Evaluation of MHC in CACC Platooning under Disturbance Scenarios

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by

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to obtain the degree of Master of Science
at the Delft University of Technology,

Student number:	5464099	
Project duration:	July 30, 2023 – June 30, 2024	
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TU Delft

Preface

The journey of this research began with a profound interest in the transformative potential of automated vehicle technologies and their implications for modern transportation systems. The advent of Cooperative Adaptive Cruise Control (CACC) and its integration into vehicle platooning represents a significant leap towards achieving safer, more efficient, and comfort road travel. However, the seamless deployment of these technologies necessitates a rigorous examination of their operational challenges, ethical considerations, and the interaction between human drivers and automated systems.

This thesis is a culmination of extensive research conducted to explore these multifaceted aspects. It delves into the core principles of Meaningful Human Control (MHC) within CACC systems, emphasizing the importance of maintaining human oversight and accountability in the era of increasing automation. The study provides a comprehensive evaluation framework that assesses the performance of CACC platoons under disturbance scenarios, bridging the gap between theoretical advancements and practical applications.

The research presented here has been guided by the support and insights of many individuals. First and foremost, my heartfelt appreciation goes to all the committee members. You ignited my passion for learning and patiently guided me throughout my research, the valuable feedback and contributions that have significantly enriched this work. Your tireless mentorship was the cornerstone of my successful thesis project. I extend my deepest gratitude to my daily supervisor, Lucas, for your unwavering guidance, encouragement, and intellectual mentorship throughout this process. Additionally, I acknowledge the data and resources provided by Simeon Calvert, which were instrumental in the successful completion of this study.

This thesis is dedicated to my family and friends, whose unwavering support and patience have been my bedrock throughout this academic journey. Their belief in my capabilities has been a constant source of motivation. Even though my family members were far away from the Netherlands during the entire journey, their constant support kept me going. Especially, Heartfelt thanks to my parents for their strong financial and emotional support.

As we stand on the brink of a new era in transportation, I hope that this research will contribute to the ongoing dialogue on the integration of automated vehicle technologies. By addressing the challenges and opportunities presented by CACC systems, I aspire to pave the way for safer and more reliable transportation solutions that harmoniously blend technological innovation with human values.

Xiaoyang Dong
Rotterdam, May 2024

Abstract

Platooning has become a useful area for better transportation efficiency on highway driving. As Co-operative and Automated Vehicles continue to evolve and integrate , it is important to have insights into their implications, emphasizing the need for rigorous real-world assessments. In general, platoon formation is monitored by Cooperative Adaptive Cruise Control (CACC), which uses real-time vehicle-to-vehicle (V2V) communication to exchange vehicle status information, improving the control reaction as platoon members adjust to their surroundings. Automated systems can normally drive vehicles to perform planned behaviors based on the pre-setting by humans, but if the platoon encounters disturbances, the extent to which the automated system can still follow human intentions is still unknown. This research uses field operational test (FOT) data from the CACC platoon on an arterial corridor to assess the platoon's performance when disrupted during the test. This research applies the concept of meaningful human control with focus on tracking condition. Additionally, this study will focus on human 'reasons', both distal and proximal. An evaluation framework for platoons is created by categorizing 'Tracking' into three main metrics: comfort, safety, and local stability. Furthermore, this study demonstrates that disturbance has variable degrees of detrimental impact on the platoon's tracking state, and that these effects may be recovered when the disturbance has concluded; however, different disturbance situations indicate different recoveries. The evaluation methodology of this paper provides insight into the tracking performance of CAVs, which can help road authorities build infrastructure for their wider deployment of CAVs. Last but not least, this study may provide guidance to automation technology organizations and automobile manufacturers on how to develop vehicles so that they follow human reasons more closely.

Keywords— Cooperative Adaptive Cruise Control; Meaningful human control; Vehicle automation; Vehicle platoon.

Contents

1 Introduction

1.1. Background

Automation vehicle technology has advanced rapidly since the beginning of the twenty-first century, with significant consequences for environmental sustainability, efficiency, and safety. These innovations are associated with reducing traffic accidents, congestion, and improving driving comfort. Cooperative Adaptive Cruise Control (CACC) is at the forefront of these developments. It uses vehicle-to-vehicle (V2V) communications to provide closely coordinated platoons, optimizing speeds and closing distance gap to improve traffic flow and safety (S. E. Shladover et al., 2018). Therefore, this research focuses on CACC as one of the automated vehicle technologies. CACC plays a key role in demonstrating the advantages of automated and cooperative vehicles. CACC enables the formation of closely coordinated vehicle platoons by allowing vehicles to communicate with each other and exchange information, including speed, distance, and road conditions. It not only improves traffic management through platooning, but also sets the way for advanced features such as intersection management and lane keeping.

However, there are several obstacles to overcome when integrating these technologies, especially when it comes to ensuring safety and ethical compliance. The broad use of automated vehicles (AVs) requires careful consideration of sensor and software system reliability, particularly in the context of unpredictable weather conditions, human-driven vehicles, and other disturbances. For instance, the ethical consequences of decisions taken by autonomous vehicles in circumstances such as unexpected movements of pedestrians or unpredictable actions by other drivers emphasize the significance of keeping strong human supervision. In order to address these obstacles, the concept of Meaningful Human Control (MHC) has been presented.

MHC ensures that, despite the high degree of automation, humans maintain significant control and monitoring abilities. This makes the breakdown of tasks more clear and increases the operational safety of the platoon by guaranteeing that decisions—especially in circumstances involving disruptions—are informed by human judgment. As a result, incorporating MHC in CACC platooning can help bridge the responsibility gap by offering a clear and ethical approach to the management of automated systems. Moreover, this study focuses on assessing the ”tracking” part of MHC in CACC platooning systems under disturbance scenarios. The goal is to provide an evaluation framework that measures the alignment of vehicle operations with MHC principles during disruptions. Using this framework, the study will investigate how disturbances affect the operations of CACC platoons and the effectiveness of human intervention.

This research aims to evaluate the tracking part of MHC for CACC platooning systems in the context of disturbance scenarios. This is accomplished by developing an evaluation framework that evaluates the extent to which the vehicle platoon responds to disturbances according to the principles of MHC. A proposal for an evaluation will be made, taking into account relevant methodologies, KPIs (key performance indicators), and evaluation criteria. This research will investigate the current understanding of CACC platooning systems, MHC principles, disturbance situations, and the evaluation framework through a comprehensive review of the literature. Furthermore, this research will also identify how disturbances affect the extent of the system under MHC conditions in CACC platooning operations. This study is not only relevant from an academic standpoint, but it will also have practical implications for various stakeholders. Through an in-depth case study analysis and limitations, this research presents practical recommendations and guidance to industry stakeholders and policymakers to improve the design and evaluation of CACC platooning systems. Lastly, the findings of this research will contribute to advancing the understanding of MHC principles, ensuring safer and more reliable CACC platooning operations in real-world scenarios.

1.2. Objectives and research questions

The objective of this research is to establish an evaluation framework with respect to the MHC tracking concept in the context of Cooperative Adaptive Cruise Control platooning systems under disturbance scenarios. A systematic approach is carried out to check if the system is still responsive to the MHC principle within CACC platooning systems while considering the challenges posed by disturbances.

To summarize the structure of this research, the first step is to identify the disturbance time that has a major influence on the performance of CACC platooning systems. This provides valuable information on the specific challenges that need to be addressed to ensure MHC in the face of disturbances. Then, the data from the database (S. Calvert, 2020) is then analyzed to obtain valuable information on the parameters, indicators, and vehicle trajectories. One of the main areas of interest for this study is to propose an evaluation that includes relevant methodologies for evaluating MHC in CACC platooning systems facing disturbances. The findings of this examination indicate changes in the platoon's ability to monitor human motives in the face of disturbance. The results show changes in the platoon's performance before, during, and after the disturbance, allowing us to better understand how and to what extent the disturbance affects the platoon's capabilities.

The objective of this study is summed up in the following research question:

Does disturbance have an effect on the capability of CACC platoon to track human reasons?

Since research cannot include every aspect of the topic, it is essential to dissect the main question into more specific steps that collectively address the overarching concern.

- 1.Evaluation Methodology
  How to evaluate the tracking condition of Meaningful Human Control (MHC) for Cooperative Adaptive Cruise Control (CACC) platooning?

- 2.Incidence and Context of Disturbances
  When and where do these disturbances occur during the test?

- 3.Impact Assessment
  To what extent do these disturbances affect the platoon's capability to track human reason?

1.3. Outline of the thesis

This paper consists of five chapters, the first of which is the introduction. In Chapter 2 an overview of the theoretical framework will be given, and in the basis of the literature review the key concepts regarding MHC in CACC platooning systems facing disturbances will be explained. Chapter 3 discusses the methodology used for this study. Chapter 4 provides an in-depth analysis of the study's findings. Chapter 5 concludes the thesis by discussing limits and future research directions. This paper uses OpenAI to check the fluency and completeness of writing.

2

Related work

This chapter conducts a comprehensive review of existing literature and relevant industry standards to gain a thorough understanding of Cooperative Adaptive Cruise Control (CACC) platooning systems, Meaningful Human Control (MHC) principles, disturbance scenarios, evaluation methodologies, and the existing data set from the CACC Field Operational Test. Analyze and synthesize the findings from the literature to identify the gaps in current research and highlight the key concepts, theories, and approaches relevant to MHC in CACC platooning systems facing disturbances.

2.1. Meaningful human control, Tracking and Reasons

The concept of MHC was first introduced in 2015, in the context of autonomous weapons systems. In the ”Open Letter from AI & Robotic Researchers,” published in 2015 by the Future of Life Institute (AI and Robotics Researchers, 2015), popular scientists suggested a ban on ”offensive autonomous weapons beyond meaningful human control.” This means that automated systems must be designed and set up in such a way that humans, not computers and their algorithms, always retain control over the decisions. This ensures that humans remain morally responsible for the actions of the systems (Santoni de Sio and Van den Hoven, 2018). Along the same lines, this is also stated from the study of (S. C. Calvert, van Arem, et al., 2020), where it is stated that MHC involves humans who can maintain control over an automated system, even when they are not actively performing driving tasks.

Santoni de Sio and van den Hoven (2018) identify two general necessary conditions to ensure that an autonomous system remains under meaningful human control: tracking and tracing. First, a “tracking” condition, which states that the system must be able to respond to relevant facts in the environment in which it operates as well as the relevant reasons of the humans who designed and implemented it, which means that the tracking condition requires a system to be responsive to the relevant human reasons to act. Secondly, a ”tracing” condition states that the system must be constructed in a way that makes it possible to always trace back the results of its operations to at least one human along the chain of design and operation. This study focuses on the ”tracking” condition, as it relates to the primary aim of assessing how disturbances impact the capability of CACC platooning systems to maintain adherence to human reasons. Focusing on the tracking condition allows this study to specifically analyze how these systems react to environmental changes and the capability to maintain human control under varying conditions, crucial to ensure their reliability and safety in real-world scenarios.

Policymakers strive to create guidelines that balance ethical and safety concerns with technology advancements for autonomous systems. MHC is a key topic in political conversations as governments strive to balance innovation and accountability. Tsamados and Taddeo (2023) state that keeping human control is crucial in preventing unforeseen outcomes in domains like military applications, autonomous cars, and artificial intelligence. Along similar lines, in technological contexts, MHC is essential for the design and engineering of systems that involve human decision-making in the loop. According to Piera et al. (2022), technical specialists and engineers are responsible for incorporating MHC into complicated system architecture and guaranteeing human control over autonomous operations.

The emphasis on integrating human oversight within the architecture of autonomous systems not only addresses immediate technical challenges but also broadens the scope of MHC’s implications. It has been connected to human-vehicle interaction and philosophy of action, opening up possibilities for interdisciplinary research on MHC and the ethical design of automated driving systems. This connection can be of interest to experts in traffic psychology, traffic engineering, and engineering in general, as well as philosophers of action (Mecacci and Santoni de Sio). Calvert et al. (2020) introduce the concept of MHC as a function of a framework of ADS. Then he presented that it is necessary to include MHC in the design of CAVs, which can be highlighted with some practical examples (S. C. Calvert et al.). Calvert et al. (2020) also showed that MHC can be applied as the core control concept in automated vehicle systems, allowing interaction with other road users and learning to improve performance.

Regarding automated driving, MHC highlights the need for human intervention—that is, making sure that important human control and monitoring can still be exercised over the vehicle's actions, even at high automation levels. This idea is crucial for handling moral dilemmas, liability concerns, and guaranteeing the public acceptance and safety of CACC systems. The state-of-the-art, however, indicates a substantial knowledge vacuum regarding the successful integration of MHC into CACC frameworks, particularly in disturbance-filled environments. More specifically, there is a lack of empirical information concerning the CACC platoon's actual use. To address this gap, this study leverages the data collected from a Field-Operational-Test (FOT) with CACC vehicles which provides an empirical evaluation process. Analyzing these data sets will provide important insights into the real-world performance and challenges associated with CACC systems under different disturbance scenarios. Therefore, it might be an interesting contribution to the literature to better understand the implementation of MHC principles in autonomous driving.

As we discussed earlier, the tracking condition requires a system to be responsive to the relevant human reasons to act. According to Mecacci and Santoni de Sio (2020), concluded that human control over a system is possible when it can change its behavior according to human reasons. The term "Reasons" here can refer to many items on different layers. In general, there are several reasons for taking a specific action. For this, they introduced a proximity scale of the reasons for tracking condition (Figure 2.1). In 2023, S. C. Calvert et al. conduct an integrated system proximity framework for MHC, using a proximity scale of reasons (Figure 2.2).

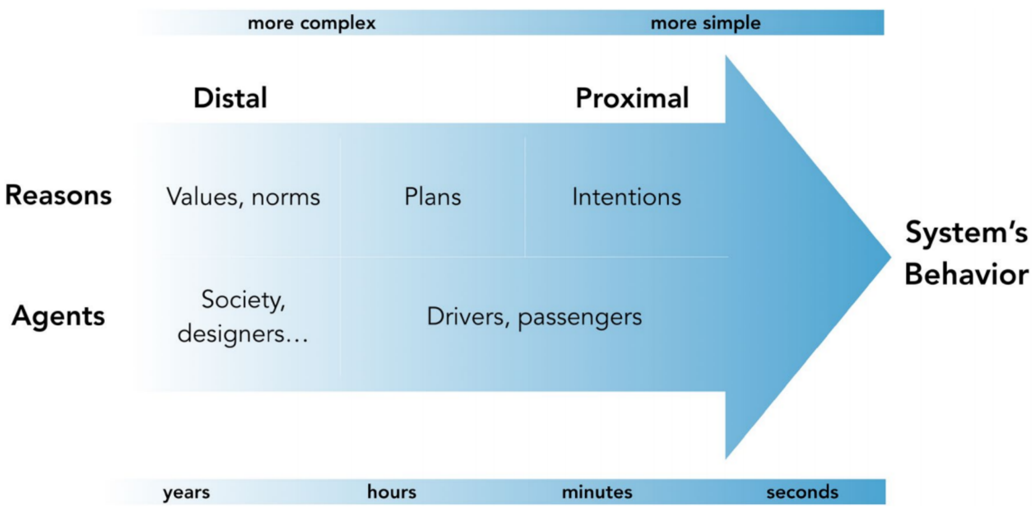

Figure 2.1: Proximity scale of reasons(from Mecacci and Santoni de Sio, 2020)

Additionally, platoon behavior is impacted by several elements, creating a complex multi-agent system. There are several reasons why agents should be tracked. Individual freedom and independence policies may prioritize proximal causes over distant ones, giving people more control. When adopting tracking, it's important to analyze contrary reasons and principles in a socially acceptable and feasible manner (S. C. Calvert, Heikoop, et al., 2020).

Chai and Wong (2015) suggest that drivers should optimize their driving for safety, efficiency, and comfort. Zhu et al. (2020) claimed that the main task of car-following is controlling vehicle velocity to keep safe and comfortable following gaps. Autonomous car-following velocity control has the promise of mitigating drivers' workload, improving traffic safety, and increasing road capacity. The primary goal of FOT design is to optimize system performance in interactions with infrastructure and other vehicles (S. C. Calvert and van Arem, 2020). The performance criteria here include minimizing variance between speeds and time-headway.

