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PHD THESIS

Exploiting Connected Autonomous Vehicles to Improve Mixed Traffic Safety and Efficiency in Realistic Scenarios

Author:
Mohit Garg

Supervisor:
Dr. Mélanie Bouroche

25th July 2024

Declaration

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Abstract

Human-driven vehicles (HDVs) produce stop-and-go waves i.e., high speed variations, due to humans' large-reaction times and perception errors. This leads to decrease in both traffic safety and efficiency. In contrast, connected autonomous vehicles (CAVs) exploit information from surrounding vehicles via V2V communication, which enables them to adapt their speed based on the precise information (position, speed and acceleration) from the vehicles ahead of them within their communication range. This is expected to result in improved traffic safety and efficiency in pure CAV traffic. In the near future, however, CAVs and HDVs will coexist on the road (mixed traffic), and it may take decades to transform existing transportation systems into fully connected and autonomous environments. In mixed traffic scenarios, information exchange among vehicles may not always be possible due to the presence of human-driven vehicles that do not have communication capabilities. Furthermore, as wireless vehicular networks are unreliable, information from other vehicles can be delayed or lost, which brings more challenges for CAVs in utilizing information from other vehicles.

While the impact of CAVs on traffic safety and efficiency at different market penetration rates (MPRs) has been studied extensively, CAVs have typically been assumed to operate in large-scale traffic scenarios with perfect communication. The few studies that consider imperfect communication include only a very small number of vehicles. Furthermore, most existing work on investigating the impact of CAVs in mixed traffic and unreliable communication environments is based on the simple predecessor-following information flow topology, where a CAV takes information only from the vehicle it follows. In such scenarios, a CAV degrades its longitudinal driving mode to sensor-based control if the preceding vehicle is a HDV, or when it cannot obtain information due to communication failures. This results in reductions in both traffic safety and efficiency. Although traffic safety can be improved by

increasing the CAV time headway, this is at the expense of a reduction in traffic efficiency. To avoid CAV mode degradation, a number of studies propose equipping HDVs with communication devices. While this approach can avoid CAV mode degradation if the preceding vehicle is a HDV, it cannot avoid degradation in case of communication failures. In addition, the cost of retrofitting HDVs with communication-capability is likely to be prohibitive for at least a proportion of their owners.

Exploiting information from multiple leading vehicles within their communication range might increase the resilience of CAV control algorithms, contributing to improved traffic safety and efficiency (compared to single-vehicle information-based control). While a few researchers have attempted to develop CAV car-following control algorithms considering information from more than one leading vehicle, for CAVs operation in unreliable communication and/or mixed traffic environment, most of these studies assume that the number and type of vehicles they can get information from is fixed, which does not hold in the presence of communication failures or HDVs. In recent years, a few robust car-following control algorithms have been developed for CAVs operation in mixed traffic environment that can handle varying the number and type of vehicles they can get information from, but they have only been validated in very limited scenarios for a small number of vehicles (with a fixed sequence of CAVs and HDVs) in a platoon, assuming perfect communication. These three assumptions (fully connected traffic, perfect communication or fixed sequence of vehicles) are unrealistic to investigate the impact of CAVs on mixed traffic safety and efficiency in realistic scenarios in terms of traffic composition (mixed traffic), communication (not assumed to be reliable) and traffic scenario with real traffic demand (i.e., typically a large number of vehicles).

To fill these research gaps, the goal of this work is to investigate the impact of CAV penetration rates when they can exploit information received from multiple, rather than a single, leading vehicles in realistic scenarios. To accomplish this, firstly, a car-following control algorithm is designed for CAVs to be able to cope with varying numbers and types of vehicles they can get information from for CAV operation in mixed traffic and unreliable communication environments. Then, CAV controller parameters are tuned such that it can provide significant improvement in both mixed traffic safety and efficiency. Finally, in order to better adapt to varying the number and type of vehicles they can get information

