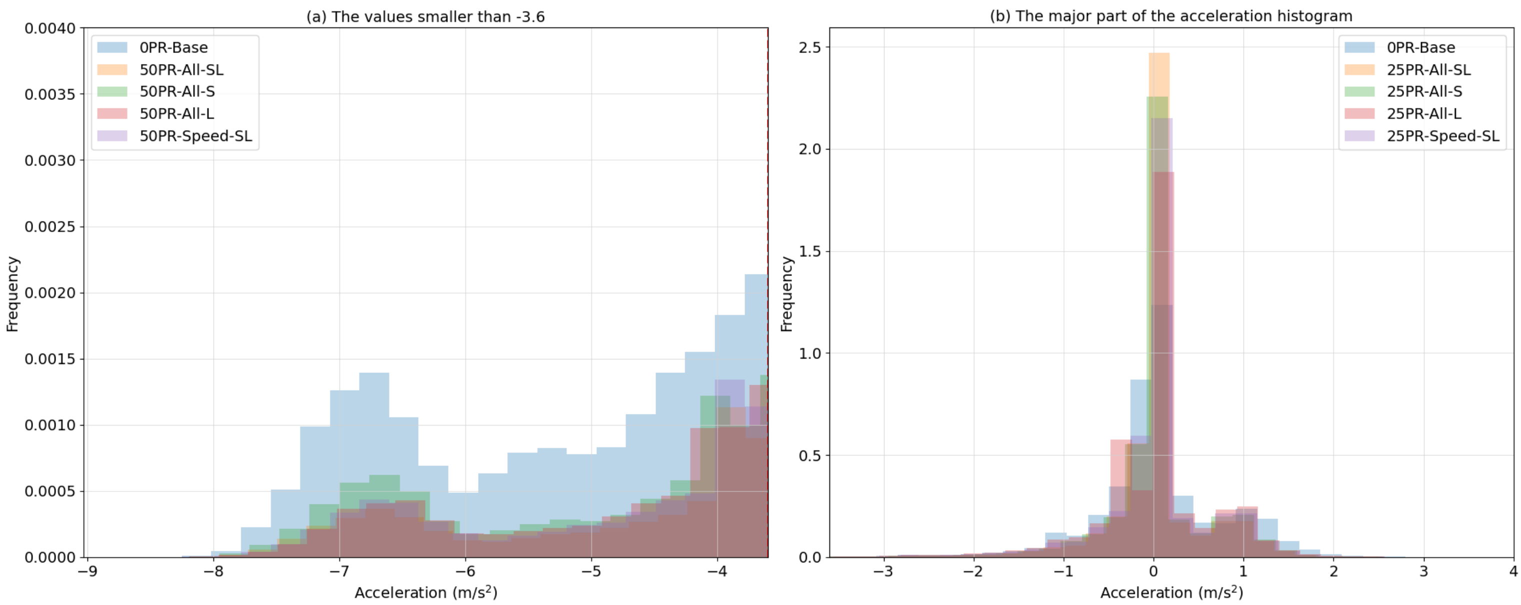

Figure C.3: Acceleration Histogram for 50PR scenarios

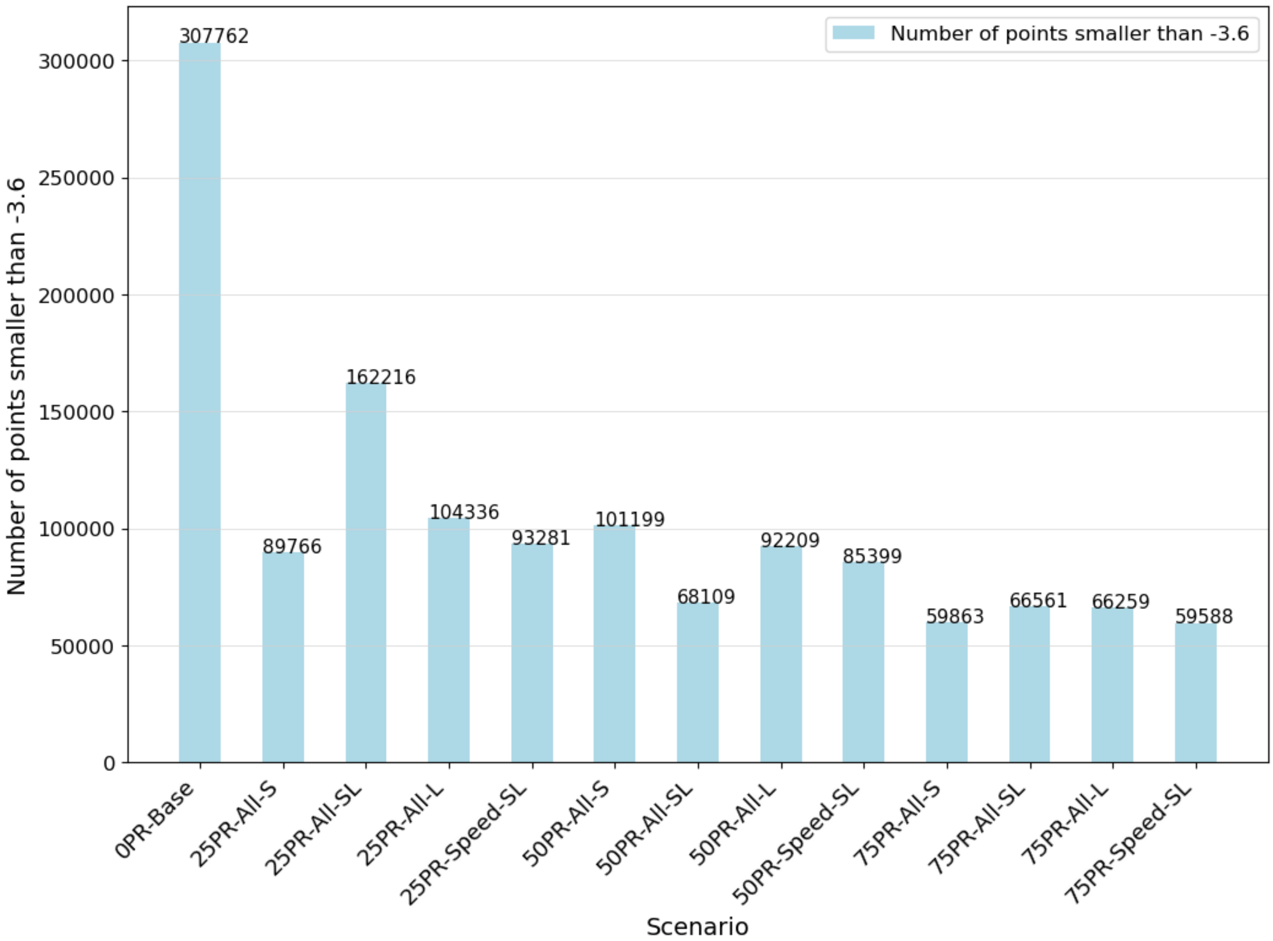

Figure C.4: The number of points smaller than the threshold for all scenarios

C.4. Transition control related output

Table C.1: Number of transition controls of different types - 50PR Scenarios

Transition type (Total number/ number per km)	50PR-All-SL	50PR-All-S	50PR-All-L	50PR-Speed-SL
DIDC	81500/ 2.29	80093/ 2.31	87683/ 2.36	84321/ 2.33
DIAC	77527/ 2.18	76056/ 2.20	84362/ 2.27	80842/ 2.24
AIDC	2543/ 0.07	1842/ 0.05	2838/ 0.08	2639/ 0.07
Time of ACC activated	89.52%	90.57 %	88.35%	89.24%

Table C.2: Number of transition control causes - 50 PR Scenarios

Transition Causes (Total number/ number per km)	50PR-All-SL	50PR-All-S	50PR-All-L	50PR-Speed-SL
Approach Lower Speed Leader	1599/ 0.04	1842/ 0.05	1728/0.05	1869/ 0.05
*AccDecelThreshold	2682/ 0.08	2204/ 0.06	2625/ 0.07	3098/ 0.09
Lower Speed Bound	1723/ 0.05	1039/ 0.03	3204/ 0.09	4106/ 0.11
**FCW	35280/ 0.99	28547/ 0.82	39117/ 1.05	35626/ 0.99
Lane Change	76919/ 2.16	75178/ 2.17	83496/ 2.24	79698/ 2.21
Driver Decision Activate	77527/ 2.18	76056/ 2.20	84362/ 2.27	80842/ 2.24

*AccDecelThreshold: ACC systems meet the minimum deceleration rate of the operational design domain.
**FCW: Forward collision warning.

Table C.3: Percentage of transition control around ramps and the bottleneck

Scenario	Around Ramps	Around Bottleneck
50PR-All-SL	51.30	27.19
50PR-All-S	53.32	27.74
50PR-All-L	51.85	29.09
50PR-Speed-SL	53.44	29.10

Table C.4: Percentage of transition control causes at the bottleneck

Scenario	Lane Change	Lower Speed Bound	FCW
50PR-All-SL	24.66	93.73	66.19
50PR-All-S	25.23	89.99	69.70
50PR-All-L	27.19	94.94	60.90
50PR-Speed-SL	26.75	92.77	65.21

D

Fundamental Diagrams

This chapter shows the fundamental diagrams for all scenarios separately, with the color of the plots representing the simulation time. The fundamental diagrams were for the bottleneck.