2.2. Cooperative Adaptive Cruise Control platooning

In recent years, CACC platooning—which is a group of vehicles maintaining proximity and coordinated movement through the use of CACC systems—has received a lot of interest. Previous research focused on the functionality

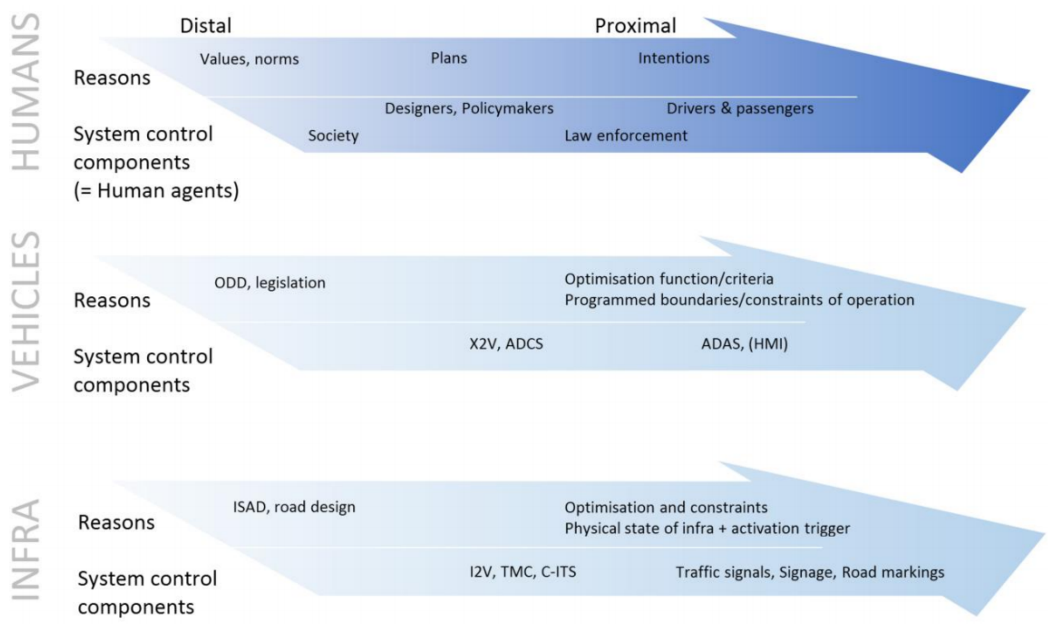

Figure 2.2: Integrated system proximity framework for MHC (from S. C. Calvert et al., 2023)

of the CACC platoon (Naus et al., 2010), traffic flow impact (J. Chen et al., 2019; Yan-yan et al., 2018), road safety (Mahdinia et al., 2020), and possible advantages. To give an idea, previous research indicates that CACC platooning can improve traffic flow, decrease traffic jams, shorten travel times, and improve intersection performance (S. C. Calvert et al., 2021). CACC platooning improves traffic efficiency by reducing inter-vehicle distances and allowing for coordinated acceleration and deceleration. According to Lioris et al. (2017) and Mahmassani (2016), CACC-based vehicle platooning systems significantly improve driver comfort and traffic safety. Ioannou and Chien (1993) showed that adaptive cruise control systems are capable of maintaining strong performance and adjusting well to disturbances, while maintaining high levels of safety and efficiency.

The NHTSA (National Highway Traffic Safety Administration) (Harding et al., 2014) report describes the enhanced safety that V2V communications potentially offer in many pre-crash scenarios. CACC can be viewed as a milestone, showing the tangible advantages of vehicular cooperation and automation (Lu and Shladover, 2018). Moreover, it serves as a foundation for more complicated features like intersection management, lane keeping, and advanced autonomous driving (Ozioko et al., 2022). Hence, CACC plays a crucial role in shaping the future of transportation by demonstrating the potential of cooperative technologies. And now, CACC platooning has emerged as a promising technology to improve traffic efficiency, reduce fuel consumption, and sustainability (Alam, 2014). Recent advances in CACC show significant progress. Researchers and engineers have successfully implemented systems that automatically alter vehicle speeds and maintain ideal spacing, reducing the chance of collisions and traffic congestion. CACC has been shown in studies to improve traffic safety, increase roadway capacity, and address current transportation concerns.

Even though there is a lot of research on CACC platoons right now, most of them have not included insights into MHC and have instead concentrated on overall system performance. Zhong et al. (2020) examined high-resolution vehicle trajectory data obtained from microscopic simulation in an effort to quantify these effects. Hu et al. (2021) investigate an eco-platooning problem for CAVs under mixed traffic flow. It is important to note that some research has started to look at how ”humans” fit into the system as a whole. Stefansson et al. (2019) propose a controller design framework for autonomous truck platoons to ensure safe interaction with a human-driven car. Chu et al. (2019) propose a model-based deep reinforcement learning (DRL) algorithm for the CACC of connected vehicles. A Human-in-the-Platoon CACC (HiP-CACC) controller is proposed for connected and automated vehicles to “include” human drivers in the platooning process (Y. Zhang et al., 2020). Although CACC offers benefits such as improved traffic flow and fuel efficiency, platoon behavior should always be able to follow human decisions accepted and agreed upon (S. C. Calvert et al., 2018). CACC systems operate within specific operational design domains (ODDs) (Suo and Sarma, 2019) and have limitations in handling unexpected situations or complex moral decisions. By implementing MHC, human drivers can retain control over critical aspects of the platooning system, ensuring that they can be in control when necessary and take responsibility for the actions of the automated system.

With the introduction of CAVs, there has been extensive deliberation regarding safety and the necessary level of advancement for their deployment on roads (Meyer and Beiker, 2019). The integration of automated vehicles into our daily lives raises critical questions regarding safety, ethics, and technical barriers to their widespread adoption (Bonnefon et al., 2020). Concerns about the safety of CAVs are inherently linked to ethical considerations, as decisions programmed into these vehicles carry potential moral implications (Gill, 2021). The ethical framework within which CAVs operate must ensure not only the physical safety of individuals but also the adherence to societal values and norms. One of the pivotal concerns with automated vehicles is that it lies in the reliability of the systems and the complexity of decision-making capabilities, particularly in real-world scenarios characterized by unpredictable and diverse situations. Effective solutions must be developed to ensure the safe deployment of automated technologies in the face of various disturbances, such as the reliability of sensors and software in bad weather, the decision-making challenges presented by an unexpected pedestrian on the road, or unexpected maneuvers by other human-driven vehicles.

The promise of automated vehicles hinges not only on their technical prowess but also on their ability to seamlessly integrate into the fabric of human society—addressing concerns of trust, acceptance, and the preservation of human intention in a world increasingly mediated by technology. Although the technical capabilities of CACC have been thoroughly investigated, future developments in automated driving systems will still benefit from knowledge of the interactions and influences that human drivers have on these automated systems. Previous studies have looked closely at a number of topics, including traffic safety and stability (Yao et al., 2020), traffic flow (S. E. Shladover et al., 2012), fuel consumption and emissions (Alam, 2014). A strong foundation is provided by research on the benefits to the environment, traffic flow, and stability of CACC platooning. Nevertheless, there is a lack of human aspect literature. There are many unanswered questions regarding how drivers see and trust these systems, how they adjust to giving up control to automated procedures, and when they might need or choose to reject automated judgements. It is crucial to take these factors into account in order to ensure that CACC meets both its technological objectives and the expectations and values of humans.

The questions of accountability and responsibility have a strong link to the gaps in vehicle control (S. C. Calvert et al., 2023). By decreasing human error and improving traffic flow, the integration of CACC into platooning offers important safety benefits. Despite this, it also presents possible hazards related to automated control systems, including susceptibility to system failures and the difficulty of delayed human reactions during emergencies.

Given the CAV algorithms' privacy and deep learning black-box nature, which prevents them from being transparent and interpretable, it is challenging to identify the real causes of the accident and assign responsibility (Xu et al., 2021). For example, in the case of a sensor malfunction or an unanticipated environmental circumstance, a CACC platoon can respond improperly, triggering a series of events that could threaten the safety of other road users and passengers in autonomous cars. These safety concerns highlight an important ”responsibility gap”, a situation in which it is unclear who should be held accountable for autonomous system behaviors. In traditional driving, the human driver is often responsible, but determining responsibility becomes more difficult in a completely or entirely automated setting. Before automated vehicles are operational, autonomous driving technologies must be tested to ensure their safety in real-world scenarios.

However, since the test drive and pilot testing of these automated vehicles began, some car accidents and sometimes fatal accidents have occurred. Among them, Uber's first pedestrian fatal accident in March 2018 clearly showed the limitations of recognition sensors and the errors in the automatic vehicle sensor judgement algorithm (Schoettle, 2017). Even on the freeway, the connected vehicle platoon will also face a dynamic and unpredictable environment, including the interaction between CAVs and the surroundings.

2.3. Evaluation

For evaluating MHC in CACC platooning systems, appropriate evaluation methodologies, key performance indicators (KPIs), and assessment criteria are crucial. Heikoop et al. (2019) proposed a quantitative framework for evaluating human behavior with automated driving systems, which have some inspiration for evaluating MHC in CACC platooning systems. They provide an assessment of the human component of the human-machine interaction with ADS, presenting a quantification of human behavior regarding driving tasks and levels of automation. S. Shladover et al., (2018) gives a category to analyze the performance of the car-following model. An AV following system needs to serve several purposes, the relevant measures of performance are stated as maintaining the desired gap behind the preceding vehicle, minimizing the speed difference relative to the preceding vehicle, minimizing accelerations and jerks to ensure ride quality, subject to maintaining small gaps and speed difference errors, providing string stability and respond safely to disturbances, including cut-in and cut-out maneuvers of other vehicles.

In transition from theory to practice, field operational tests (FOTs) have been conducted by Calvert et al. (2020). These tests involve real-world driving scenarios with CACC vehicles, providing valuable insight into the practical implementation of CACC platooning and its impact on traffic dynamics. Furthermore, research has explored the integration of CACC platooning with intelligent transportation systems (ITS) and vehicle-to-infrastructure (V2I) communication. Using communication technologies, CACC platooning can be enhanced with features such as cooperative merging and coordinated intersection crossing, further improving traffic efficiency and safety. This practical application provides a link between the abstract evaluation of CACC and the tangible outcomes observed on the roads.

For any complex system, there is a trade-off between different performance goals, requiring a search for compromise solutions to balance the degree of implementation of these goals. Other highly correlated performance indicators, in this case, driver's comfort and safety, and designer's plans are derived from these more elementary measures of the platoon system. This is exactly the evaluation framework that this study hopes to obtain. Through these basic elements, it can reflect the agent's goal, and ultimately reflect it to the tracking condition in the MHC.

Integrating MHC into CACC platooning, as discussed in section 2.2, requires a deep knowledge of human behavior and its influence on automated systems. This section describes evaluation approaches, such as those presented by S. Shladover et al., (2018), that give a systematic way to examine human aspects. This aids in the development of systems that not only maximize technical performance, but also meet the expectations and capabilities of human.

2.4. Disturbance

Factors affecting the normal operation of a vehicle platoon come from various sources. Aria et al. (2016) mentioned the disturbance posed by system failures when describing the challenges and concerns of autonomous driving systems. In Chen et al. (2018) research on distributed robust control of the connected driving system, the modeling process defines several external factors including irregular geometrical surfaces, bad weather, and emergencies which will lead to terrible driving conditions. Xiao et al., (2017) introduced several typical string disturbances on the vehicle-following response. The five representative traffic scenarios: stop and go, hard brake, cut-in, cut-out, and approaching. There is also a category of disturbances where Roca et al., (2018) mention that there will be environmental factors that affect the platoon's actions, like the quality of the road and weather conditions. For the influence of the disturbance, Dai et al. (2022) claim that for any CAV in an infinite platoon of vehicles, the desired gap, speed and speed difference of the CAV could be changed by an external disturbance. Vahidi and Sciarretta (2018) mentioned some upcoming disturbances, such as hills, curves, slow traffic, state of traffic signals, and movement of neighboring vehicles. In the area of road section control, research indeed shows that the formation of platooning can improve the capacity of the road (Qiu et al., 2015; Xavier, 2009). However, intersection, the main bottleneck in urban traffic, places greater emphasis on the regulation of individual vehicles and lacks the corresponding control mechanism for platooning (H. Zhu, 2019). Despite the introduction of V2X communication, TTG, and GTE in the test, it is still hard to guarantee that the effect of intersections on platoon is nonexistent on a road where more than just CAVs are present. Another situation is where the platoon is affected by other vehicles (non-test vehicles). Studies of these behaviors mention cut-in, cut-out (Basiri et al., 2020) and forward vehicles (Lu and Shladover, 2017).

In practice, disturbances may arise from any vehicle in a network. Still, the disturbances caused by the head vehicle pass through the entire vehicle network and hence have the greatest influence on the network performance (L. Zhang and Orosz, 2016). The same condition is also mentioned in Öncü et al. (2011) that in dense traffic conditions, a momentary disturbance (e.g. a slight deceleration of the predecessor) can trigger a chain of reactions in the rest of the follower vehicles. In most of the control and simulation studies, they defined disturbance as preceding vehicle states (like speed) (Besselink and Johansson, 2017; Silva et al., 2020). These disturbances are from the leading vehicles and originally from external (e.g. other vehicles; infrastructure). The FOT researchers also discussed some of the disturbances encountered throughout the experiment. S. C. Calvert and van Arem (2020) described incidents that happened throughout the experiment that had an impact on platoon operations. First, the vehicle slows down before the intersection as it approaches another vehicle. Second, the platoon stops for a short time at the end of the queue at the traffic signal. Third, the platoon is constrained by a non-test vehicle ahead and cannot proceed freely at its desired speed. The locations with the highest numbers are those in the vicinity of the intersections, both before and after the intersections. These are the locations where other cars cut-through to get to a specific lane to get off the main road before the intersection, as well as the merge points after the intersection when a lane drop occurs, causing other vehicles to join the platoon. The operating circumstances surrounding CACC may not always be ideal. Control systems must be able to efficiently manage stochastic disturbances and uncertainties arising from a variety of sources, including other vehicles and the system.

3

Research methodology

This chapter provides a description of the methodology used to answer the research questions in Chapter 1. In this chapter, data sources and data processes are introduced and explained. Following on, an evaluation framework was built with real-world data. Then, the process of framework construction (Using what KPI, what is the weight of different metrics etc.)

3.1. Test Description

This section describes the experimental sources of the data. Helps the reader to grasp the experimental material, which leads to a better understanding of the data employed.The following subsections describe the area of experiment, the vehicle setup, and the conducted tests.

3.1.1. Field-operational-test area

The FOT (Field-operational-test) of Cooperative Intelligent Transport Systems (C-ITS) was conducted on a provincial arterial road equipped by the Province of Noord-Holland (PNH). Figure 3.1 shows the test corridor of the road, coded as N205. This road spans about 12 km and incorporates five iTS intersections. These iTS intersections are equipped with Green-time extension (GTE) for CACC platoons and Time-to-Green (TTG) communication. A platoon of test vehicles transmits CAM (Cooperative Awareness Message) messages to the Intelligent Transport System (iTS). If the iTS receives at least two CAM messages from vehicles within the platoon, signalling that platooning is in effect, it triggers a request to extend the green-light phase at the traffic signal controller. Meanwhile, the traffic signal controller consistently sends Time-to-Green (TTG) messages that approaching vehicles can use to determine the remaining time until the light turns green. With this information, the platoon may either slow down to navigate the intersection safely or be ready to stop if an extension of the green phase is not feasible.

The maximum speed on the corridor varies between 80 km/h and 100 km/h, with a reduction to 70 km/h at three intersections. The majority of the corridor is made up of two lanes in each direction, with additional lanes on either side of most intersections. The addition of extra lanes helps to facilitate the movement of vehicles between each other, as they must switch lanes to leave the road and often merge when the number of lanes goes back to two after the intersection. Furthermore, there are fluctuations in speed limits along the corridor; The maximum speed allowed near the intersections is 70 km/h, whereas between intersections it is 100 km/h. The speed limit for the corridor and the intersections in the southern section of the road is set at 80 km/h.

3.1.2. Vehicles set-up

S. Calvert utilized seven Toyota Prius vehicles installed with a Cooperative Adaptive Cruise Control (CACC) system. This system allows those vehicles to follow each other at short headway and react to changes in speed and acceleration of the leading vehicles in milliseconds. The default setting for these vehicles is a gap time of 0.6 s increased by a nominal standstill distance of 5 m. Each vehicle is equipped with a computer connected to the vehicle's on-board network, the computer has safe access to the CACC system detectors. The vehicles are also equipped with wireless Wi-Fi communication technology to communicate with each other and with iTS. Each vehicle has a 4G Internet connection for wireless communication, to connect software and logging data.

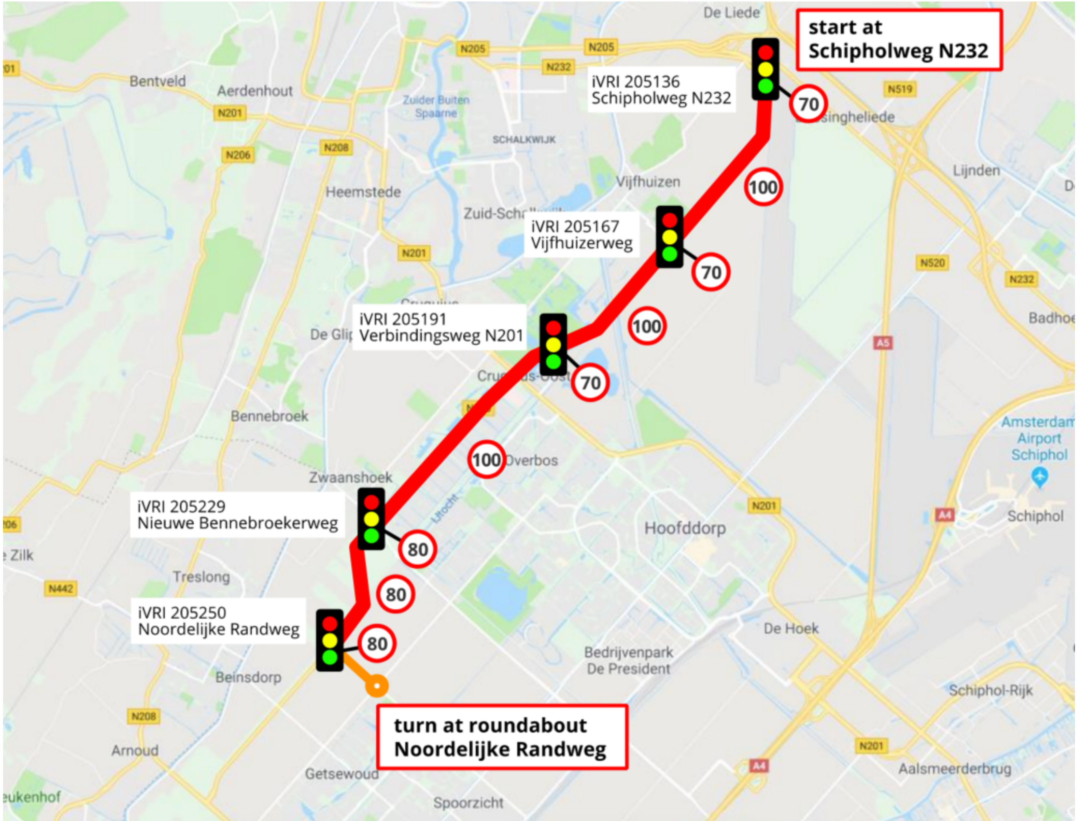

Figure 3.1: Test corridor for the FOT (red): The N205 road with the intelligent intersections indicated as well as the turning section (orange). (S. C. Calvert, Klunder, et al., 2020)

3.1.3. Conducted tests

The FOT took place during a regular working week and involved the utilization of five scenario types, which were based on vehicle modes and communication types.