from, in mixed traffic and unreliable communication environments, an adaptive information weights assignment approach is developed for the proposed controller. These approaches are evaluated using simulation studies of CAVs in realistic communication and traffic scenarios at different market penetration rates, using real motorway traffic data (the M50 motorway, in Ireland). Considering realistic scenarios in terms of imperfect communication, humans large reaction time and perception errors, and traffic scenarios, these simulation studies assess the effect of different penetration rates of CAVs on traffic safety and efficiency using the time-to-collision (TTC) performance metric (for the safety evaluation), as well as the travel time metric (to evaluate traffic efficiency). Results have reported two primary findings. Firstly, they show that imperfections in V2V communication links and drivers large reaction time have adverse effects on both safety and efficiency. Secondly, they illustrate that by properly tuning of CAV controller parameters (control gains and time headways), in realistic scenarios both traffic safety and efficiency still improve significantly as the CAV penetration rate increases. The results of this work thus represent a significant step towards the deployment of CAVs on motorways in the near future.

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Conferences

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Contents

Declaration	i
Abstract	iii
Acknowledgements	vii
Publications	ix
Contents	xi
List of Figures	xv
List of Tables	xix
List of Acronyms	xxi
1 Introduction	1
1.1 Motivations	3
1.2 Challenges	4
1.2.1 Challenges due to Unreliable Communication	5
1.2.2 Challenges due to Mixed Traffic	6
1.2.3 Challenges due to Mixed Traffic with Unreliable Communication	6
1.3 Existing Approaches	7
1.4 Research Questions	10
1.5 Thesis Approach	11
1.6 Contributions	12
1.7 Scope	15
1.8 Organization	16
1.9 Summary	17
2 Background	19
2.1 Levels of Automation	19
2.2 Communication Technologies	20
2.3 Car-following Control	22
2.3.1 Control Architecture	22
2.3.2 Spacing Policies	24
2.3.3 Information Flow Topologies	25
2.4 Lateral Control	25
2.5 Summary	28

3	Related Work	29
3.1	Control Strategies to Address Unreliable Communication	29
3.1.1	Homogeneous CACC Systems	30
3.1.2	Heterogeneous CACC Systems	35
3.2	Control Strategies to Address Mixed Traffic	40
3.2.1	Predecessor-Following IFT-based Control	42
3.2.2	Multiple-Predecessor-Following IFT-based Control	45
3.2.3	Managed Lane and Platooning Strategies	50
3.3	Control Strategies to Address Mixed Traffic with Unreliable Communication . .	53
3.4	Knowledge Gaps Analysis and Research Questions	57
3.5	Baseline Approach	61
3.6	Summary	63
4	System Model	65
4.1	Car-following Models	65
4.1.1	HDV Car-following Model	66
4.1.2	CACC Car-following Model	68
4.1.3	ACC Car-following Model	70
4.2	Lane-changing Models	71
4.3	Assumptions	72
4.4	Summary	75
5	Design	77
5.1	Motivation	78
5.2	PF IFT-based Control	78
5.2.1	PF IFT-based Controller Model	80
5.2.2	The PLOEG controller	81
5.2.3	Extending the PLOEG Controller in Mixed Traffic and Unreliable Com- munication Environments	82
5.2.4	Cautious Car-following Approach	83
5.3	MPF IFT-based Control	84
5.3.1	Controller Design	86
5.3.2	Controller Parameters Tuning	88
5.3.3	An Adaptive Distance-based Control Approach for Controller Parameters Tuning	92
5.3.4	Stability Analysis	96
5.4	Summary	97
6	Implementation	99
6.1	Simulator Choice	99
6.1.1	Traffic Simulators	100
6.1.2	Network Simulators	101
6.1.3	Vehicular Network Simulators	101
6.1.4	Analysis	102
6.2	Simulation Set-up	102
6.3	Control Algorithms Implementation	104
6.3.1	Car-following Control in SUMO	105
6.3.2	V2V Communication Protocols and Applications in Veins	107