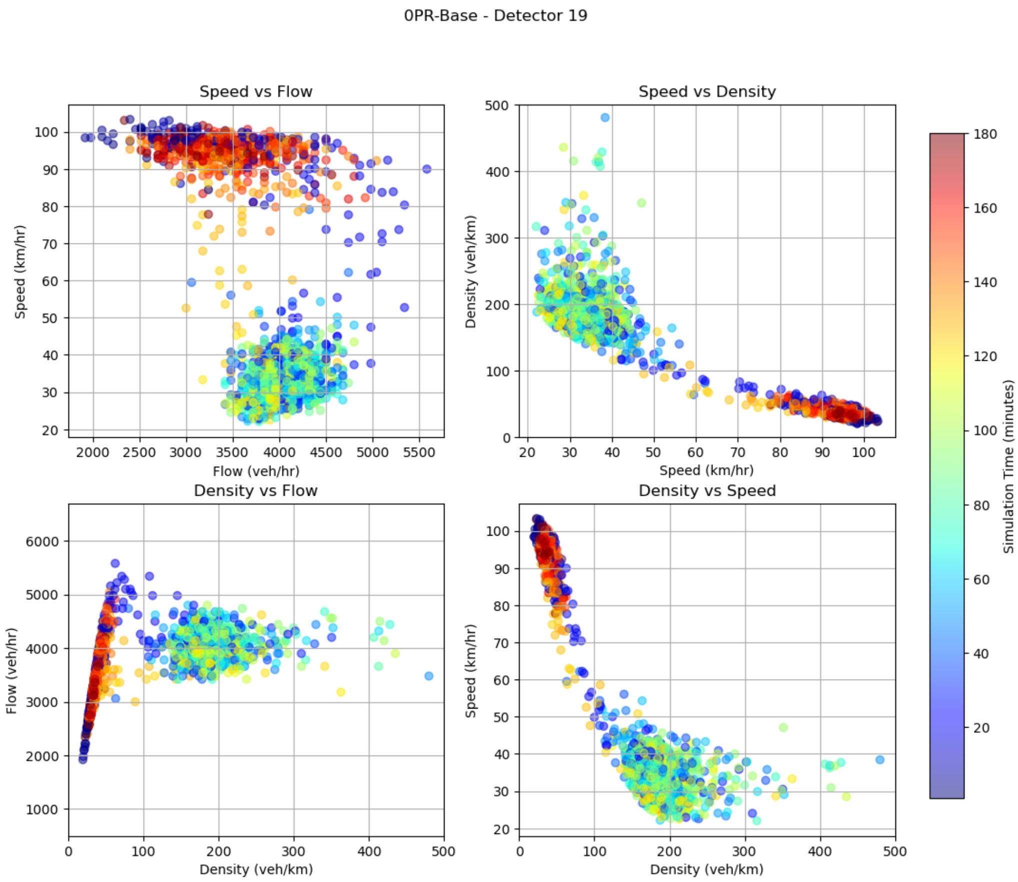

Figure D.1: Fundamental Diagrams - 0PR-Base

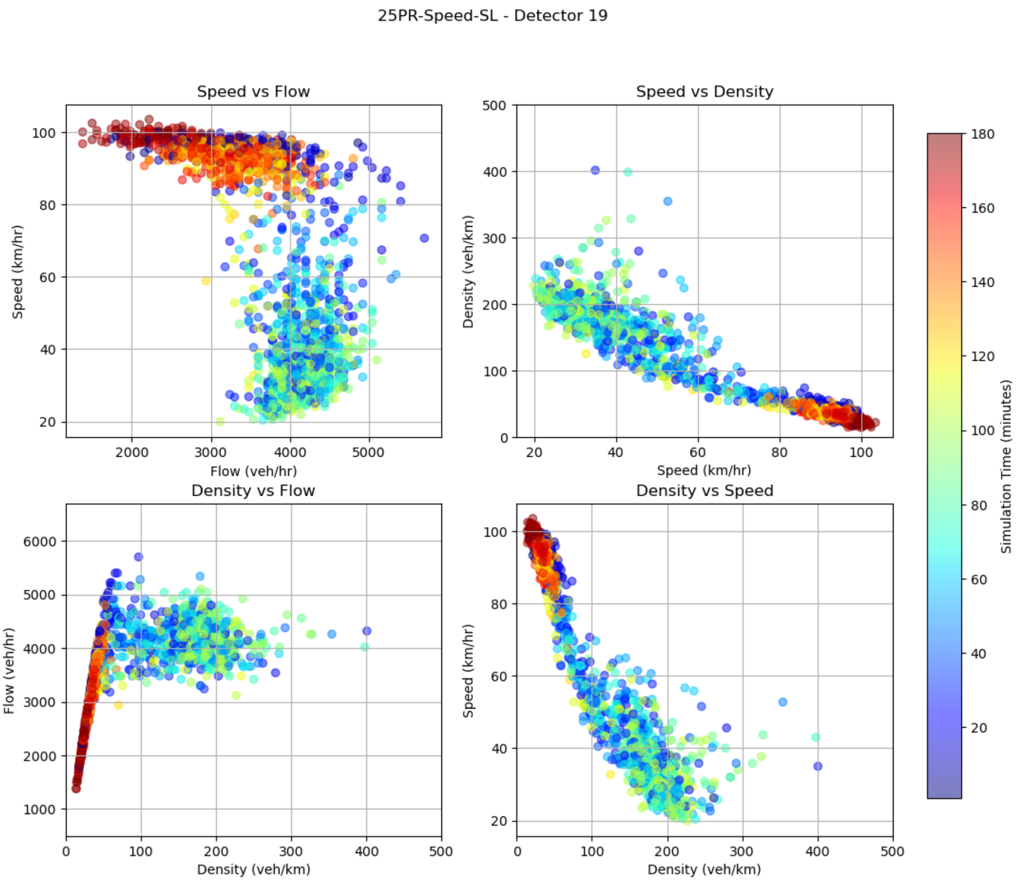

Figure D.2: Fundamental Diagrams - 25PR-All-SL