- A) Manual driving
- B) Manual driving with green recognition
- C) ACC mode with green recognition
- D) CACC mode with green recognition
- E) CACC mode with green recognition and green-phase extension

In this study, any stop-and-go traffic flow was not included in the approach and Scenario E was utilized instead because the evaluation is not sensitive when the vehicle is stopped. Extending green lights reduces this common stop-and-go traffic, leading to smoother drives across test areas. In this scenario, the CACC mode was not active at all times; therefore, the data was evaluated only during the CACC activation period.

The FOT of scenario E consists of two tests of 7-vehicle platoon. In the raw data, these two tests are labeled 'session 05' and 'session 06' and these data were used for the evaluation framework which '05' and '06' means the test date. To minimize the possibility of being overtaken by other vehicles during the test, the platoon was driven in the right-most lane when there were multiple lanes. During the experiment, the CACC system could change the speed of the vehicle according to the leading vehicle. Throughout the experiment, the vehicles began their journey at Schipholweg N232, initially traveling in platoon formation from the North to the South of the corridor. Upon reaching the end of the corridor at Noordelijke Randweg, the vehicles executed a U-turn at the roundabout and traveled back along the road on the opposite carriageway, proceeding from South to North. Upon completion of a full circuit, the vehicles returned to prepare for the next run.

The experiment was conducted secretly, without prior public disclosure, to prevent other road users from being aware of the tests. This approach aimed to avoid attracting unwanted attention or effects from external road users beyond their natural interactions and reactions. This strategy helped to ensure that the representatives of the CACC platoon were under normal traffic conditions.

3.2. Data Description

This section describes in full the data utilized in this study. The data utilized was obtained from the testing of Cooperative Intelligent Systems in the Netherlands undertaken by S. Calvert (2020). The data used in this study are from CACC Field Operational Test 2018 Noord Holland (S. Calvert, 2020). Data were collected to demonstrate the feasibility of CACC platooning and V2I/I2V communication, as well as to investigate its potential effects on traffic flow and safety in an urban environment. The primary purpose of their study was to obtain insight into the effects of CACC platooning combined with iTS (Intelligent Traffic Signals) on traffic flow and safety. Beyond that, they gathered an extensive quantity of data unrelated to their investigation for the benefit of future research.

The data used in this study is intended to assess the impact of disturbance on the CACC platoon's capacity to track human reasons. Each data set in the database represents the parameters of each vehicle in the platoon during an experimental scenario. Vehicle data is time-stamped, making it easy to compare various datasets. For instance, vehicle data include GPS position (latitude and longitude), vehicle speed, vehicle gear, brake pedal position, throttle pedal position, wheel position, acceleration, cruise speed setting, distance to target, and CACC control state. Moreover, not all experimental scenarios and vehicle data were necessary for this study; additional data processing is required to find relevant data elements concerning the research objectives. Before evaluation, some preparation is required to convert the raw data into usable parameters.

3.2.1. Data pre-processing

In this study, a data processing pipeline was developed to analyze the behavior of vehicle platoons under various conditions, specifically focusing on Cooperative Adaptive Cruise Control (CACC) platooning systems. In Figure 3.2, the data processing pipeline is depicted, beginning with the retrieval of raw data from designated directories (Step 1). Each subsequent step is methodically outlined, from the identification of individual sessions (Step 2) to the final structured data set ready for analysis (Step 6). The primary objective was to extract, align, and structure time-series data from FOT data, facilitating subsequent analysis of vehicle dynamics and platoon interactions. The process is described as Figure 3.2.

The initial step involved the retrieval of raw data files from designated directories corresponding to different platoon scenarios. Each file contained comprehensive logs of vehicle telemetry and state information, encapsulated within structured data formats. For each session identified by the filename within the scenario directory, the script initiates a data processing sequence. This step is crucial for segregating data by individual sessions, ensuring that analyzes can be performed on discrete sets of vehicle interactions within specific environmental and operational contexts. Within each session, vehicles are individually identified and a uniform time vector is established. This vector is essential for aligning data points between different vehicles and sensors, as sampling rates or data recording moments can vary. A fixed time step of 0.1 seconds is adopted to standardize the time base across all data points. The core of data processing involves aligning various data streams, such as vehicle speed, acceleration, GPS coordinates, and control states, to the standardized time vector. This alignment process corrects for any discrepancies in data recording timestamps, ensuring that each parameter of different vehicles can be directly compared or aggregated at identical time intervals. For instance, key variables, including vehicle ID, leader vehicle ID, speed, acceleration, and distance to target are extracted for each vehicle in the platoon. This extraction is tailored to capture both the dynamic behaviour of each vehicle and the spatial relationships within the platoon, such as distances and relative speeds between the leader and follower vehicles. The extracted variables are structured into a comprehensive dataset, organized by session. This structured format facilitates easy access to specific data slices for analysis, such as vehicle following dynamics, response to control inputs, and positional accuracy.

To maintain a clean working environment and ensure data integrity, the script selectively retains only the variables essential for ongoing analysis, removing all others from the workspace. This step minimizes memory usage and prevents any potential data cross-contamination between processing loops. Upon completion of the data processing for all sessions, the script outputs a structured summary of the processed data. This summary provides an immediate overview of the available data, ready for further analysis or visualization.

This data processing methodology enables a detailed and nuanced analysis of CACC platoon behavior, laying the foundation for investigating the impacts of various disturbances on platoon dynamics and vehicle control strategies. The analysis is based on accurate and synchronized data sets that have been systematically structured and aligned, allowing for the reliable identification of patterns, anomalies, and causal relationships.

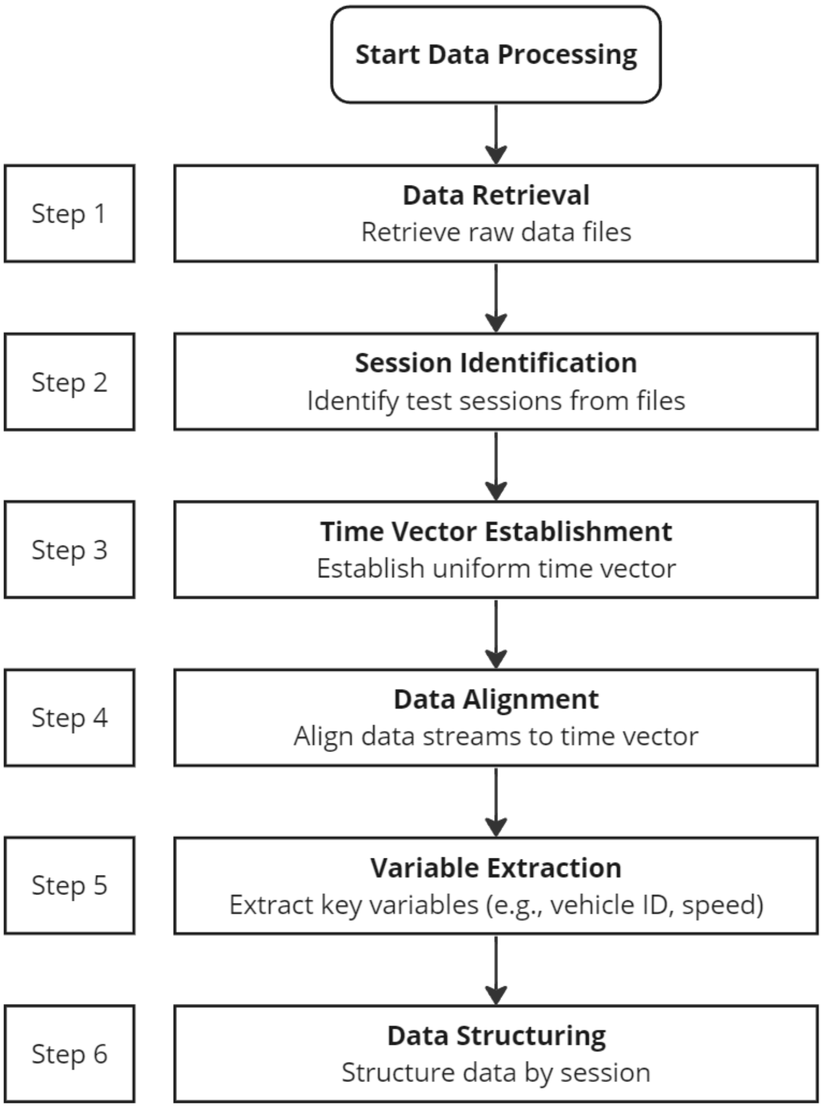

Figure 3.2: Data processing flow chart

3.2.2. Data exploration

Analysis of trajectory and speed profiles from two test sessions provides insight into vehicle dynamics and behavior within the platoon. As shown in Figure 3.3-Figure 3.6, these data provide insight to evaluate the performance of the CACC system.

Both test sessions revealed distinct patterns of vehicle behavior. For example, the trajectory plots represent the movement of the vehicle platoon during the test, including forward motion, pausing, platoon break-ups, and regrouping efforts. These patterns provide insight into how the platoon functions under different conditions. In session 3-05, at the 610th second, the seven-vehicle platoon broke up (Figure 3.7). Vehicles with IDs 6, 1, and 4 were near the end of the platoon and did not complete the regrouping process before the conclusion of the test. This finding demonstrates that, while brief platoon breakups are common, the consequences of these disturbances can vary greatly depending on the conditions.

Another significant occurrence occurred at the 860th second of Session 3-05, when vehicle 7 briefly separated from the platoon. After a 10-second stop, vehicle 7 drove quickly to catch up with the platoon and successfully reassembled by the 930th second. Several factors can impact whether a vehicle successfully regroups a platoon following a break-up. These factors include whether the vehicle behind is not in a free-flowing condition to complete the catch-up, whether the distance is too large for the system to manage, driver decisions not to regroup,

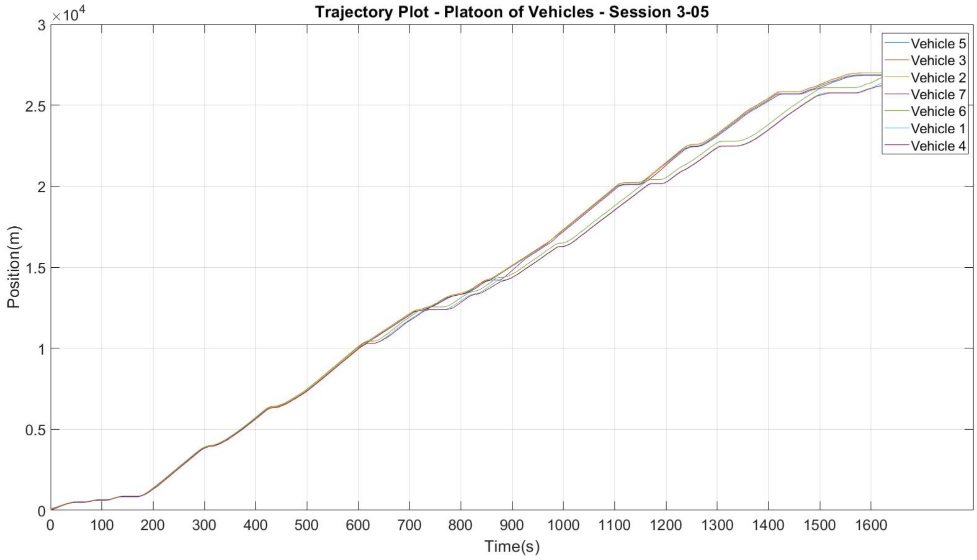

Figure 3.3: Trajectory plot Session 05

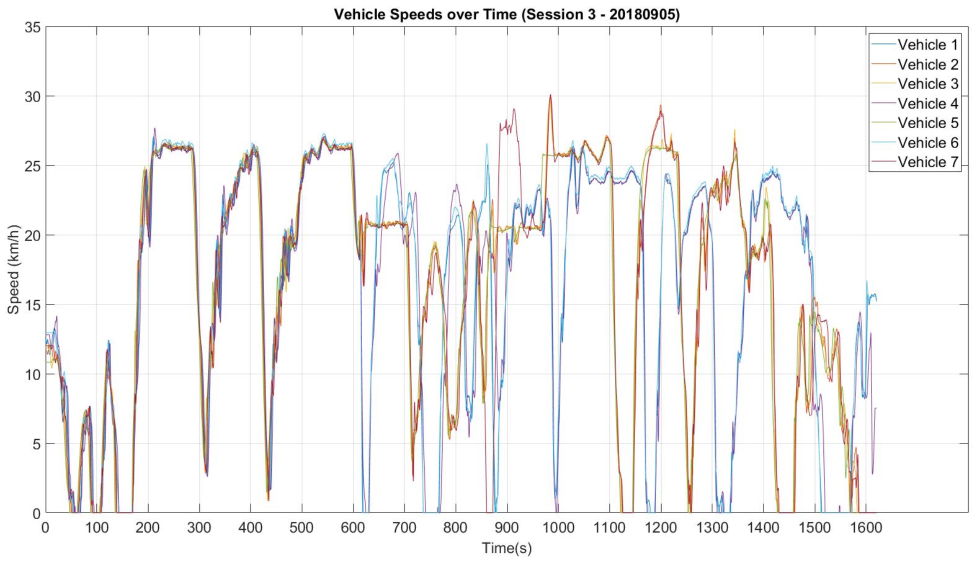

Figure 3.4: Speed plot Session 05

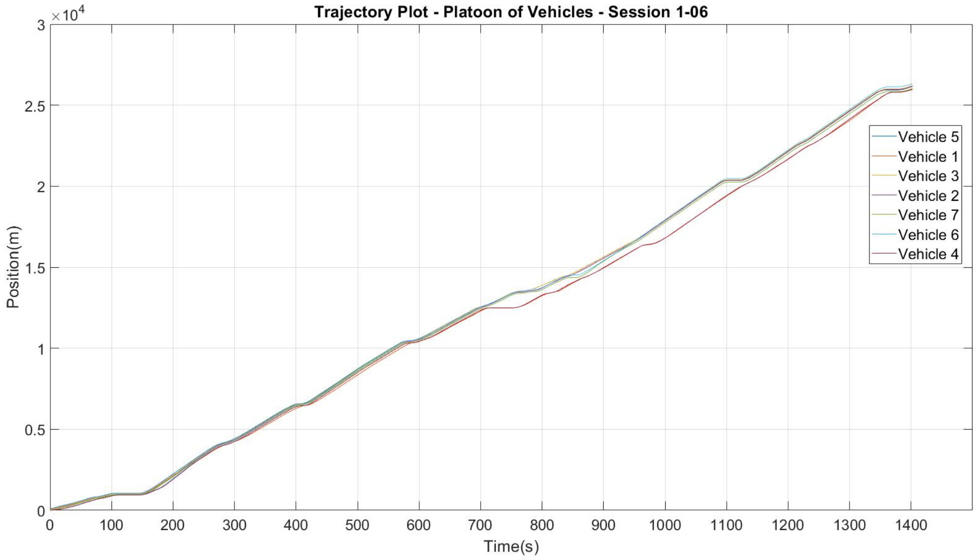

Figure 3.5: Trajectory plot Session 06

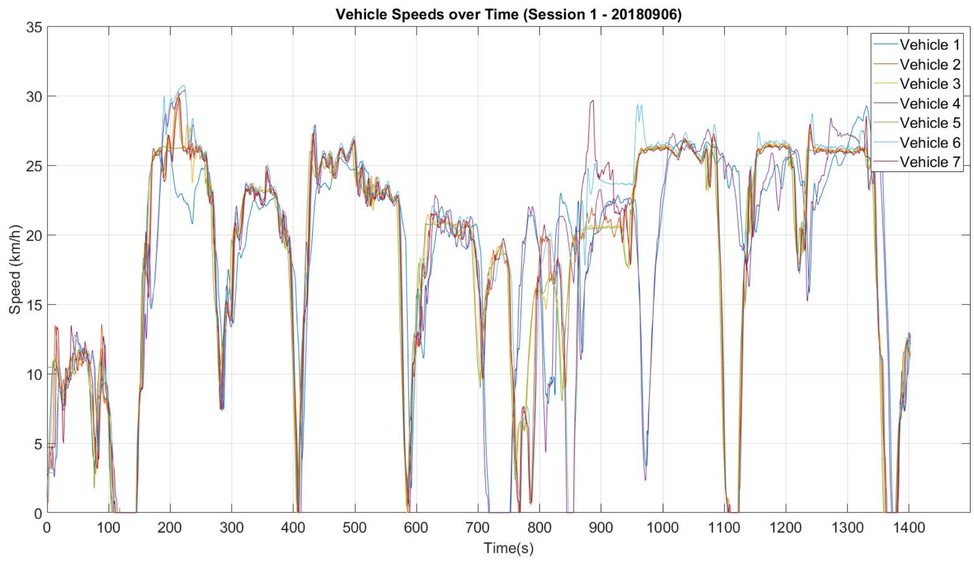

Figure 3.6: speed plot Session 06

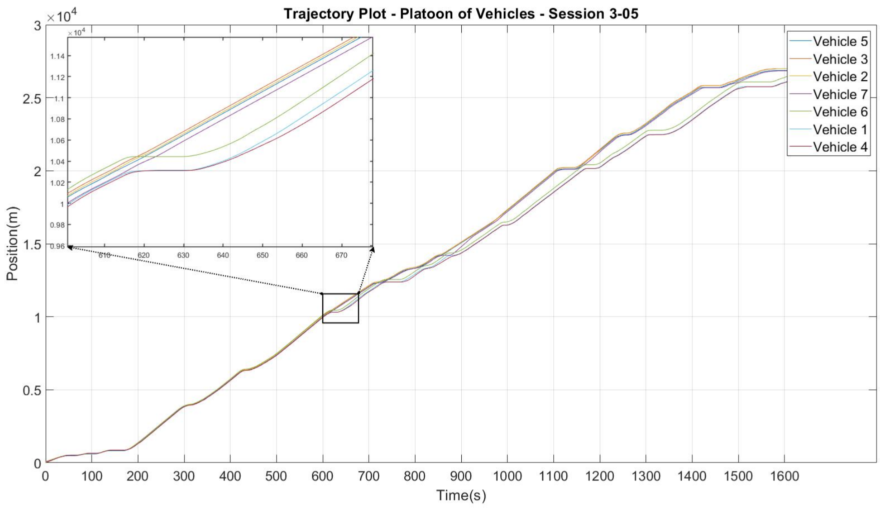

Figure 3.7: Break-up for case2

external constraints such as a red light or speed limit restrictions, among others. However, this research will not go further into the motives behind a vehicle's decision to regroup or not. Instead, it is critical to establish that if a platoon breaks apart and does not rejoin, the platoon is regarded to have separated into two different platoon systems. Because if they do not regroup, the disturbance received by the platoon may not affect the separated parts. The reasons include the transmission of disturbance within the platoon mentioned before and the time when the disturbance occurs, which cannot be determine, etc.