6.4	Summary	109
7	Evaluation	111
7.1	Evaluation Objectives	111
7.2	Evaluation Setup	112
7.2.1	Traffic Scenarios	113
7.2.2	Communication Network Simulation	116
7.2.3	Performance Metrics	117
7.2.4	Evaluation Scenarios	120
7.3	Evaluation of PF IFT-based Control	122
7.3.1	Effect of Unreliable V2V Communication Links	122
7.3.2	Effect of Large Reaction Times and Perception Errors	125
7.3.3	Cautious Car-following Approach	128
7.3.4	Evaluation of PF IFT-based CAV Control in Free-flow and Saturated Traffic Conditions	131
7.3.5	Evaluation Summary of PF IFT-based Control	133
7.4	Evaluation of MPF IFT-based Control	134
7.4.1	Effect of Unreliable V2V Communication Links	134
7.4.2	Control Parameter Tuning Evaluation	140
7.4.3	Effect of Large Reaction Times and Perception Errors	142
7.4.4	Adaptive Information Weights Assignment Approach	143
7.4.5	Proposed Approach and Baseline Comparison	145
7.4.6	Evaluation of MPF IFT-based Control in Free-Flow and Saturated Traffic Conditions	148
7.4.7	Evaluation Summary of MPF IFT-based Control	149
7.5	Evaluation Challenges	151
7.6	Summary	152
8	Conclusions and Future Scope	155
8.1	Thesis Contributions	155
8.2	Limitations	158
8.3	Future Research Directions	160
	Bibliography	163

List of Figures

1.1	CAV longitudinal control degradation in the presence of communication failures.	5
1.2	CAV longitudinal control degradation in mixed traffic.	7
1.3	Various Information Flow Topologies (IFTs) for a string of vehicles performing car-following.	8
2.1	Automated driving levels [Galvani, 2019].	20
2.2	Car-following control systems.	23
2.3	Hierarchical longitudinal control architecture.	23
2.4	General Car-following Control Structure [Milanés and Shladover, 2014]. . . .	24
2.5	Various Information Flow Topologies (IFTs) for a string of vehicles performing car-following.	26
2.6	Hierarchical lateral control architecture.	27
3.1	Master-slave based CACC operation, where e_i and $u_{i,c}$ are the inter-vehicle distance error, and desired acceleration of the vehicle i (computed in the preceding vehicle $i-1$) respectively [Xing et al., 2020].	33
3.2	CACC Clustering Strategies [Zhong et al., 2020].	51
4.1	Flow chart of the different control modes of ACC-CACC car-following models.	68
5.1	Predecessor-following-IFT-based control design.	79
5.2	Predecessor-following-IFT-based control design for CAVs in mixed traffic environment.	83
5.3	Multiple-predecessor-following-IFT-based control design.	85

5.4	Multiple-predecessor-following-IFT-based control design for CAVs in mixed traffic environment.	87
5.5	Controller parameters (time headway and control gains) tuning based on the number of safety conflicts at different penetration rates of CAVs (20%, 40%, 70%, 100%), with and without packet drops	90
5.6	Controller parameters (time headway and control gains) tuning based on travel time at different penetration rates of CAVs (20%, 40%, 70%, 100%), with and without packet drops	91
5.7	CAVs control using information from multiple leading vehicles in mixed traffic	94
6.1	Plexe simulation framework [Segata et al., 2022].	103
6.2	Plexe Car-following Models [Segata et al., 2014].	105
6.3	V2V communication [Jia et al., 2021].	108
7.1	Rendering of the M50 motorway road network	114
7.2	Screenshot of realistic traffic scenario along M50 motorway, Ireland using SUMO	115
7.3	Number and location of safety conflicts using the MPF IFT-based CAV control at 0% penetration rate	123
7.4	Travel time rate (min/km) using the PF IFT-based CAV control at different penetration rates, with and without packet drops, (a) MPR 0%, (b) MPR 20% and PER 0%, (c) MPR 20% and PER 70%, (d) MPR 40% and PER 0%, (e) MPR 40% and PER 70%, (f) MPR 70% and PER 0%, (g) MPR 70% and PER 70%, (h) MPR 100% and PER 0%, (i) MPR 100% and PER 70%	126
7.5	Traffic safety and efficiency performance using the PF IFT-based CAV control at different penetration rates, with and without packet drops.	127
7.6	Traffic safety and efficiency performance using the PF IFT-based CAV control at different penetration rates, packet error rates, and human driver reaction times.	128