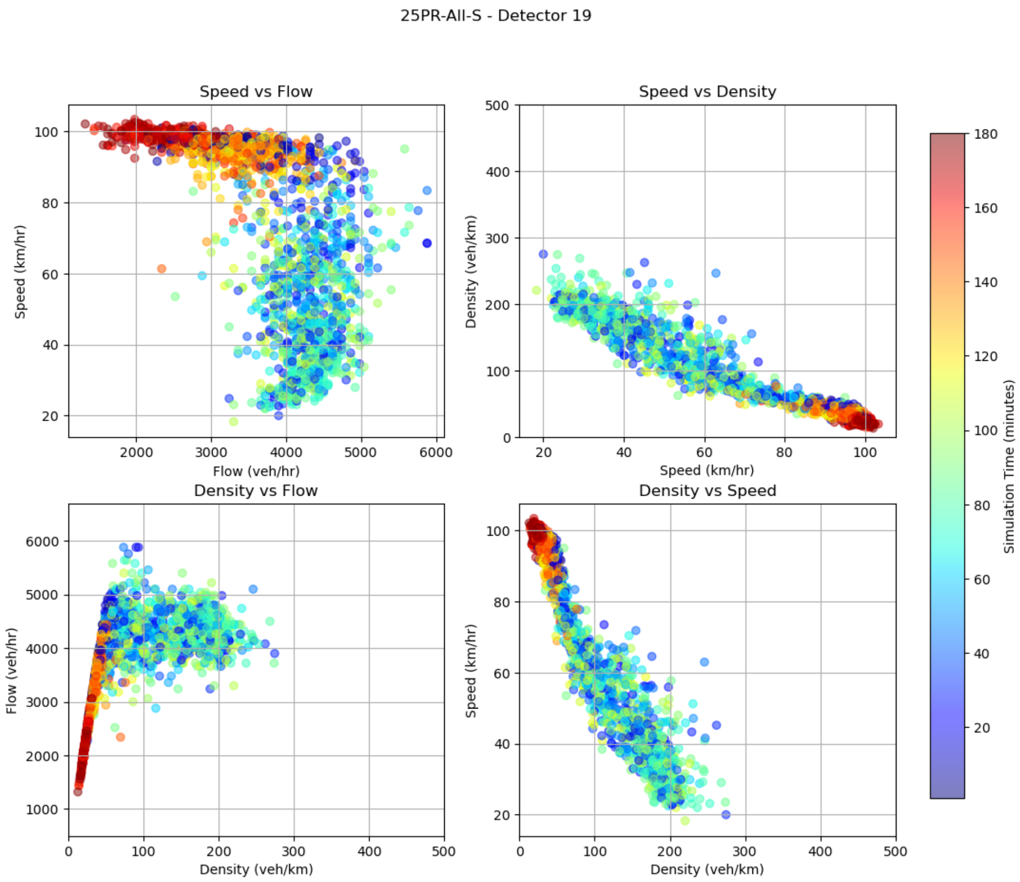

Figure D.3: Fundamental Diagrams - 25PR-All-S

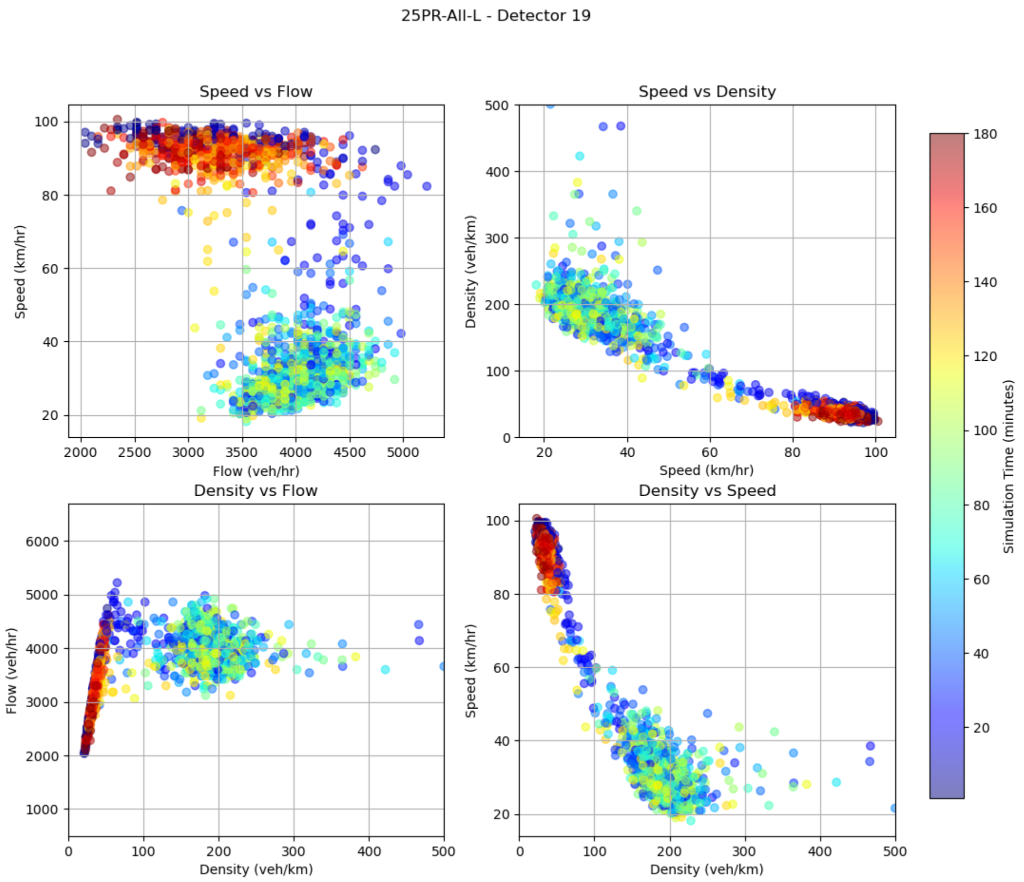

Figure D.4: Fundamental Diagrams - 25PR-All-L

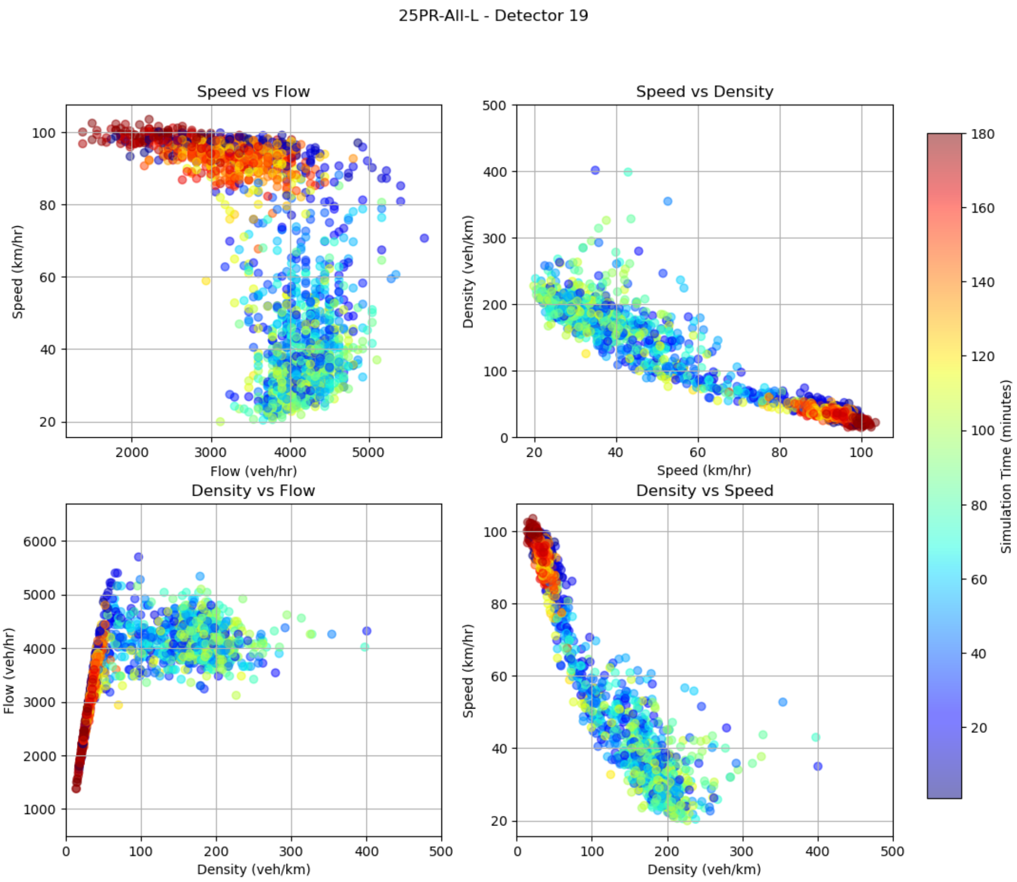