In contrast, if vehicles that fall out of the platoon during the break-up successfully catch up and regroup, they are considered a whole system for the purposes of this research. In session 06, it was observed that Vehicle 1 looked to follow the platoon but displayed some unusual behavior in its speed profile (Figure 3.8). Further investigation revealed that Vehicle 1 varied between 'following other vehicles,' 'not following,' and 'following' from the 200th to the 700th second. This behavior probably involves a series of positional changes within the vehicle platoon, which finally led to Vehicle 1 regrouping the platoon and following Vehicle 4. Unfortunately I do not know what happened to this vehicle during this period, it is possible that the complex traffic flow, or that the vehicle's failure sensor. To compensate for this, in the future, interviews with the driver or video data connected with digital data could do better.

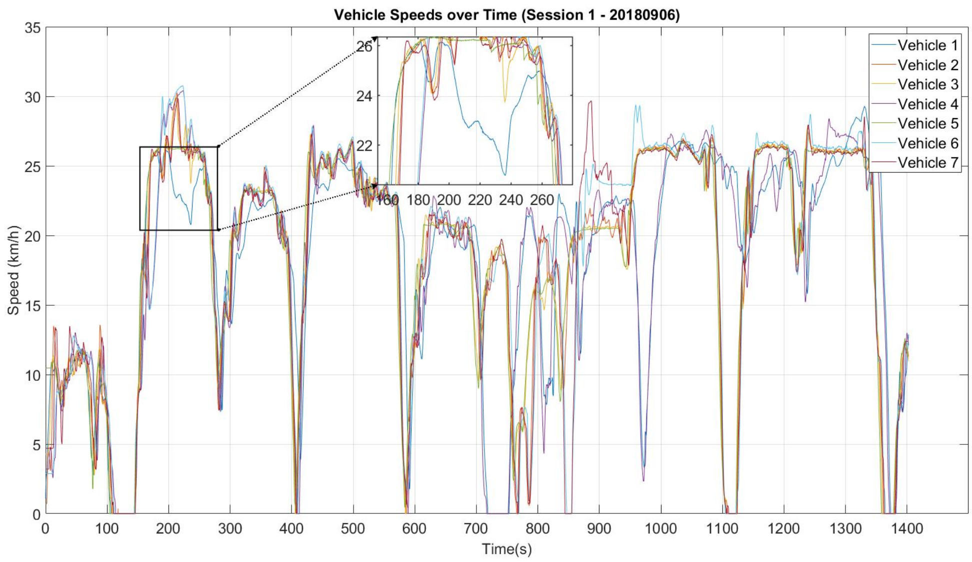

Figure 3.8: zoom-in version for session 06, vehicle 1

External factors, such as non-participating vehicles cutting into the platoon, also had a significant impact on platoon trajectory and speed profiles. Cut-ins can be identified and assessed for their influence on the platoon by evaluating the leader. The trajectory and speed profile data from the two test sessions demonstrate the multidimensional nature of vehicle platooning. Maybe in future research, when paired with additional supporting data, this method yields a more complete and comprehensive knowledge of platoon activities.

3.3. Disturbance and Disengagement

In the context of Cooperative Adaptive Cruise Control (CACC) platooning systems, disturbances can be any conditions or events that disrupt the normal operation of autonomous vehicle platoon. These disturbances may be caused by a number of things, such as inadequate lane markings, hardware or software malfunctions in the vehicle, unfavorable traffic conditions like unplanned construction or accidents, and environmental elements like bad weather or blocked sensors. A typical disturbance scenario is shown in Figure 3.9 (Fernandes and Nunes, 2012), where one vehicle of a platoon has to reduce its speed from a stable velocity v_{stb} to a lower velocity v_{low} and then maintains this speed for a period of time before accelerating back to its initial velocity.

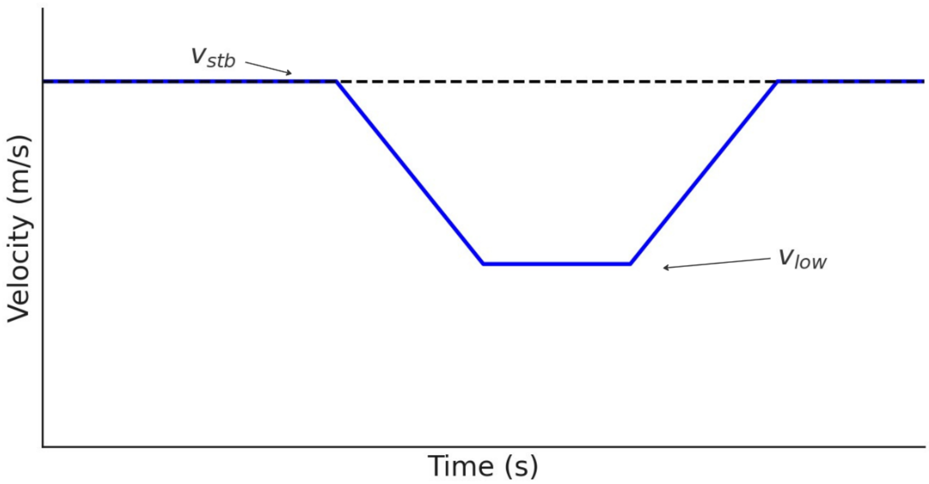

Figure 3.9: One typical disturbance scenario

The variety of types and intensities of disturbances makes it difficult to determine which disturbances affect autonomous driving systems. The complex nature of vehicle behavior in real-world scenarios and the unpredictability of disturbances provide challenges to systematic analysis. Field Operational Test (FOT) data often lack reliable evidence to identify the occurrence of disturbances. Furthermore, the complexity of vehicle behavior and the nature of real-world data make it challenging to establish a definitive metric to define and measure disturbances.

Disengagement reports provide a tangible link to real-world disturbances. According to California Department of Motor Vehicles (2016), disengagement occurs when the automation mode is deactivated due to a failure or when the safe operation requires the autonomous vehicle test driver to take manual control. These reports detail instances in which the autonomous mode was deactivated. Research on road facilities for the disengagement of autonomous driving has been conducted in Korea. A study conducted by KICT (Korea Institute of Civil Engineering and Building Technology) analyzed the environmental factors that limit sensor recognition and the infrastructure that sensors primarily recognize, and through these analyzes, determined the requirements for improving road facilities (KICT and SANE, 2017). The analysis results show that in terms of facilities, lanes and road signs are the main facilities affected by sensor recognition. In terms of environment, rain at night, direct sunlight or backlight, poor lane markings, etc. are the main factors that affect recognition (Park and Yun, 2018). Besides, Park and Yun used AHP (analytic hierarchy process) to analyze the factors of road conditions, and the results showed that if road conditions can be accurately identified during the driving of an autonomous vehicle, vehicle safety can be ensured. The priorities of these factors are organized in the following order: traffic flow management infrastructure, individual road infrastructure barriers, and traffic lights (Favarò et al., 2018).A more specific and comprehensive summary of the causes of disengagement was concluded by Boggs et al. (2020). As illustrated in Figure 3.10, the common reasons for disengagement, as articulated by vehicle manufacturers, were categorized into six groups. These groups encompass control discrepancy, environmental and other road users, hardware and software discrepancy, perception discrepancy, planning discrepancy, and operator takeover.

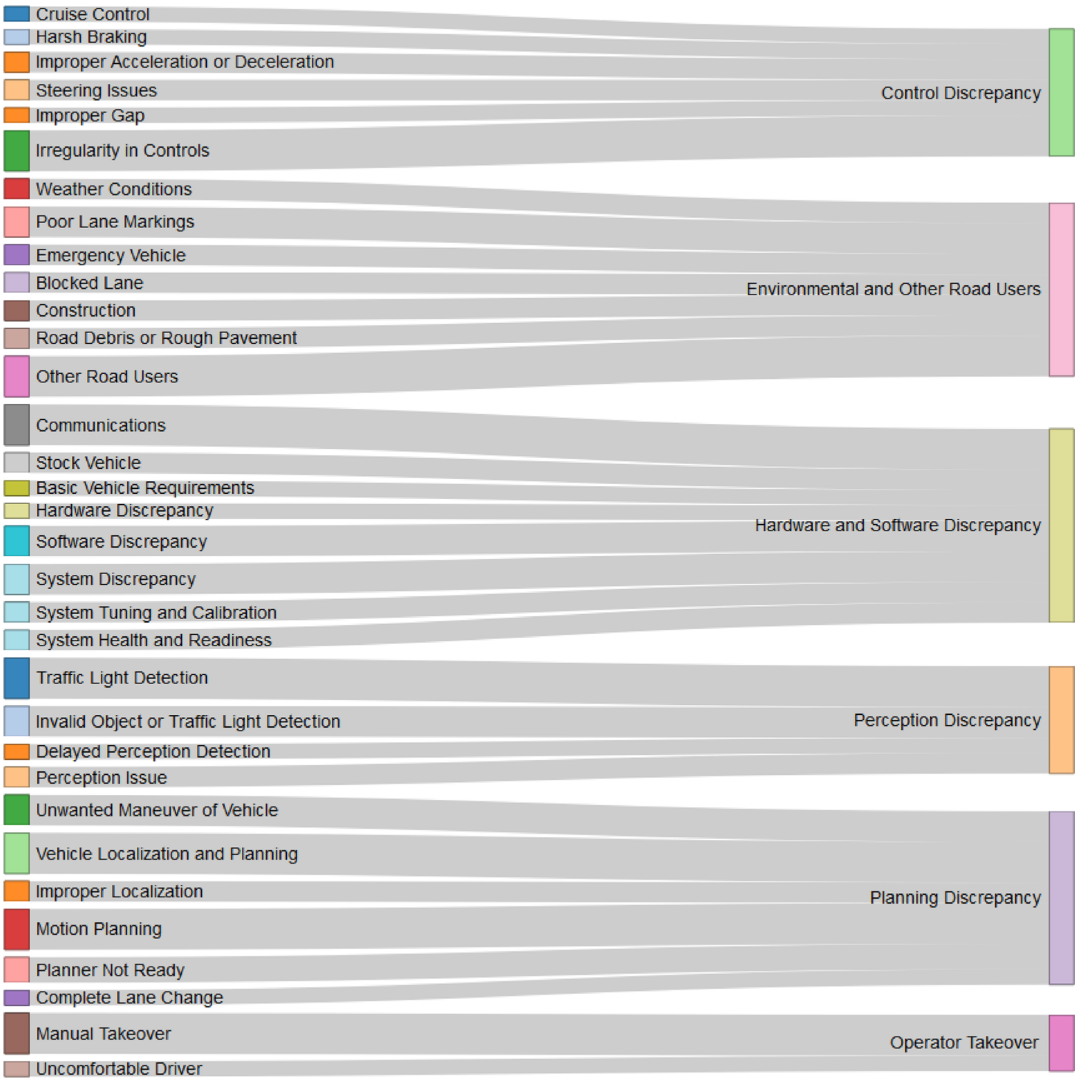

Figure 3.10: Categorization of disengagements causes.(Boggs et al., 2020)

The comprehensive analysis of disturbances affecting CACC platooning systems, illuminated by our literature review and FOT test, reveals infrastructure, traffic conditions, automated systems, and unexpected road events play a pivotal role. In particular, the categorization of reasons for disengagement into six distinct groups—control discrepancy, environmental and other road users, hardware and software discrepancy, perception discrepancy, planning discrepancy, and operator takeover—provides a structured framework for understanding the connection between disturbances and causes of disengagement. The overlap between the disturbances identified in the literature and the causes of disengagements reported in practice is not merely coincidental but illustrates the fundamental vulnerability of current CACC systems to these factors. So, disengagement can be used as one of the approaches to evaluate if there is a disturbance. Studies by other researchers have also confirmed that disturbance is indeed related to disengagement. For instance, Roh and Im (2020) point out that environmental disturbances such as rain, direct sunlight, and poor lane markings directly impact the sensor performance, leading to a higher propensity for disengagement. This correlation is further substantiated by real-world disengagement reports, which frequently cite these environmental and infrastructural inadequacies as precipitating factors.

Recognizing these insights, it becomes evident that disturbances—encompassing a broad spectrum of environmental, infrastructural, and traffic-related factors—serve as the primary catalysts for the disengagement of autonomous vehicles. The evidence overwhelmingly supports the conclusion that disturbances precipitate a vast majority of disengagements in CACC platooning operations. Although I say that disengagement is to a large extent caused by disturbance, it still needs to be aware of this point in our analysis: it is not the case that the absence of disengagement means the absence of disturbance. This is also mentioned in Rojas et al. (2023), the system may have failed during operation without causing an accident or disengagement which is not captured in the safety evaluation. This result is important for our later evaluation process: assume that disengagement was caused by disturbances in this FOT experiment, but no disengagement happened does not mean that no disturbance occurred.

3.4. Evaluation framework

According to the discussion on the MHC tracking part, reasons, and FOT data set, a framework is proposed for the evaluation of the CACC platoons, which is shown in Figure 3.12. The modules form a structure with two parts, MHC and CACC. For MHC, the tracking condition concludes the driver's intention and FOT designer's plans, they can be distinguished into three reasons, namely, comfort, safety and local stability. Combined with the content of the FOT, the driver's intent and the designer's plans, with the definition of Mecacci & Santoni de Sio, the reasons is shown in Figure 3.11. For CACC, the raw data is from FOT experimental data for every single ACC vehicle in CACC platoon. To evaluate the three different reasons, three KPIs were defined from the data to correspond to each of the reasons, which are jerk, time headway and TTC (Time-to-collision). The roles of the modules and their interactions are explained below based on the two parts.

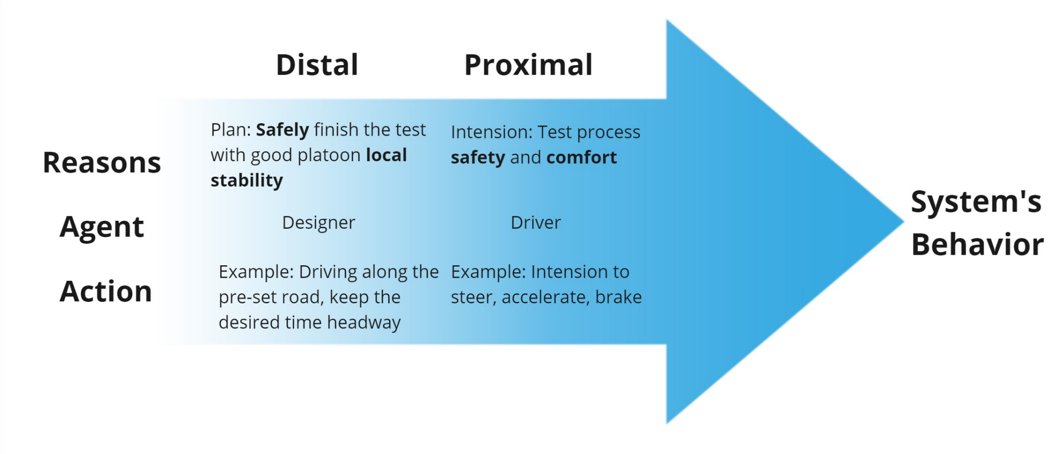

Figure 3.11: Proximal reasons and Distal reason in FOT test

MHC

Combining the purpose of our FOT experiment with the temporal dimension of disturbance, selected the **FOT designer** and **Test drivers** involved in the experiment as agents to get closer to the proximal reasons. Other agents such as automated driving system manufacturers, policymakers, etc. are not considered in it for the time being, and other road users (other vehicles) are considered as disturbances rather than as agents for the subject of the evaluation. For tracking conditions, three reasons from two agents are involved in the framework. Comfort refers to the possible discomfort caused by sudden acceleration or deceleration of the driver in the vehicle. It is considered to be comfortable if the vehicle is driven at a constant speed (Yang et al., 2022). Defined the safety reasons for both drivers and vehicle designers as the necessity for vehicles to avoid collisions. The local stability refers to the platoon tracking the default time headway. If the time headway between two vehicles is just in line with the pre-setting value, then it is regarded as a good performance.