7.7	Traffic safety and efficiency performance using the PF IFT-based CAV control at different penetration rates, packet error rates, and time headways (smaller CAV 0.6s, HDV 1.5s), (larger CAV 1s, HDV 2s) for a reaction time of 0.5s.	130
7.8	Traffic safety and efficiency performance using the PF IFT-based CAV control in free-flow traffic condition at different penetration rates, with and without packet drops.	132
7.9	Traffic safety and efficiency performance using the PF IFT-based CAV control in saturated traffic conditions at different penetration rates, with and without packet drops.	132
7.10	Number and location of safety conflicts using the MPF IFT-based CAV control at 0% penetration rate	135
7.11	Travel time rate (min/km) using the MPF IFT-based CAV control at different penetration rates, with and without packet drops, (a) MPR 0%, (b) MPR 20% and PER 0%, (c) MPR 20% and PER 70%, (d) MPR 40% and PER 0%, (e) MPR 40% and PER 70%, (f) MPR 70% and PER 0%, (g) MPR 70% and PER 70%, (h) MPR 100% and PER 0%, (i) MPR 100% and PER 70%	137
7.12	Traffic safety and efficiency at CAV different penetration rates, packet error rates, and controllers.	140
7.13	Effect on controller parameters tuning for specific MPR on the number of safety conflicts and travel time at different penetration rates and packet error rates.	141
7.14	Number of safety conflicts and travel time for both PF-IFT and MPR-tuned MPF-IFT controllers, for different penetration rates and packet error rates, considering large human reaction times.	143
7.15	Number of safety conflicts and travel time for both MPR-tuned MPF IFT and Adaptive-tuned MPF IFT controllers, for different penetration rates and packet error rates, considering large human reaction times.	144

7.16 Traffic safety and efficiency performance using the MPF IFT-based CAV control in free-flow traffic condition at different penetration rates, with and without packet drops.	148
7.17 Traffic safety and efficiency performance using the MPF IFT-based CAV control in saturated traffic condition at different penetration rates, with and without packet drops.	149

List of Tables

3.1	Summary of the different car-following control strategies for homogeneous CACC systems in unreliable communication environments	34
3.2	Summary of the different car-following control strategies for heterogeneous CACC systems in unreliable communication environments	41
3.3	Comparative study of the control strategies based on the predecessor-following IFT for CAVs operation in mixed traffic and their impact on traffic performance	44
3.4	Comparative study of the car-following control strategies based on the multiple-predecessor-following IFT for CAVs coordination in mixed traffic and their impact on traffic performance	49
3.5	Comparative study of the managed lane and platooning strategies for CAVs operation in mixed traffic and their impact on traffic performance	54
3.6	Comparative study of the control strategies of CAVs coordination in mixed traffic with unreliable communication and their impact on traffic performance	57
3.7	Summary of various existing baseline approaches	62
4.1	Car-following model parameters for simulated HDVs	67
4.2	Driver state device parameters simulating drivers' imperfection	67
4.3	Car-following model parameters for simulated CAVs	71
7.1	V2V communication protocol related simulation parameters	117
7.2	Evaluation scenarios summary	121
7.3	Number and location of safety conflicts using the PF IFT-based CAV control at different penetration rates, with and without packet drops	124
7.4	Summary of the effect of human driver's large reaction time on traffic safety and efficiency results, compared to smaller human reaction times	128

7.5	Summary of traffic safety and efficiency results with larger time headways, compared to shorter time headways	130
7.6	Comparison of safety conflicts at different penetration rates of CAVs	131
7.7	Comparison of overall travel time at different penetration rates of CAVs . .	131
7.8	Number and location of safety conflicts using the MPF IFT-based CAV control at different penetration rates, with and without packet drops	138
7.9	Summary of the effects of multiple leading vehicle information on traffic safety and efficiency results, compared to single leader vehicle information .	140
7.10	Summary of the effect of controller parameters tuning for specific MPR on traffic safety and efficiency results	142
7.11	Summary of traffic safety and efficiency results with different weights assigned to different leading vehicles, compared to same weights assigned to leading vehicles	145
7.12	Comparison of safety conflicts at different penetration rates of CAVs	145
7.13	Comparison of overall travel time at different penetration rates of CAVs . .	146
7.14	Comparison of traffic safety performance between the proposed control approach and the baseline approach	147
7.15	Comparison of traffic efficiency performance between the proposed control approach and the baseline approach	147