Figure D.5: Fundamental Diagrams - 25PR-Speed-SL

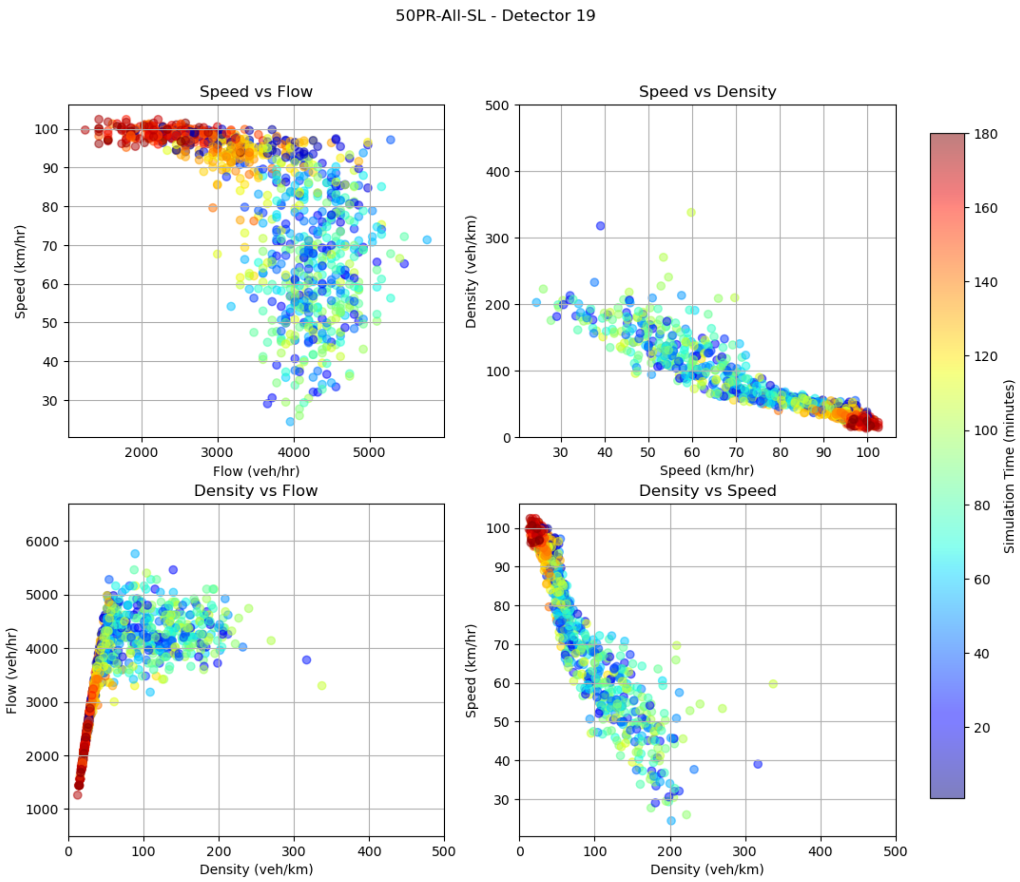

Figure D.6: Fundamental Diagrams - 50PR-All-SL

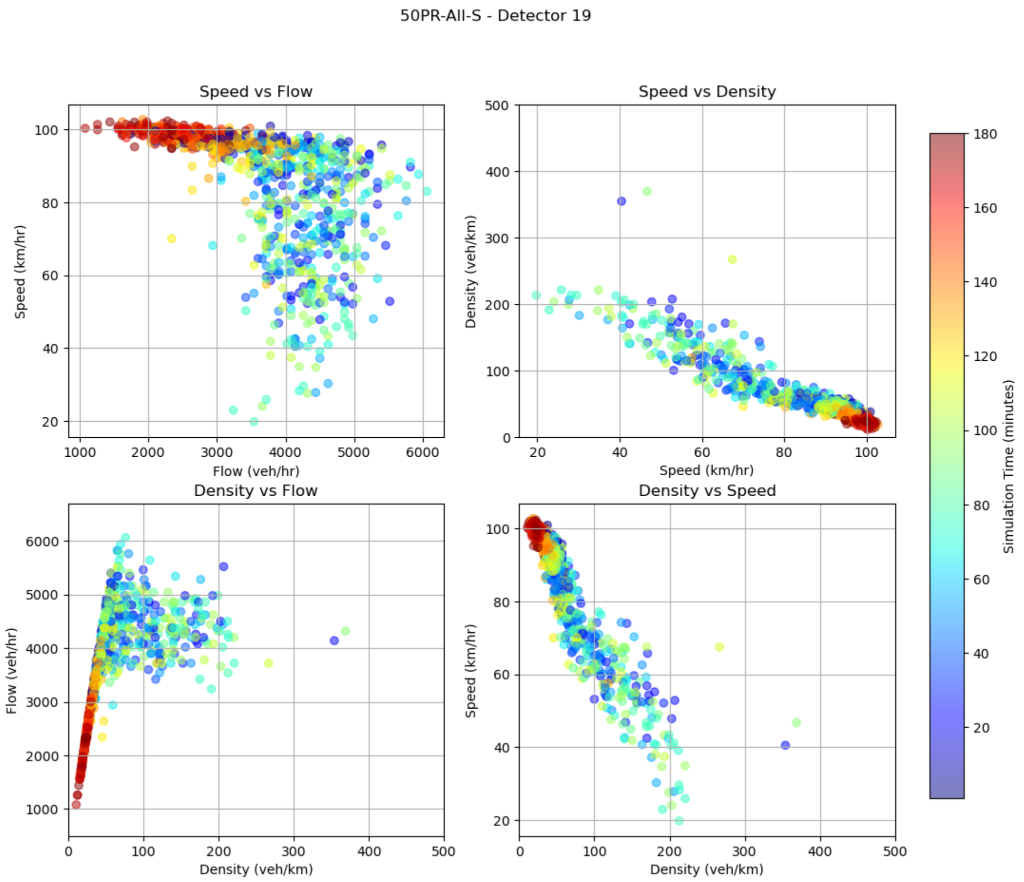