CACC

Established three key performance indexes (KPIs) to assess the reasons of both drivers and vehicle designers during the test. The KPIs were selected based on the fact that they had been used in other study to analyse the corresponding reasons and that KPI data could be found in existing datasets. These KPIs include jerk, time-to-collision (TTC), and time headway. To evaluate these KPIs, utilized data collected during testing, including acceleration/deceleration, distance headway, and speed. The details of how to used this data to calculate the KPIs will be described in the next subsection.

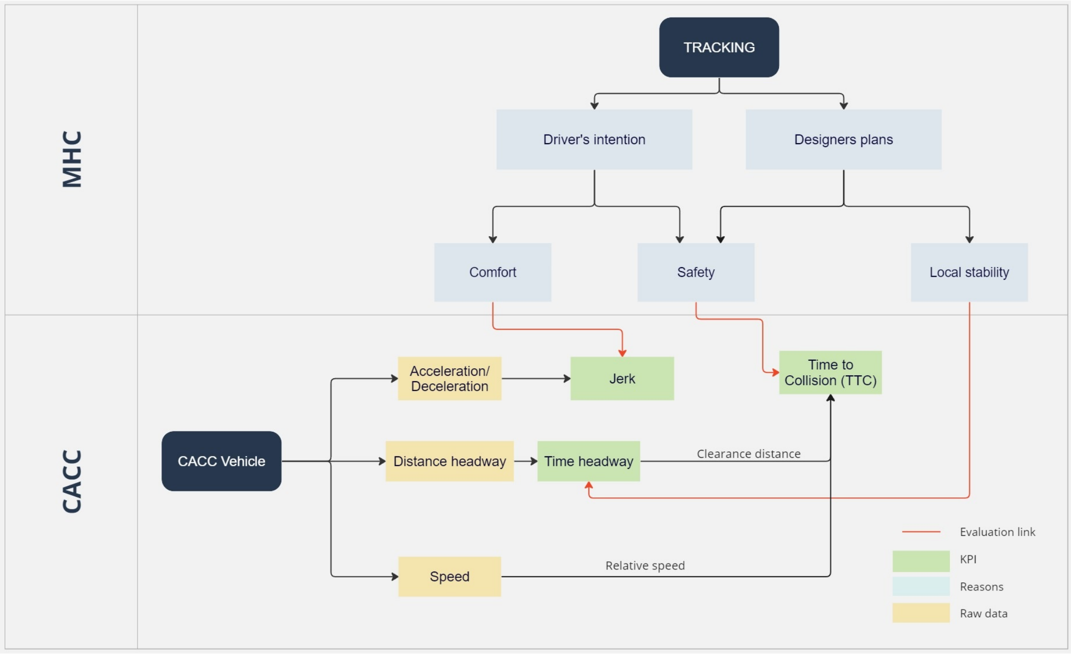

Figure 3.12: Evaluation framework

As tracking considers the extent to which the system fulfills human reasons, for these three reasons, defined three scores for this study. Inspired by S. C. Calvert and Mecacci (2020), they defined the tracking based on two elements, duration and safety, duration should be minimised to create positive MHC and safety maximized. They calculated tracking as a sum of the driver's safety reasons and duration. Similar to their approach to tracking evaluation, this study defined tracking as:

$$Tracking = E_{safety} + E_{comfort} + E_{stable} \tag{3.1}$$

where E_{safety}, $E_{comfort}$ and E_{stable} are the individual score of reasons, and $Tracking$ is the overall score for tracking condition. The metrics produced by different modalities vary widely, it is necessary to normalize these scores to a uniform scale before they can be effectively combined (Jain et al., 2005). This research normalised each of these metrics to a score between 0 and 1; when this score is close to 1 it indicates that the system is poor at tracking this one reason, and when the score is close to 0 it indicates that the system is tracking human reasons. It is important to note that, although using the term "score" here, in the actual assessment, higher scores represent worse conditions.

3.4.1. Comfort

Jerk, defined as the change rate of acceleration, was used to measure driving comfort. Jacobson et al. (1980) stated that jerk has a strong influence on the comfort of passengers. Jerk quantifies how rapidly the vehicle acceleration or deceleration is changing.

$$jerk(t) = \dot{a}(t) \tag{3.2}$$

where $jerk(t)$ is defined as the derivation of acceleration $a(t)$.

Calculate the comfort score within a range of 0 to 1, divide the absolute value of jerk by the maximum acceleration that is still considered comfortable, along with its corresponding time stamp. This denominator was determined based on findings from de Winkel et al., 2023, where passenger/driver comfort was categorized as 'terrible' if acceleration exceeded $2.12ms^2$. Additionally, multiplied the maximum acceleration by the time stamp to account for the variation of acceleration to get the maximum jerk value.

A normalization for the jerk feature was constructed as:

$$E_{comfort}(t) = \frac{|jerk(t)|}{a_{max} * dt} \tag{3.3}$$

3.4.2. Safety

"Time-to-collision" (TTC) is a surrogate safety measure which is generally defined as "the duration of time before two objects collide with initial certain conditions" (Saffarzadeh et al., 2013). TTC is one of the most frequently used time-based surrogate safety measures (Behbahani et al., 2015). TTC is the time required for two vehicles to collide if they continue at their current speeds and on the same path. In the pre-setup for the test, vehicles were not allowed to overtake, so TTC is a good way to assess the safety of the platoon. As a widely used safety indicator, it is computed as:

$$TTC(t) = -\frac{S_{(n-1),(n)}(t)}{\Delta V_{(n-1),(n)}(t)} \tag{3.4}$$

where,
t stands for time instance in seconds; $n-1$ and n represent the lead and following vehicles respectively; $(n-1),(n)$ combination denotes variables related to both the lead and following vehicles: $S_{(n-1),(n)}$ being the clearance distance, and $\Delta V_{(n-1),(n)}$ being the relative speed (lead-vehicle speed minus following-vehicle speed).

According to Svensson (1998), TTC is inversely related to accident risk, smaller TTC values indicate higher accident risks and vice versa. The basic idea is to sample the TTC values over time and to examine how often a certain driver violates a given lower safety limit or how often this limit is violated on a particular stretch of road or under particular conditions (Vogel, 2003). In the literature, different opinions can be found as to which value should be used as a safety limit range from 1.5 s (Svensson, 1998) to 5 s (Maretzke and Jacob, 1992). For FOT, the threshold needs to be determined when evaluated, denoted here by u. The safety metric cannot be standardized with the scaling of Min-Max features because the safety level does not increase linearly as the TTC decreases; to figure out how to standardize the safety metric, refer to M. Zhu, Wang, et al.(2020), the normalization of TTC is similar to their study on the safety evaluation of CAVs. A safety feature was constructed as follows:

$$E_{safety}(t) = -\log(\frac{TTC(t)}{u}), 0 < TTC \leq u \tag{3.5}$$

In this way, if TTC is less than u, the safety score will be positive. As TTC approaches zero, the TTC feature will be close to 1, which represents a very high value to near-crash situations. If TTC approaches u, it shows a safety situation. In actual analysis, if the speed of the rear vehicle is less than the speed of the front vehicle, then E_{safety} will be set to 0 to show a safe state. And set the situation when E_{safety} larger than 1 to 1 to show any TTC less than the threshold is considered unsafe.

3.4.3. Local stability

Local stability means that a vehicle can maintain its position close to a state of equilibrium (e.g., equilibrium speed and designated distance) under disturbance (Zhou et al., 2019). Local stability concerns the behavior of a pair of vehicles following each other. Local stability in this study refers to a desired time headway between two vehicles. Time headway is defined as the passed time between the arrival of the lead vehicle and the following vehicle at a designated point. Keeping a short headway within the safety bounds can improve traffic flow efficiency because short headways correspond to large roadway capacities. The desired time headway TH_d:

$$TH_d = 0.6(s) + \frac{5(m)}{v} \tag{3.6}$$

where,
v is the follower speed, 0.6 s plus nominal standstill distance 5 m is the set-up by the designer.
A simple normalization for the stability feature was constructed as:

$$E_{stability}(t) = \frac{|TH(t) - TH_d|}{max(TH(t) - TH_d)} \tag{3.7}$$

where,
TH is the actual time headway. With smaller values of stability features corresponding to better local stability.

4 Evaluation

4.1. Evaluation description

In this evaluation, the focus centers on the seven vehicles in the platoon, and as long as no platoon split occurs, the vehicle platoon is always analyzed as a whole system. The chosen time window for evaluation is tactically selected to capture standard platoon operation, covering the entire disturbance scenario. Specific disturbance scenarios are chosen to avoid as many external influences other than the main disturbance, guaranteeing the platoon's integrity during the entire evaluation time window. For example, vehicle-stopping situations are not considered; try to avoid multiple disturbances within one time window to influence the evaluation result.

The evaluation time window is segmented into three slots: before the disturbance, during the disturbance, and after the disturbance (Figure 4.1). The evaluation will compare the performance of the vehicle platoon over these three time windows, including before and during disturbance, during and after disturbance, and also before and after disturbance. This multiple comparison provides insight into the effect of the disturbance on the platoon and the change in the platoon's ability to track human reasons before and after the disturbance.

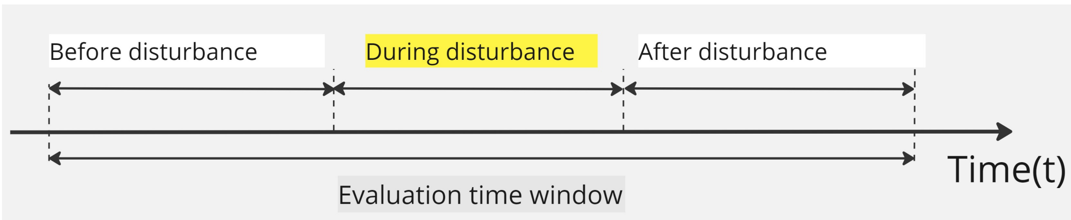

Figure 4.1: Time window representation

With the previous section on the relationship between DISTURBANCE and DISENGAGEMENT, the next focus is on how to define the disturbance time slot based on disengagement. It is very difficult to find the exact time when a vehicle is affected by a disturbance in a real-world situation. Due to the variety and complexity of the causes of disengagement, the driver's level of engagement in driving, the severity of the disturbance, the time of completion of the system decision, and the degree of impact of the disturbance on the vehicle, it becomes difficult to determine how long before disengagement the vehicle receives the effects of the disturbance.

Adopting a standardized criterion to identify the time window of disturbances from disengagement can make the research findings consistent and comparable. Although a case-by-case analysis offers the allure of high precision by accommodating the unique circumstances of each disengagement event, as mentioned in the previous section, it is challenging to make clear from the limited data collected what exactly happened in a particular place, when it started and when it ended. To address the aforementioned issue, two categories of time were proposed, the alert phase and the disengagement window itself. The alert phase is the time frame during which the vehicle system assesses the potential for a disturbance based on environmental and vehicular data. The disengagement window encapsulates the moment the automated vehicle disengages and engages. This categorization facilitates a method for evaluating the response of automated vehicles in various scenarios, ensuring comparability in research findings. The approach is influenced by the work of Janssen et al. (2019), who modified the framework of task interruptions to suit automated driving contexts and control transfer analyses. Their delineation of the takeover process into ten stages provided a detailed template from which distill the need for a simplified yet effective evaluation model (Figure 4.2). Although they divided the whole takeover process into 10 stages, such a detailed division is not needed for this study, want to find the start point as well as the end point. While Janssen et al. acknowledges the complexity in defining ”alert time” within the disengagement sequence, their suggestion of a 20 to 40 s interval. Given that the experiments were designed in advance and faced a much simpler situation than completely chaotic traffic, the shortest time was chosen as a criterion, selected 20 seconds as the lead time, and the vehicle engagement time (if possible) as the time of the end of the disturbance. This decision is based on the controlled nature of the experimental design, which contrasts with the unpredictable dynamics of real-world traffic. By adopting this 20-second criterion and marking the re-engagement of the vehicle as the disturbance's endpoint, align time window evaluation with practical considerations, as visually represented in Figure 4.3. Combined the data to find three cases in session 05 and session 06. The time points of disengagement and resumption of contact in these three cases are shown in Table 4.1. Using these time can get the final evaluation time windows for study which are shown in Table 4.2

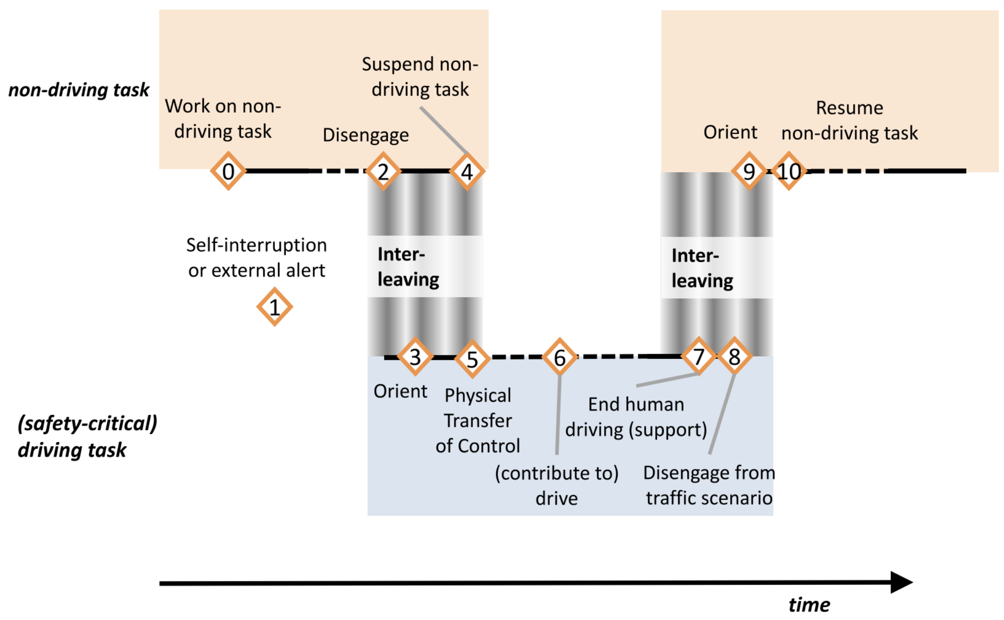

Figure 4.2: The stages of a transition of control in an automated driving context, as seen from an interruption perspective.(Janssen et al., 2019)

Table 4.1: Disengagement and engagement time

Case	Session	Disengagement (s)	Engagement (s)
1	05	311.6	339.3
2	05	1254	1261
3	06	409.3	432.2

Table 4.2: Evaluation time window

	Pre time slot (s)		Disturbance (s)		After time slot (s)	
Case	From	To	From	To	From	To
1	243.9	291.6	291.6	339.3	339.3	387
2	1207	1234	1234	1261	1261	1288
3	346.4	389.3	389.3	432.2	432.2	475.1

It is well worth making it clear that finding disengagement is only to help us identify the time window in which the disturbance took place, for the cases selected for analysis also need to combine this with other vehicle profile analyses to understand more fully what happened during this time, and ultimately combine this with a quantitative analysis to arrive at the conclusions. In addition, all disengagement cases selected in actual operations will not include disengagement to manual driving. The vehicle still maintains automatic driving, so this will not introduce other factors to influence the evaluation results.

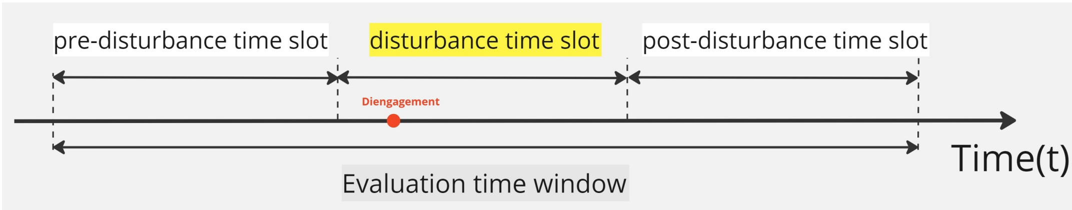

Figure 4.3: Time window representation (including disengagement)

The evaluation results visualise trend changes in each platoon's scores (safety, comfort, and local stability) and the composite score (tracking condition) throughout the disturbance scenario. For a vehicle platoon, the three scores are distributed in this way: the comfort score is based on the change in acceleration of the vehicle itself, so the comfort score is for each vehicle; for safety and local stability, it is based on an interaction between two neighbouring vehicles, so these two scores are for the two vehicles. In other words, for a vehicle platoon with n vehicles, there will be n comfort scores and $n-1$ safety and local stability scores (Figure 4.4). For ease of presentation and evaluation, the evaluation imposed local and safety stability scores on the rear vehicles of two vehicles, meaning that for the entire vehicle platoon, the LEADER has only a comfort score and the other vehicle has all the scores. Based on this, Equation 4.1 was used to evaluate platoon tracking performance.

$$Tracking = \frac{\sum_i^{n-1} E_{stability}(t)}{n-1} + \frac{\sum_i^{n-1} E_{safety}(t)}{n-1} + \frac{\sum_i^{n} E_{comfort}(t)}{n} \tag{4.1}$$

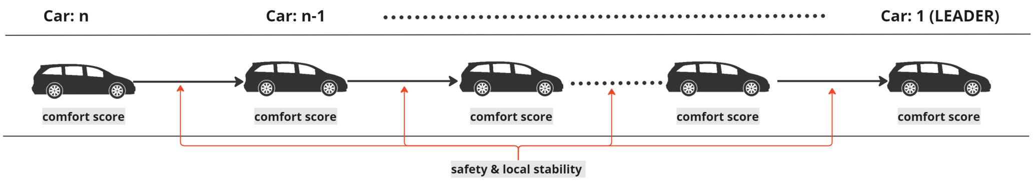

Figure 4.4: Vehicle platooning and scoring

4.2. Tracking Condition Result Analysis

4.2.1. Analysis of Individual vehicles

Before analyzing the platoon performance, qualitative analysis of individual vehicles helps us to get insight into the vehicle platoon, understand the reasons behind the unusual behaviour and ensure that the analysis of the platoon is accurate and effective. The two red dashed lines in the figure represent the dividing lines of three time windows, which are, from left to right, before disturbance, during disturbance, and after disturbance.