List of Acronyms

AV	Autonomous Vehicle
CAV	Connected Autonomous Vehicle
HDV	Human Driven Vehicle
V2V	Vehicle-to-Vehicle
V2I	Vehicle-to-Infrastructure
V2P	Vehicle-to-Pedestrian
V2X	Vehicle-to-Everything
CC	Cruise Control
ACC	Adaptive Cruise Control
CACC	Cooperative Adaptive Cruise Control
CCC	Connected Cruise Control
MPR	Market Penetration Rate
IFT	Information Flow Topology
PF	Predecessor Following
TPF	Two Predecessor Following
MPF	Multiple Predecessor Following
PLF	Predecessor Leader Following
BD	Bidirectional
BDLF	Bidirectional Leader Following
TTC	Time-to-Collision
TT	Travel Time
TTR	Travel Time Rate
DSRC	Dedicated Short Range Communication

ADAS	Advanced Driver Assistant System
CF	Car-Following
LC	Lane-Changing
PD	Proportional Derivative
PID	Proportional Integral Derivative
MPC	Model Predictive Control
IDM	Intelligent Driver Model
NHTSA	National Highway Traffic Safety Administration
SAE	Society of Automotive Engineers
OBU	On-Board Unit
RSU	Rode Side Unit
RAT	Radio Access Technology
QoS	Quality of Service
CD	Constant Distance
CTH	Constant Time Headway
VTH	Variable Time Headway
IVC	Inter Vehicle Communication
PLR	Packet Loss Ratio
PER	Packet Error Rate
BSM	Basic Safety Message
CAM	Cooperative Awareness Message
SUMO	Simulation of Urban MObility
OMNET++	Objective Modular Network Testbed in C++
VEINS	Vehicles in Network Simulation
PLEXE	Platooning Extension for Veins
VANET	Vehicular Ad Hoc Network
DSD	Driver State Device
TraCI	Traffic Control Interface

1 Introduction

According to the report on the global state of road safety [World Health Organization, 2018], about 1.35 million people die because of road accidents every year around the world. In addition, the Texas A&M Transportation Institute estimated the total travel delay due to traffic congestion to be around 8.3 billion hours by 2020, resulting in a cost of almost 192 billion dollars due to fuel wastage [Schrank et al., 2019]. Most road accidents and travel time delay are due to stop-and-go waves i.e., high speed variations produced by *Human-driven vehicles (HDVs)*, due to humans' large-reaction times and perception errors [Di Vaio et al., 2019, Papadoulis et al., 2019].

Recent technological advancements facilitated the advent of *Autonomous Vehicles (AVs)*, i.e., automated vehicle able to perform actions without any human intervention. AVs are equipped with a variety of sensors e.g., Lidar, Radar, Camera etc., that obtain raw data and information about the surrounding environment e.g., other vehicles, pedestrians, road signs. This extra information and their faster reaction times enable them to dampen stop-and-go waves and thereby improve traffic safety and efficiency [Xiao and Gao, 2010, Lefèvre et al., 2016, Sarker et al., 2020]. Although there has been a lot of research and development in the field of AV technology, there is a lack of decision making capability in AVs when they encounter driving in highly novel scenarios such as adverse weather conditions (i.e., fog, heavy rain, wind gusts), unexpected animals on road, pedestrians crossing the road, human-driven vehicle going in the wrong direction, etc., due to limitations in sensors technology (range, speed and accuracy) [Bagloee et al., 2016, Hussain and Zeadally, 2019]. The fatal Uber crash (i.e., the death of a pedestrian on 18th March 2018 involving a self-driving car) happened at a critical time for the emerging self-driving vehicle sector when manufacturing companies were expecting the arrival of driverless cars on the roads [Hancock et al., 2019].

In another accident on 23rd March 2018, a man in a Tesla autopilot car died after his car hit a concrete barrier [Jefferson and McDonald, 2019]. These accidents highlight that AVs may take wrong decisions due to a deficit in the quality and quantity of data about their surrounding environment, resulting in reduced traffic safety and efficiency [Sarker et al., 2020].