Figure D.7: Fundamental Diagrams - 50PR-All-S

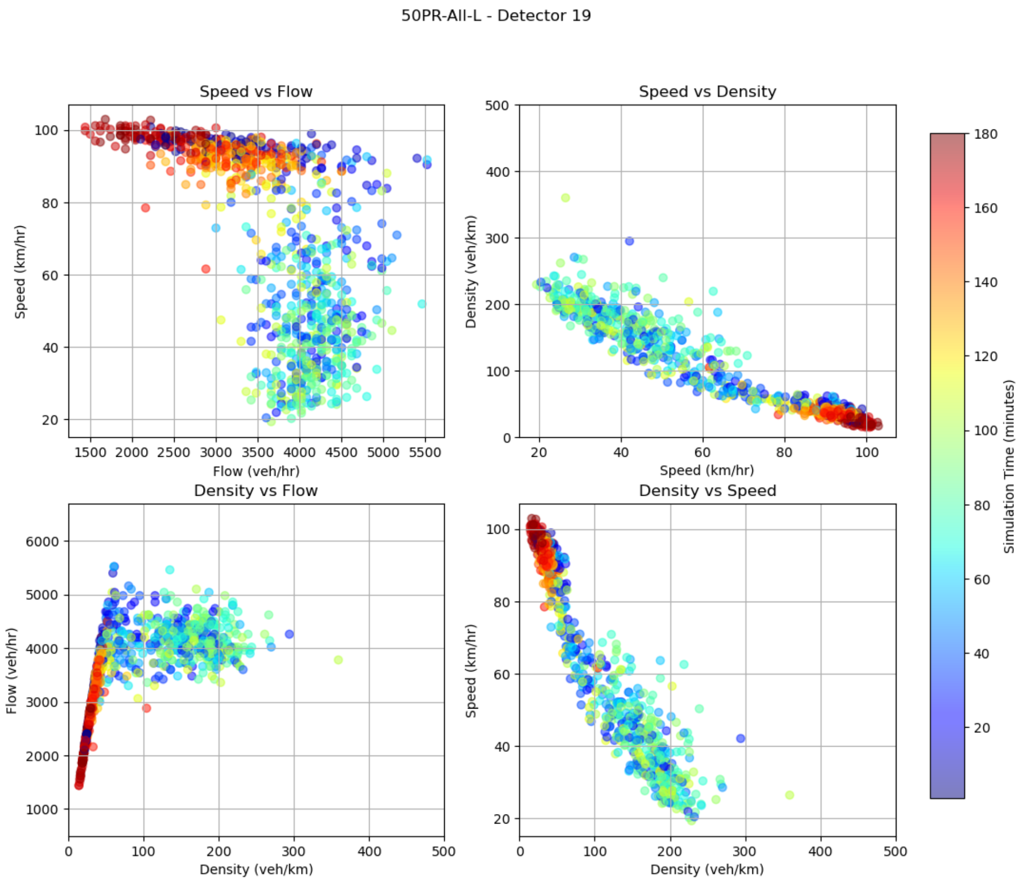

Figure D.8: Fundamental Diagrams - 50PR-All-L

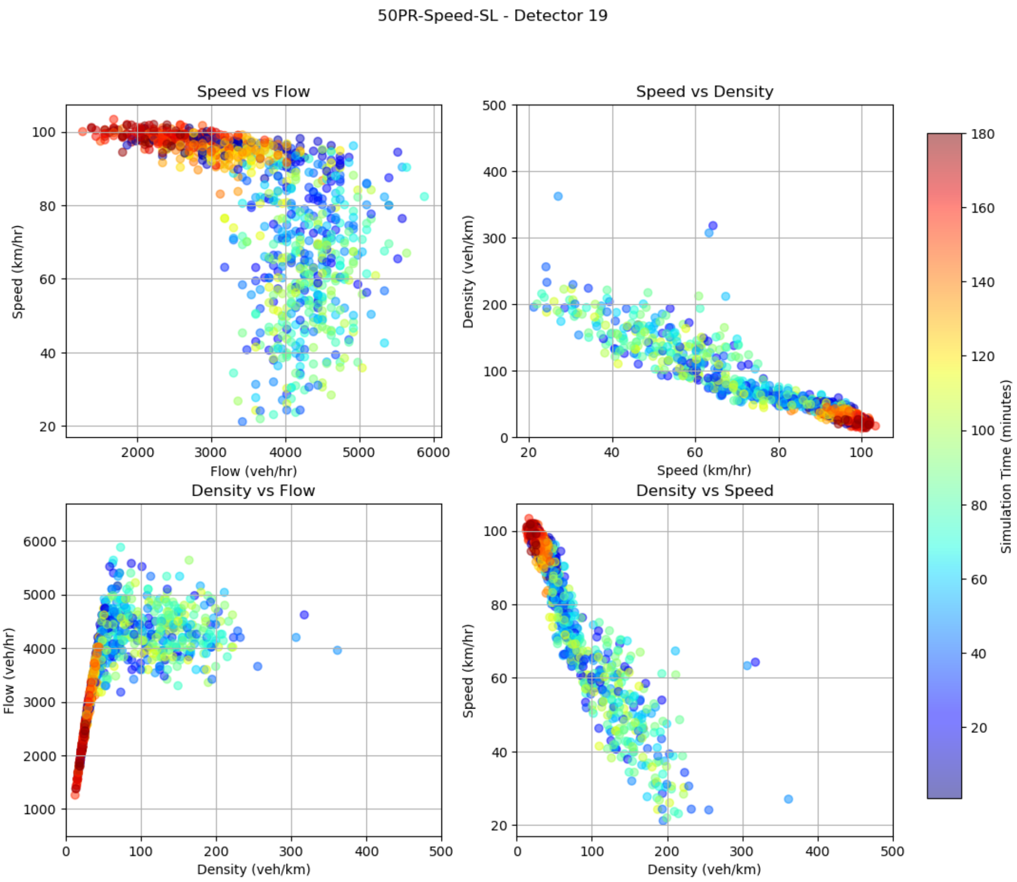