***NOTE:**

1) In all result, the order of vehicle platoon is from top to bottom, with the leading vehicle at the top and the last vehicle at the bottom.

2) In all result, higher numerical score indicates worse tracking conditions.

Firstly, the situation of each component is analyzed, and then the tracking score of the vehicle platoon is analyzed. The comfort score data exhibit oscillatory behavior, with short and frequent oscillations signifying the platoon's rapid adjustments to acceleration and speed changes. Notably, the oscillatory becomes more amplitude during the disturbance. The vehicle control system has to resort to emergency braking/sudden acceleration to avoid risk (or to get out of a hazardous situation), and these changes in acceleration are usually short and sharp. A case example is shown in Figure 4.5. The figure of local stability demonstrates a different characteristic, after the disturbance occurs, the local stability of the platoon shows a smooth change without a large amplitude, which shows that the effect of local stability on the trend of the final result is more significant (Figure 4.6). When disturbances occur, the local stability of the platoon becomes progressively worse, indicating that the platoon's following distance is slowly deviating from the preset spacing, and this apparent trend significantly affects the tracking results, both in terms of trend and magnitude. This may indicate that maintaining stable distance gap spacing is not a primary goal to ensure when faced with disturbances. Unlike the more regular fluctuations observed in comfort and local stability, safety scores demonstrate a less frequent and more random pattern (Figure 4.7). This randomness suggests that even if the vehicle is facing emergency braking or is unstable, this does not always lead to a safety issue. The sporadic peaks, representing brief excursions from safety baselines, are indicative of isolated events where the system has identified a potential risk and the control system decided to address safety issues first. The relative infrequency of these events aligns with the expectation that safety-critical responses should be exceptional rather than routine, reflecting a system calibrated to maintain high safety standards while minimizing unnecessary interventions. The diversity in the occurrence of safety-related events between vehicles can be attributed to several factors. Positioning within the platoon, for example, may shield some vehicles from direct exposure to external disturbances while leading or trailing vehicles might have to contend with the brunt of such events. Moreover, the random nature of the safety score excursions underscores the complexity of real-world driving environments. The data indicates that the platoon's safety mechanisms are capable of addressing unanticipated disturbances more effectively than the other two reasons.

After analyzing the possible impact of each component on the result, the next step is to look at the tracking condition results for the three cases.

- Case1

  In Case 1, the analysis of the vehicle platoon's tracking condition during disturbances unveils differentiated responses (Figure 4.8). The leader, Vehicle 5, is exclusively measured by comfort metrics and displays a stable line across the event phases. The leader is minimally affected by disturbances; for the leader vehicle itself, no aggressive braking or accelerating manoeuvres were made in response to the disturbance. The rear follower vehicles (Vehicles 1, 4 and 6), which embody a composite score of safety, comfort, and local stability, generally maintain steady scores, with minor fluctuations indicative of the disturbance's impact. However, closer scrutiny reveals that Vehicles 2, 3, and 7 diverge from this pattern, experiencing pronounced score spikes during the disturbance phase, the first three followers are more responsive to disturbance than the three followers at the end of the platoon. These spikes highlight a more substantial impact on these vehicles' tracking conditions and point towards a variance in how different segments of the platoon react to the same external stimulus. Possible reasons for this are that the vehicle in front causes the vehicle behind to respond earlier to reduce the impact through communication technologies such as V2V, or that the propagation of the disturbance through the platoon is gradually slowing down. Unlike local stability, this condition is defined as platoon stability (Pueboobpaphan and Van Arem, 2010). Platoon stability is concerned with the propagation of the disturbance from one vehicle to other vehicles in the same platoon. If the magnitude of the disturbance grows as it propagates to the vehicles upstream, the platoon is said to be unstable. Since this study did not introduce this as an evaluation metric, it is not discussed too much here.

The disturbance's time window, indicated by the red dashed lines, suggests an alignment with the score changes for Vehicles 2, 3, and 7, providing a temporal context to their responses. After the disturbance, vehicles seem to be recovering well, but it's not good to say if it's fully recovered to before-disturbance levels.

- Case2

  In analyzing Case 2, the leader, Vehicle 5, presents a unique case as its total score solely comprises the comfort metric (Figure 4.9). Contrary to Case 1, where the performance remained stable, Case 2 shows fluctuations suggesting that the leader's comfort is impacted during disturbances. This variation highlights a potential area for further investigation and optimization of the leader's comfort sensitivity to disturbances, considering its critical role in the platoon. Follower vehicles, carrying the cumulative burden of safety, comfort, and local stability scores, show increased scores during the disturbance period. This uptick confirms the system's recognition and response to the disturbance, underscoring a momentary decline in tracking conditions. Compared to Case 1, the vehicles in Case 2 were more severely affected by the disturbance, with peak approaching or even exceeding 2 (the maximum threshold is 3), explaining the high impact of Case 2's disturbance on the platoon or the platoon's poor responsiveness to this disturbance.

  The time window for the disturbance, delineated by red dashed lines, suggests a slight lag in the manifestation of the disturbance in the vehicle scores. This discrepancy points to a potential misalignment between the anticipated timing of the disturbance and its actual effects on the platoon. It appears that at the pre-assumed time of the end of the disturbance, the effect of the disturbance on the platoon is not yet over, which is a limitation of the way to select the disturbance window. Refining the selection of the time window could thus provide a more precise correlation between disturbance events and the vehicles' response timings, thereby enhancing the accuracy of the assessment.

  There is another point worth noting in Case 2, for the last three vehicles at the end of the platoon, their steady scores during the disturbance period reflect their non-involvement in the event. It was reconfirmed through the trajectory maps that the three vehicles had disengaged from the vehicle platoon before the disturbance and had not been able to regroup (Figure 3.7). These vehicles, being removed from the disturbance, maintain a constant tracking condition, which serves as a control comparison against the involved vehicles. Recognizing the importance of homogeneity in the analyzed sample, these detached vehicles are rightly excluded from further analysis to maintain the integrity of the study's focus on disturbance impact.

- Case3

  In Case 3, delve deeper into the analysis of vehicle platoon behaviour under disturbance conditions (Figure 4.10). Here, the graphical representation of each vehicle's total score offers further insights into the tracking condition during the disturbance phase.

  The leader's performance is similar to the findings ahead, generally stable with minor fluctuations. The followers show varied responses. Notably, Vehicle 1 exhibits a markedly poor performance that persists throughout the entire time window, rather than just during the disturbance. This continuous poor tracking condition could be indicative of underlying issues with Vehicle 1's operational parameters or its interaction with other traffic participants. It's particularly important to note that the disturbance does not appear to exacerbate its performance significantly, implying that Vehicle 1's issues are intrinsic rather than externally influenced.

  Case 3 presents a discernible pattern of disturbance propagation through the platoon. This phenomenon, characterized by a sequential delay in the tracking condition's alteration concerning each vehicle's position in the platoon, is a classic illustration of how disturbances ripple through a system. In the data, this can be seen as each following vehicle's peak in total score—which comprises safety, comfort, and local stability—occurs progressively later than the vehicle ahead of it. Such a pattern suggests that the effects of the disturbance are not immediate on following vehicles but instead take time to manifest as the disturbance propagates through the platoon.

  Although this pattern is not exclusive to Case 3 and can be inferred from the previous cases, it is in Case 3 that the propagation is most prominently observed. This clear illustration offers an important insight into the behaviour of the platoon's control systems and the inter-vehicle communication protocols that determine response times and actions. It also serves as a practical example of the system's responsiveness and the delay inherent in the propagation of information through the platoon.

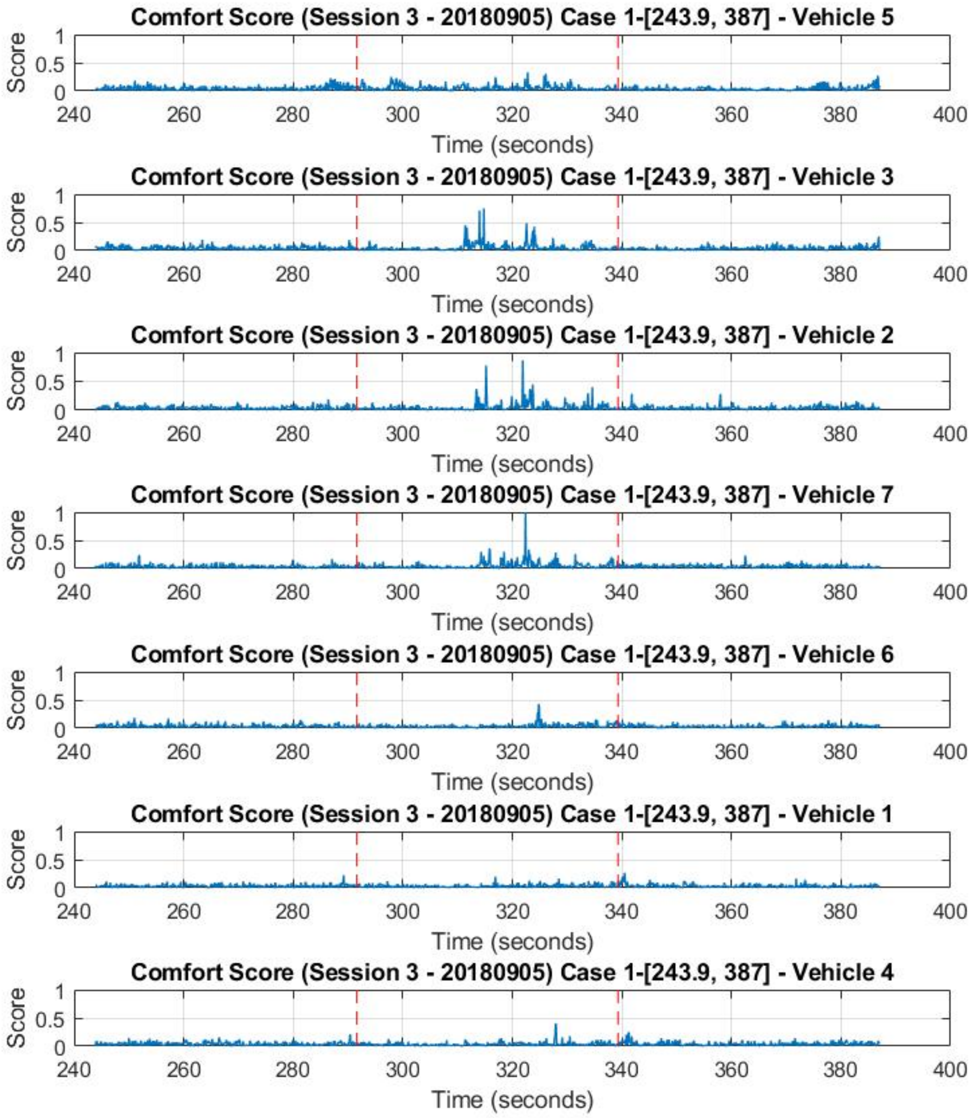

Figure 4.5: Examples of comfort in cases

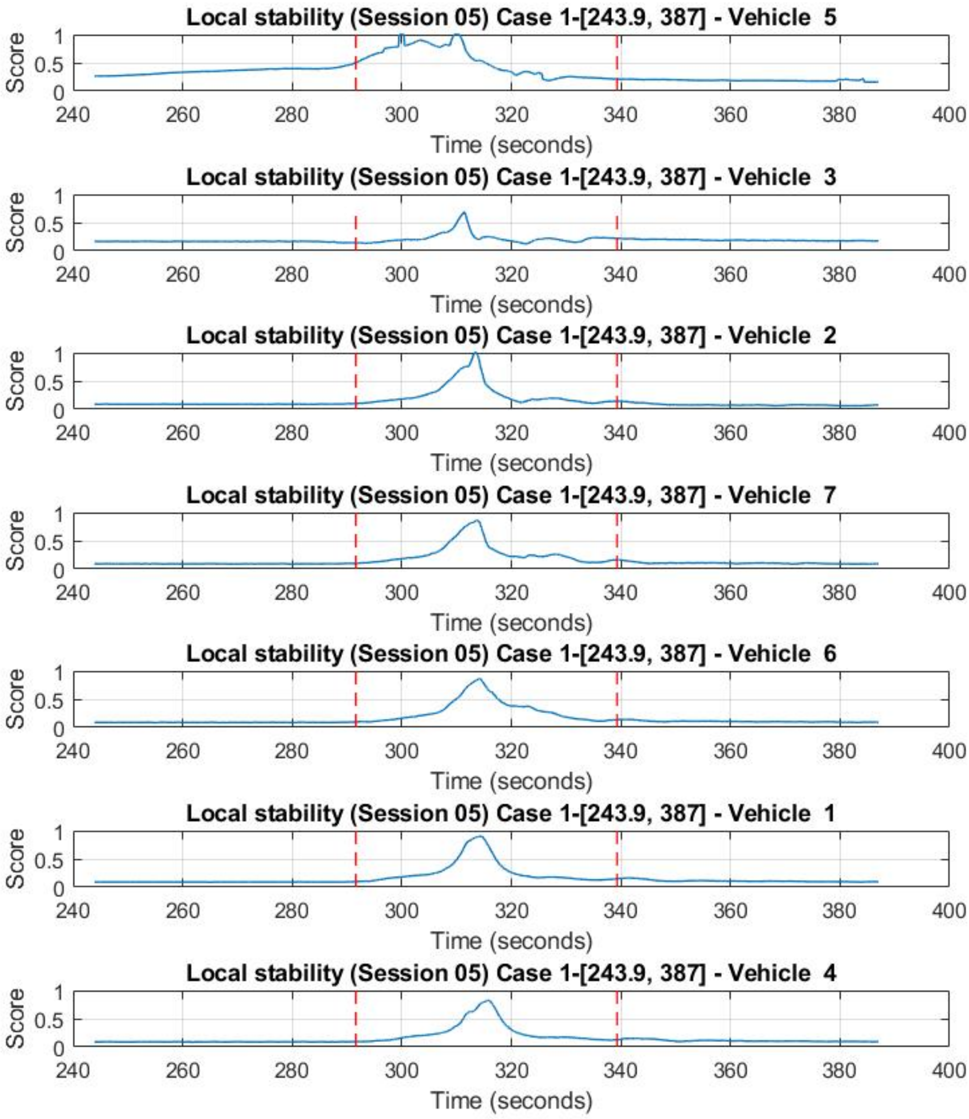

Figure 4.6: Examples of local stability in cases

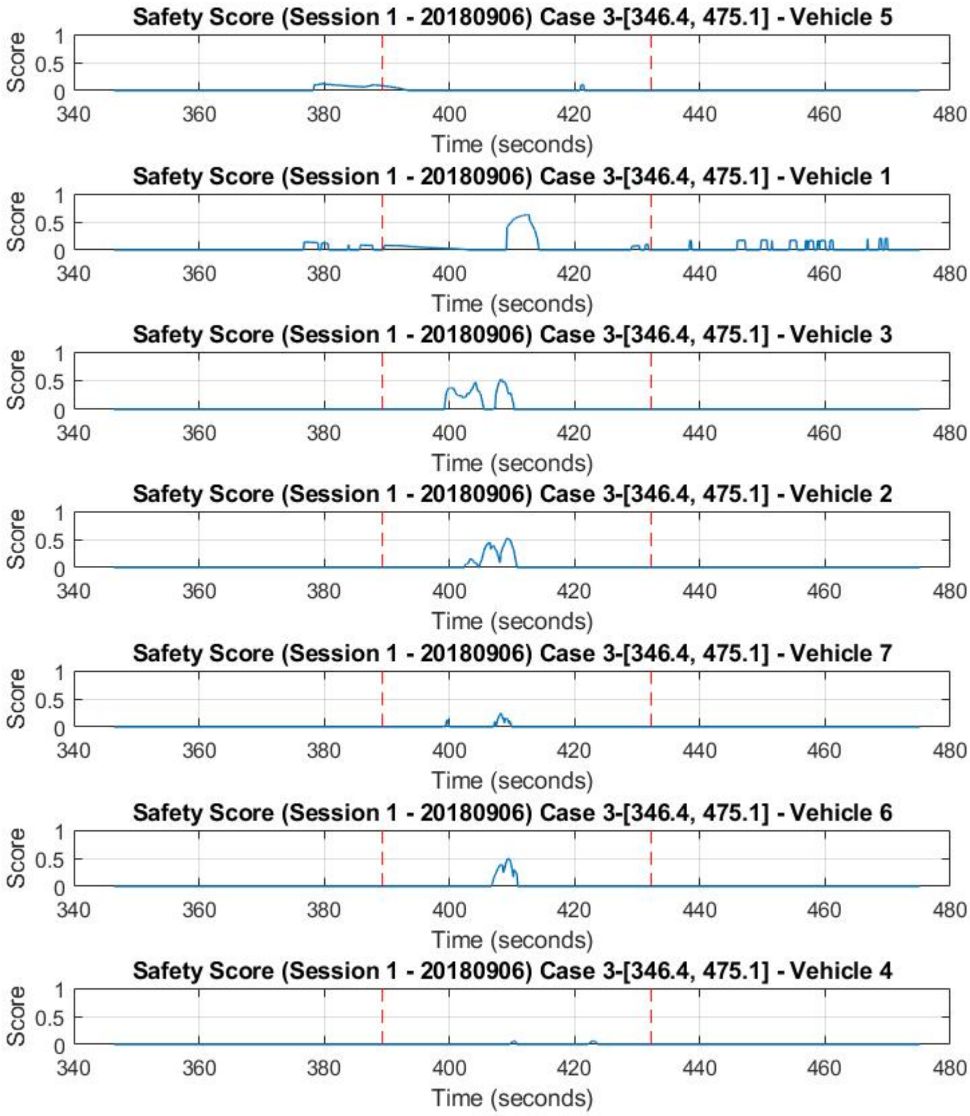

Figure 4.7: Examples of safety in cases

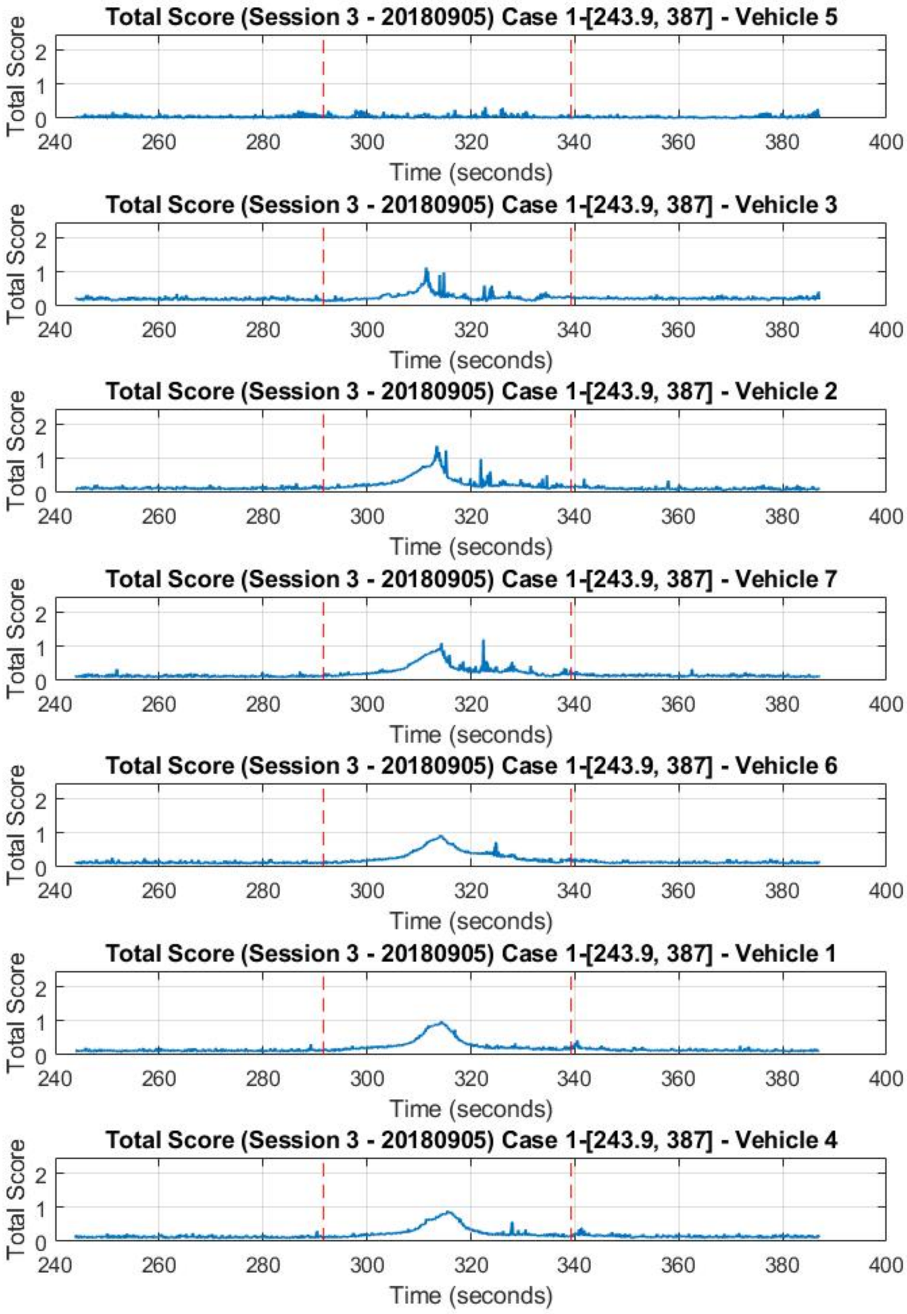

Figure 4.8: Tracking condition for Case1

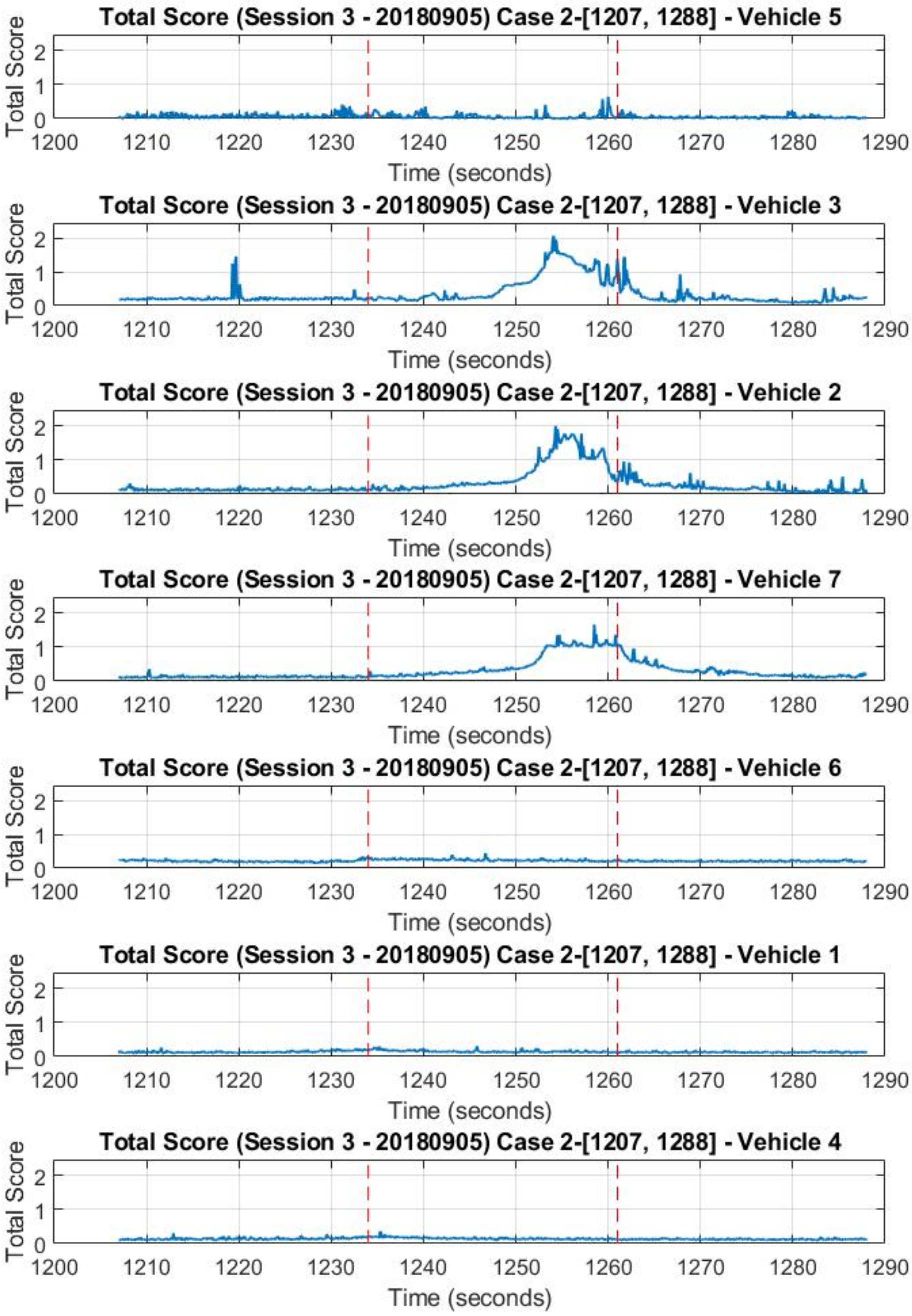

Figure 4.9: Tracking condition for Case2

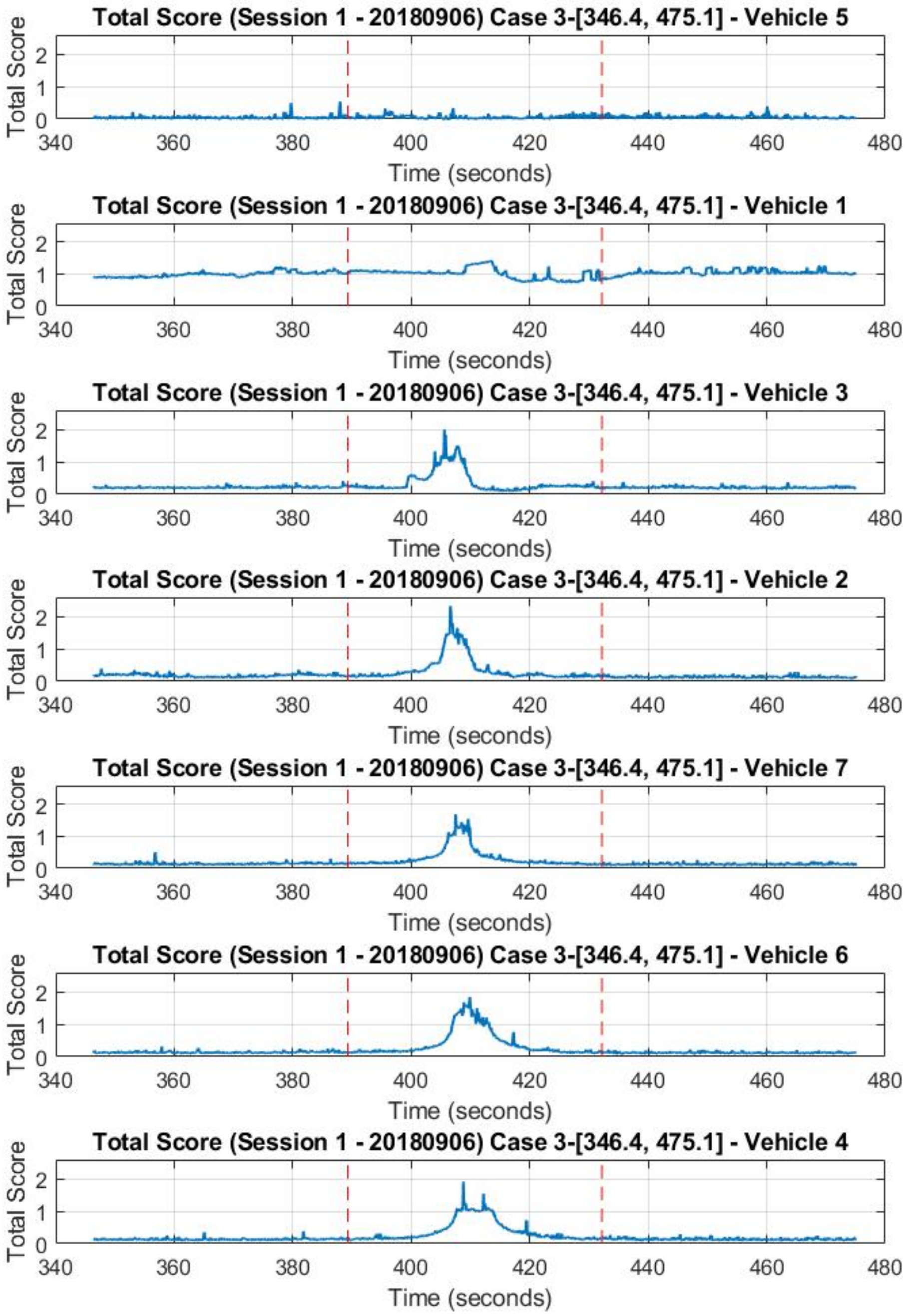

Figure 4.10: Tracking condition for Case3

4.2.2. Platoon Tracking Performance Analysis

The principal aim of this study was to investigate if disturbance affects the CACC platoon for human reasons and to what extent these effects affect the platoon's ability to track human reasons. It is particularly interested in how these disturbances might affect the platoon's tracking capability among three time windows. To investigate this, initially employed an ANOVA test. The purpose of the ANOVA was to ascertain if there were any overall differences

Table 4.3: Case 1's statistical analysis test result

(I) Case1		Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Before disturbance	During disturbance	-.14780*	0.0031	0.0000	-0.1553	-0.1403
Before disturbance	After disturbance	-.00904*	0.0031	0.0118	-0.0165	-0.0015
During disturbance	After disturbance	.13876*	0.0031	0.0000	0.1313	0.1463

*. The mean difference is significant at the 0.05 level.

Table 4.4: Case 2's statistical analysis test result

(II) Case2		Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Before disturbance	During disturbance	-.30511*	0.0124	0.0000	-0.3349	-0.2753
Before disturbance	After disturbance	-.05481*	0.0124	0.0000	-0.0846	-0.0250
During disturbance	After disturbance	.25030*	0.0124	0.0000	0.2205	0.2801

*. The mean difference is significant at the 0.05 level.

in platoon performance. It is crucial to note that this test alone cannot tell us which specific conditions are different from each time window. Therefore, following the indication of significant differences from the ANOVA test, utilized the Bonferroni Post Hoc test. The rationale behind employing the Bonferroni adjustment lies in its ability to conduct multiple pairwise comparisons. By using this method, individual comparisons can be made between different conditions to pinpoint where the significant differences lie, thus providing a more granular analysis of the platoon's response to disturbances.

- Case1
  In the Bonferroni post hoc comparison for Case 1, significant mean differences among the three phases—before the disturbance, during the disturbance, and after the disturbance—provide a statistical basis for assessing the vehicle platoon's response to the disturbance. (Table 4.3)

  A marked deterioration in the tracking condition is observed as the platoon transitions from a pre-disturbance state to one where it encounters a disturbance, with a mean difference of -0.14780 ($p < 0.001$). This pronounced difference points to the acute sensitivity of the platoon's tracking condition to disruptions and the immediate impact of disturbances on system performance.

  Following the disturbance, there is a statistically significant, albeit smaller, mean difference of -0.00904 ($p = 0.012$) between the pre-disturbance and after-disturbance conditions. This indicates that while the platoon's tracking condition improves after the disturbance—demonstrated by a mean difference of 0.13876 ($p < 0.001$) when comparing during the disturbance to after the disturbance—it does not completely return to its initial baseline state within the observed timeframe.
- Case2
  During the disturbance, the significant increase in score (mean difference = -0.3051, $p < 0.0001$) signals a substantial deterioration in the platoon's tracking condition. This marked degradation, with a confidence interval ranging from -0.3349 to -0.2753, points to the profound effect disturbances have on the system's performance. (Table 4.4)

  The recovery phase after-disturbance indicates a significant amelioration, with a mean score difference of 0.25030 ($p < 0.0001$) compared to the during-disturbance phase. However, when considering the persistent decrease in score from before the disturbance to after (mean difference = -0.05481, $p < 0.0001$), the data suggest that the platoon does not entirely return to its before-disturbance state. The existence of a time window lag, which may cause a delay in the system's full response to the disturbance, could explain why the scores do not fully revert to their initial levels.
- Case3
  For Case 3, the Bonferroni post hoc analysis based on the given ANOVA results yields an insightful narrative about the platoon's tracking condition through each phase of the disturbance. (Table 4.5)

  The analysis signifies a marked deterioration during the disturbance with a mean score reduction of -0.15297 ($p < 0.0001$) from the pre-disturbance phase. The negative value here, given that a higher score indicates worse conditions, suggests a substantial decline in the platoon's tracking condition due to the disturbance. The confidence interval, not encompassing zero, reinforces the significance and magnitude of this change.

Table 4.5: Case 3's statistical analysis test result

(III) Case3		Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Before disturbance	During disturbance	-.15297*	0.0090	0.0000	-0.1744	-0.1315
Before disturbance	After disturbance	0.00042	0.0090	1.0000	-0.0210	0.0219
During disturbance	After disturbance	.15339*	0.0090	0.0000	0.1319	0.1749

*. The mean difference is significant at the 0.05 level.

Interestingly, the mean difference in scores from the before-disturbance phase to the after-disturbance phase is negligible and non-significant (mean difference = 0.00042, p = 1.0000). This finding suggests that the platoon's tracking condition after-disturbance is virtually indistinguishable from the pre-disturbance condition, indicating a full recovery. This is an important point to note, as it demonstrates the platoon's ability to return to its original state once the disturbance has ceased.

However, when directly comparing the during-disturbance phase to the after-disturbance phase, there is a significant mean increase in the score (mean difference = 0.15339, p < 0.0001), which again suggests improvement as the condition after-disturbance is significantly better than during the disturbance. The positive mean difference and its corresponding confidence interval show that the platoon's tracking condition has substantially recovered from the disturbed state.

4.2.3. Platoon Tracking Performance Effect Size Analysis

Effect size analysis is essential because it tells us how much the disturbances matter; it quantifies the real-world impact of these effects on CACC platooning systems beyond mere statistical significance. Cohen's d measured the effect size of the pairwise comparisons between varying observations, and the descriptors for magnitudes of 0.01, 0.20, 0.50, 0.80, 1.20, and 2.0 were suggested as the critical reference values corresponding to very small, small, medium, large, very large, and huge, respectively (Cohen, 2013; Sawilowsky, 2009). These values provide a general rule for gauging the practical significance of the difference between means, with larger absolute values of d indicating a larger effect size. Note that the significance level was set to 5% in the above analyses.

Cohen's d is a statistical measure used to quantify the effect size of an experimental intervention or the difference between two means. It is widely utilized in the fields of psychology, education, and social science to assess the magnitude of treatment effects and differences between groups.