Figure D.9: Fundamental Diagrams - 50PR-Speed-SL

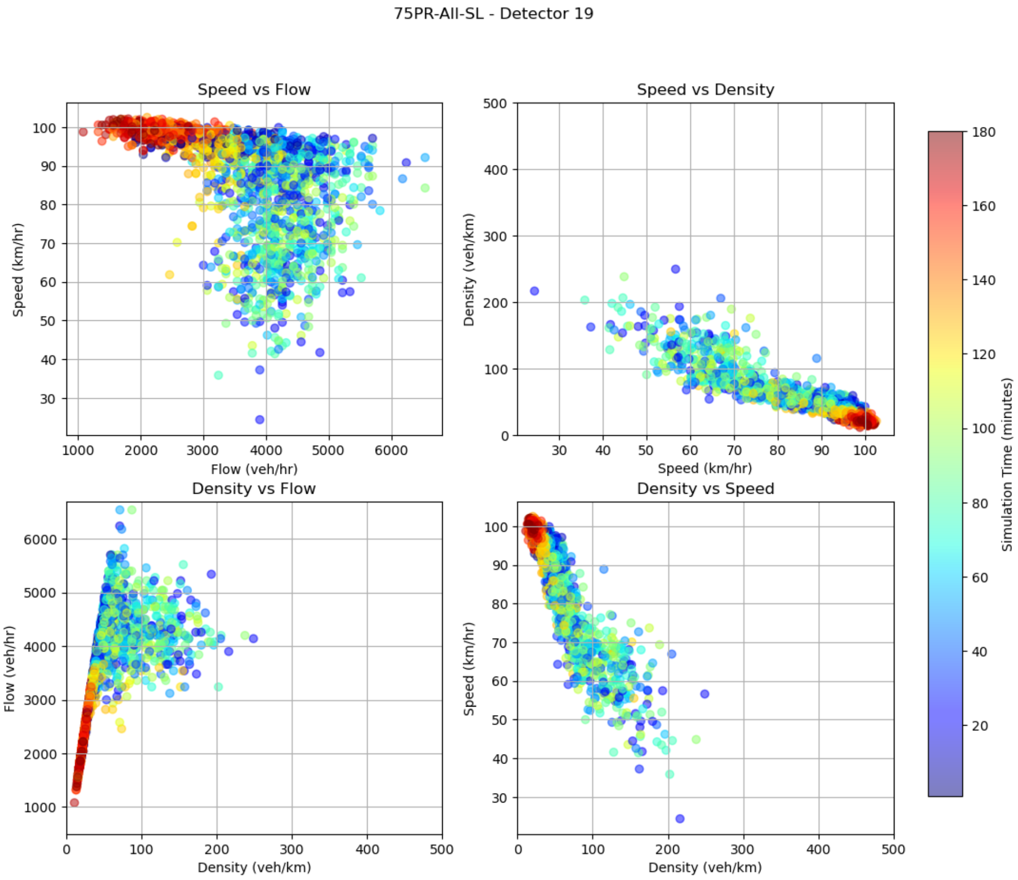

Figure D.10: Fundamental Diagrams - 75PR-All-SL

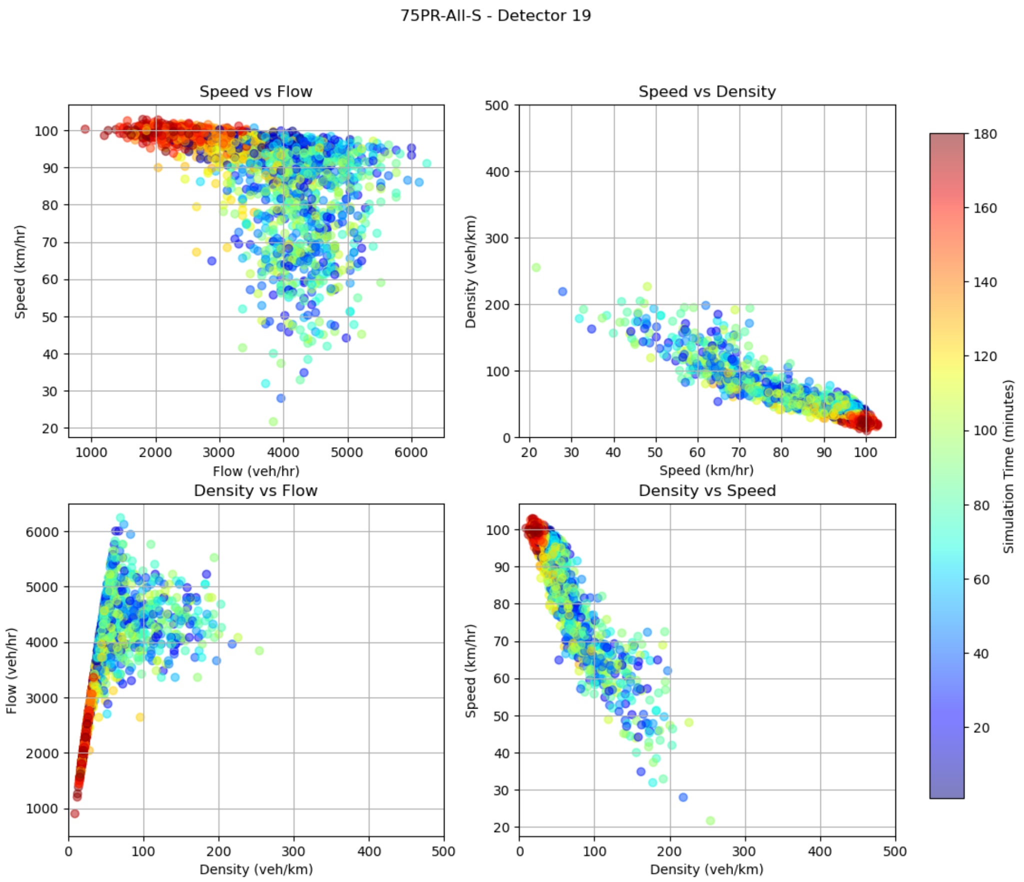

Figure D.11: Fundamental Diagrams - 75PR-All-S