The formula for Cohen's d is given by:

$$d = \frac{\bar{X}_1 - \bar{X}_2}{SD_{pooled}}$$

where $\bar{X}_1$ and $\bar{X}_2$ are the sample means of the two groups and SD_{pooled} is the pooled standard deviation. The pooled standard deviation is calculated as the square root of the average of the squared standard deviations for each group.

$$SD_{pooled} = \sqrt{\frac{SD_1^2 + SD_2^2}{2}}$$

where SD_1 and SD_2 are the standard deviations of the two groups.

- Case1 (Table 4.6)

  Before vs. During: The pooled standard deviation is 0.15055, and Cohen's d is 0.98179. This represents a large effect size, indicating that the disturbance had a substantial impact on the performance metric during the event compared to the before-disturbance measurements.

  During vs. After: The pooled standard deviation is 0.15225, and Cohen's d is -0.91144. This is also a large effect size but in the opposite direction. The negative sign indicates that the performance metric decreased after the disturbance, moving back toward the before-disturbance level.

  Before vs. After: The pooled standard deviation is 0.058396, and Cohen's d is 0.15482. This effect size is smaller than the other two, falling in the small to medium range. It suggests that there was a slight but not substantial difference in the performance metric from before the disturbance to after it.

These effect sizes show a significant impact during the disturbance that partially reverses after the event. The small effect size from Before to After indicates that overall performance metrics may have largely stabilized after the initial disruption.

- Case2 (Table 4.7)

  Before vs. During: The pooled standard deviation is approximately 0.329811, and Cohen's d is 0.925117. This is a large effect size according to Cohen's conventions, indicating a substantial increase in the performance metric during the disturbance compared to the Before-disturbance condition.

  During vs. After: The pooled standard deviation is 0.348302, and Cohen's d is -0.718630. The negative value of Cohen's d indicates a large effect size in the opposite direction, with a significant decrease in the performance metric after the disturbance compared to during the disturbance.

  Before vs. After: The pooled standard deviation is 0.145076, and Cohen's d is 0.377826. This represents a medium effect size, suggesting a moderate change in the performance metric from the Before-disturbance to the after-disturbance condition.

- Case3 (Table 4.8)

  Before vs. During: The effect size (Cohen's d) of 0.427541 suggests a moderate effect of the disturbance on the performance metric. This indicates that during the disturbance, there was a noticeable change in the metric compared to the before-disturbance state.

  During vs. After: The effect size (Cohen's d) of −0.418274 also suggests a moderate effect size but in the opposite direction. The negative sign indicates that the performance metric decreased after the disturbance ended, moving closer to the Before-disturbance level.

  Before vs. After: The effect size (Cohen's d) of −0.001328 is very close to zero, indicating that there is no practical difference in the performance metric from before the disturbance to after it. This implies that any changes that occurred during the disturbance were not sustained and the after-disturbance measures returned to near Before-disturbance levels.

  The near-zero effect size for the Before vs. After comparison is consistent with the idea that the system's performance was stable over time despite the temporary disturbance.

Table 4.6: Effect sizes (Cohen's d) for Case 1

Comparison	Pooled SD	Cohen's d	Magnitudes
Before vs. During	0.15055	0.98179	Large
During vs. After	0.15225	-0.91144	Large
Before vs. After	0.058396	0.15482	Small

Table 4.7: Effect sizes (Cohen's d) for Case 2

Comparison	Pooled SD	Cohen's d	Magnitudes
Before vs. During	0.329811	0.925117	Large
During vs. After	0.348302	-0.718630	Large
Before vs. After	0.145076	0.377826	Medium

Table 4.8: Effect sizes (Cohen's d) for Case 3

Comparison	Pooled SD	Cohen's d	Magnitudes
Before vs. During	0.357800	0.427541	Medium
During vs. After	0.366729	-0.418274	Medium
Before vs. After	0.315492	-0.001328	Very small

4.2.4. Result and Discussion

The impact of disturbances on CACC platoons has been analyzed through the examination of components such as safety, comfort, and local stability to produce the final results about 'tracking'.

Upon examining the platoon average total score, which is calculated based on the number of vehicles in the platoon, along with analyzes of individual vehicles and statistical data, it becomes evident that the tracking condition of the platoon exhibits a clear and consistent pattern across three distinct phases: before disturbance, during disturbance, and after disturbance.

In Case 1, the platoon tracking condition remained relatively stable until the onset of a disturbance, where a pronounced spike in the total score denoted a significant degradation in condition Figure 4.12. The after-disturbance phase depicted a decrease in score, indicating a recovery toward the before-disturbance state, yet statistical analysis suggests this recovery was not complete. This implies that while the platoon is capable of mitigating the impact of disturbances, the residuals of the disruption linger, preventing a full return to baseline conditions.

The outcomes from Case 2 reinforced these findings. The introduction of a disturbance resulted in a similar, significant increase in the score. However, the continued increase in the average total score after disturbance, along with indications of a time-window lag, indicates that the system's response to the disturbance was not immediate. It implies that the system's processes, after beginning recovery, may take longer to fully compensate for the disturbance's effects.

In Case 3, the disturbance elicited a sharp peak in the average total score, but the subsequent recovery was notably distinct. The after-disturbance phase scores returned to a level statistically indistinguishable from the before-disturbance phase, denoting a complete recovery of the platoon's tracking condition. This suggests that the platoon's adaptive mechanisms were fully effective in this instance, allowing the system to nullify the disturbance's impact over time.

Collectively, these findings demonstrate a platoon system that is responsive to external disturbances, but shows variability in its ability to recover. Although Case 3 offers an example of complete recovery, Cases 1 and 2 highlight opportunities to improve the adaptive control strategies of the platoon. The ability to recover from disturbances is a critical aspect of platoon operation, which requires further attention to ensure resilience in varying conditions. This research contributes to the understanding of autonomous vehicle platoons under disturbance and informs the ongoing development of robust control systems capable of maintaining stable tracking conditions.

All three cases demonstrated statistically significant changes in the platoon's ability to track human intentions when experiencing disturbance, proving that disturbance does affect the platoon's tracking condition. The platoon responded differently to the different cases. Firstly, case 1 demonstrated that the platoon did not return to the before-disturbance level of tracking condition, even though the platoon completed a certain level of response after the disturbance ended. condition was not restored to the level before the disturbance, this disturbance explains the platoon's resilience having some problems. Case 2 shows that in some cases the platoon does not recover immediately, which may be related to the choice of the time window but may still indicate that the platoon does not recover quickly. Case 3 provides an example of perfect recovery, where the platoon demonstrated a decrease in tracking ability while experiencing the disturbance, but after the disturbance was over the platoon returned to its original state, demonstrating strong resilience. (Figure 4.11)

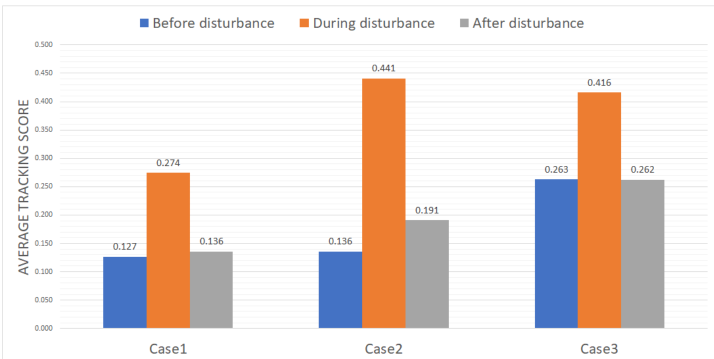

Figure 4.11: Average tracking score for three cases

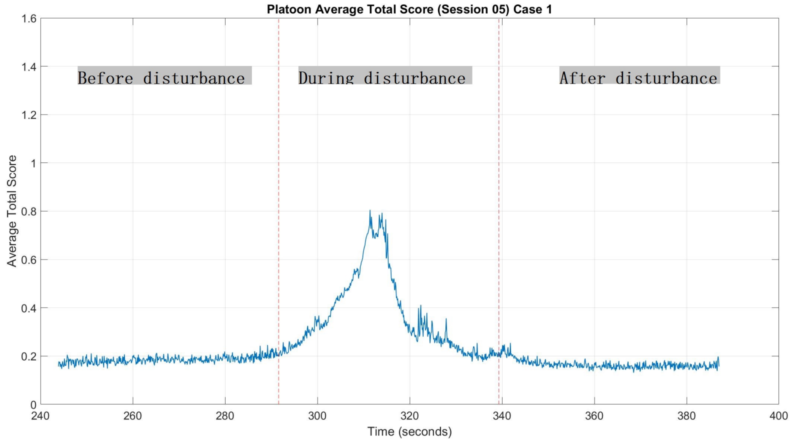

Figure 4.12: Average Tracking condition for Case1

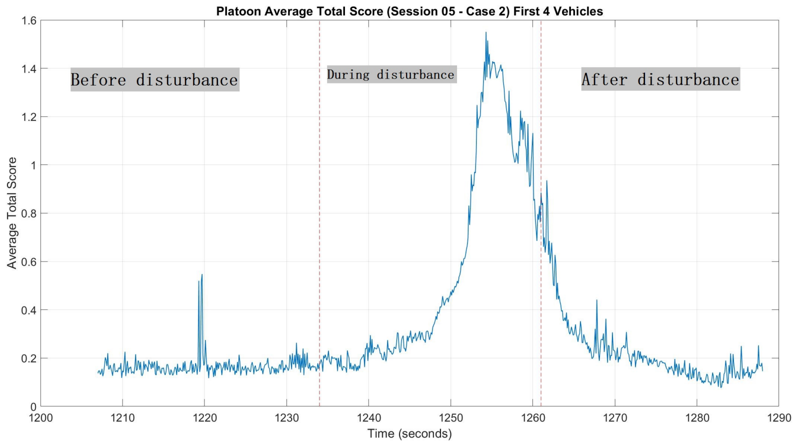

Figure 4.13: Average Tracking condition for Case2

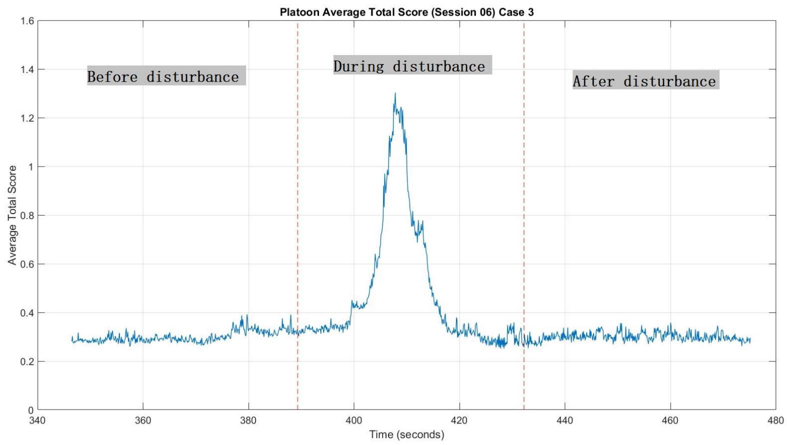

Figure 4.14: Average Tracking condition for Case3

5
Conclusion

The last chapter will begin with a review of the findings of Chapter 4, followed by a discussion based on the current literature study and answer the research question. Then, practical implications are discussed. The chapter concludes by discussing the limitations of the study and presenting recommendations for further research.

5.1. Conclusion

This research evaluates the effect of disturbances on the capability of CACC platoons to track human behaviors in terms of safety, comfort, and local stability. Based on a comprehensive analysis and evaluations, this research demonstrated that the ability of the CACC platoon to maintain effective tracking remains limited under disturbance conditions, highlighting their robustness and adaptability in challenging environments. The findings show that under the MHC concept, the effects of disturbance on the platoon do exist and that the platoon's ability to track human causes when disturbed receives an impact that varies for different disturbance scenarios, both in terms of degree of impact, duration of impact, and resilience. The study revealed that disturbances had a direct impact on platoon dynamics, particularly on the platoons' ability to closely follow the behaviors of human drivers. In addition, the impacts were quantified by employing statistical methods like ANOVA and Bonferroni Post Hoc tests, along with effect size analyses through Cohen's d. The implications of these findings were significant for the integration of MHC principles in autonomous driving technologies. The study's findings show that to enhance the safety and reliability of CACC platoons, a more thorough incorporation of human oversight is required.

The implications of these findings are significant for the integration of MHC principles in autonomous driving technologies. Our results suggest that to enhance the reliability and safety of CACC platoons, a more robust incorporation of human oversight is necessary. As illustrated by our analysis of Cohen's d values across different cases, when evaluating our automated vehicle system according to the principles of Meaningful Human Control, the results showed fluctuations in tracking, probably due to disturbances. This study also provided empirical evidence of the potential problem and areas for improvement in CAV technologies. The research result can provide a direction to facilitate policymakers, road authorities, or automated system developers to evaluate the performance of their systems in case of disturbances and to provide quantitative evaluation criteria so that they can check if and how much the improvements improve the system after identifying the problem and improving it.

5.2. Discussion

Given that the findings of this study differ slightly from the conclusions obtained by the other studies covered in Chapter 2, a discussion of the findings of this study is necessary. Similarly to the findings of Chen et al., 2018 (2018), this study confirmed that disturbances such as bad weather and complex road geometries critically impact the performance of the CACC platoon. This alignment with the literature emphasizes the universal challenges faced by CACC systems in different research and operational settings.

Moreover, the quantification of performance degradation using Cohen's d provides a robust statistical foundation that adds to the body of evidence in autonomous vehicle research. For example, Vahidi and Sciarretta, 2018 (2018) discussed how external disturbances such as traffic density and road conditions could challenge CACC systems. The effects sizes observed in this study ($d = 0.41$ to $d = 0.98$) not only validate these concerns, but also provide quantified information on the severity of these impacts, suggesting that disturbances can lead to significant reductions in the performance of the system.

In addition, while this study discovered that CACC systems' performance can deteriorate in the face of unexpected environmental and operational disturbances, Ioannou and Chien (1993) demonstrated that adaptive cruise control systems, including CACC, can maintain robust performance and adapt effectively to disturbances without significantly compromising safety or efficiency. They claim that the system's inbuilt flexibility and real-time reaction capabilities allow it to handle a variety of disturbances while remaining stable and efficient. This gap might be explained by the current study's limitations, notably its dependence on existing datasets from CACC field operational testing, which may not capture all real-world factors or scenarios. These challenges highlight the importance of continued study to better understand and improve the performance of CACC systems in a variety of real-world circumstances.

5.3. Practical Implications

This study has some practical implications about potential issues and prospects for the development of CAV technology. The findings of this study may benefit policymakers by developing regulations and norms to enable the safe integration of CAVs into current transportation infrastructures. Along similar lines, the findings of this study can help policymakers to develop regulations that prioritize public safety by addressing the possible dangers and disturbances associated with CAVs. Moreover, the findings of this study may provide automated system developers with a framework for evaluating the performance of their systems in various disturbance situations, resulting in more robust and reliable CAV systems. Identifying and tracking particular disturbances could encourage ongoing progress and innovation in CAV technology, making it more adaptable and efficient.

In summary, the study's practical implications play an important role in directing the safe, effective, and innovative development of CAV technology, which will benefit a wide variety of stakeholders, from policymakers to developers. Finally, insights into potential for growth inform strategic planning and resource allocation, ensuring that the progress of CAV technology is in line with the demands of the future. In combination, the above benefits considerably improve the overall reliability, security, and efficiency of CAV systems, facilitating their effective incorporation into current transportation networks.

5.4. Limitation

This study, like other studies, has substantial limitations, some of which propose interesting possibilities for further research. First, the findings of this research may be context-specific and applicable to the specific CACC platooning systems and the disturbance scenarios considered. The research is heavily based on the analysis of existing data sets from CACC field operational tests. Due to its reliance on pre-existing data sets from CACC field operational tests, the research is limited since it might not account for the most recent developments and practical problems in CAV technology. Furthermore, biases and inconsistencies may be introduced by the multiple tests' varied data gathering techniques and quality standards, which could compromise the validity of the results.

For instance, this study did not extract the occurrence of "disturbance" directly from the data, therefore, had to infer the presence of disturbance by associating it with other factors. This indirect technique contains possible errors and assumptions that may fail to reflect the nuances of real-world disturbances. Furthermore, this study uses disengagement to identify the existence or absence of disturbance, which, while demonstrated robustly in the literature analysis, has significant limitations. This approach may ignore subtler types of disruption that may not result in disengagement, thus reducing the findings' comprehensiveness and reliability. To begin with, the occurrence of disengagement and disturbance is not synchronized, resulting in a deviation from our time window in case 2. Second, simply disengaging does not provide a clear picture of the real disturbance. It is feasible to make certain assumptions based on other factors, such as vehicle speed or trajectory maps, although this is also not accurate. Knowing the particular disturbance will help future researchers improve the infrastructure or autonomous driving systems to better accommodate this disturbance. Future research should aim to refine the data collection and analysis methods to better identify and characterize disturbances. Expanding the datasets to include more varied and extensive scenarios could enhance the generalizability of the findings. Furthermore, the metrics used in this study are traffic-related metrics, and in the future more metrics could be introduced if the operation of the CACC platoon in collaboration with MHC with cross-disciplinary experts in ethics and law is essential to address the broader implications of integrating MHC in autonomous vehicle technologies. Lastly, developing more advanced algorithms that can adaptively respond to unexpected disturbances could significantly improve the practical deployment of CACC systems.

Although this research considers ethical and legal implications, it may not fully address all the ethical and legal complexities associated with the integration of MHC into CACC platooning systems. Firstly, the stakeholders included in this study for tracking are the test designer and the driver, both of which are stakeholders that are clearly present in the test. However, in a real traffic environment, the stakeholders that need to track may also include society, government, other road users, and passengers. So not all stakeholders are involved in this study. Further research and collaboration with legal and ethical experts are essential to fully understand and address these considerations. By acknowledging these limitations, future research can build upon this work and address these concerns to further advance the understanding and implementation of MHC in CACC platooning systems facing disturbances.

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