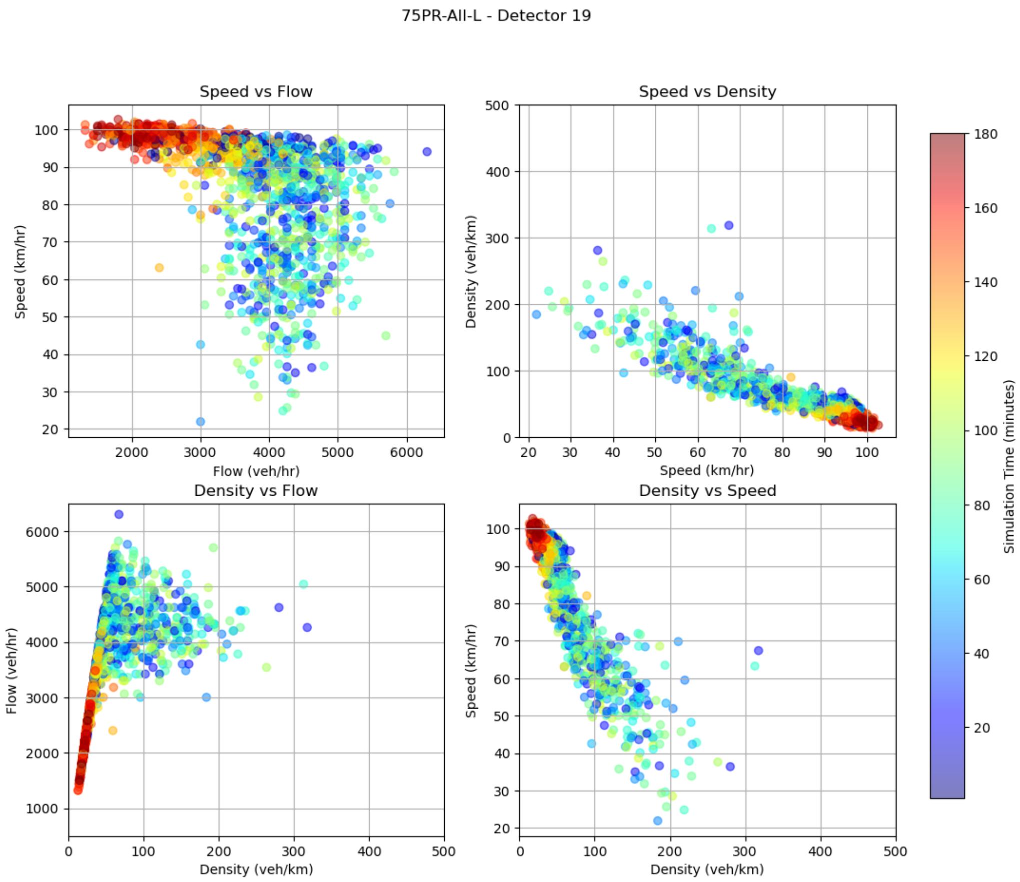

Figure D.12: Fundamental Diagrams - 75PR-All-L

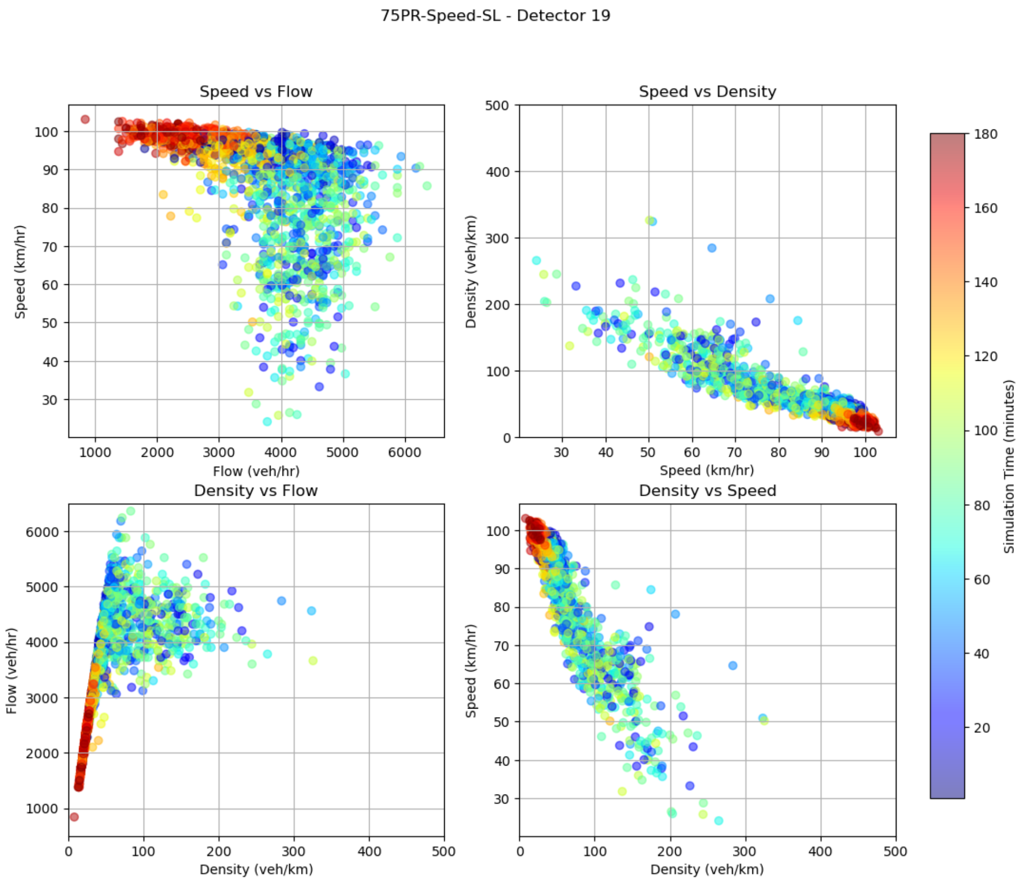

Figure D.13: Fundamental Diagrams - 75PR-Speed-SL