Another recent technological advancement relates to vehicles communicating with other vehicles (V2V), infrastructure (V2I), and pedestrian (V2P), generally termed as *V2X communication* [Wang et al., 2019b]. Many radio access technologies have been proposed for V2X communication such as WiFi, Bluetooth, DSRC, C-V2X, and 5G [Wang et al., 2019b]. Such communication-equipped autonomous vehicles are called *Connected Autonomous Vehicles (CAVs)*. CAVs have the potential to improve traffic safety and efficiency by sharing information about themselves (such as their position, speed and acceleration) and various parameters of their traffic environment in real-time with other vehicles and infrastructure via V2X communication. As a consequence, CAVs have a better situation awareness of surrounding vehicles and events such as accidents and traffic jams that are out of the range of their on-board sensors [Sarker et al., 2020]. By exploiting information from surrounding vehicles via V2V communication, CAVs usually employ a car-following control strategy i.e., adapting their speed based on information from one or more surrounding vehicles, for their autonomous driving behavior in the longitudinal direction. This has the potential to improve both traffic safety and efficiency [Guanetti et al., 2018, Tian et al., 2018].

While CAVs have the potential to improve traffic performance in a fully connected environment, they face additional challenges in their driving when they interact with HDVs in mixed-traffic scenarios due to the uncertainty in human's driving behavior e.g., larger reaction times, perception errors, etc. [Ivanchev et al., 2019]. Another challenging problem in utilizing CAVs technology is the unreliability of wireless communication networks. Delays and packet losses in communication links due to dense traffic, communication interference, channel fading, etc., may jeopardize CAVs driving behavior and negatively affect traffic performance in terms of reduced traffic safety and efficiency [Montanaro et al., 2019]. This work investigates whether a CAV car-following control strategy can improve traffic safety and efficiency for CAVs operation in realistic scenarios, i.e., mixed traffic, unreliable

communication, large-scale traffic, etc.

This chapter first provides the motivation for this work, and the challenges in the research area of CAVs operation in mixed traffic and unreliable communication environments. Following this, the research questions, the approach chosen to address research questions, thesis contributions, and the scope of the work are presented. Lastly, the thesis organization and the summary of this chapter are outlined.

1.1 Motivations

CAVs have the potential to improve traffic safety and efficiency by controlling their driving behavior, and enable cooperation using onboard sensors information as well as information obtained from other vehicles and RSU-equipped infrastructure via V2X communication [Guanetti et al., 2018]. The V2X communication enables vehicles to adopt effective car-following control strategies where the vehicles exchange information to cooperate with surrounding vehicles, thereby improving traffic safety and efficiency [Santini et al., 2017]. A car-following strategy defines how an ego vehicle maintains the desired gap with its immediate leading vehicle [Li et al., 2023]. *Adaptive cruise control (ACC)* and *cooperative adaptive cruise control (CACC)* are two major car-following control strategies employed in CAVs for their autonomous driving behavior in the longitudinal direction. ACC allows vehicles to follow their immediate leading vehicles based on sensors-only perception, while CACC allows vehicles to follow each other with a shorter time headway¹ by enabling the ego vehicle to receive information (e.g., position, speed, and acceleration) from its leading vehicle through V2V communication links in addition to information obtained using on-board sensors such as radar and lidar [O’Hara et al., 2015, Wang et al., 2019a]. The deployment of CAVs on the road can improve both traffic safety and efficiency by leveraging the CACC technology to allow following the leading vehicle with a short time headway [Yao et al., 2020, Talebpour and Mahmassani, 2016].

While CAVs have the potential to provide significant improvements in traffic safety and efficiency, it is predicted that at most 24.8% of vehicles will be CAVs by 2045 [Bansal and

¹The time headway denotes the time taken by a vehicle to cover the distance between its front bumper and its leading vehicle’s front bumper.

Kockelman, 2017]. For a long time, mixed traffic i.e., vehicles with different longitudinal and lateral control, and communication capabilities (Human-driven vehicles, Connected human-driven vehicles, Autonomous vehicles, CAVs) will coexist [Liu et al., 2018, Galvani, 2019, Ahangar et al., 2021]. In mixed traffic environments, CAVs face additional challenges in their driving when they interact with *human-driven vehicles (HDVs)* due to the uncertainty in human’s driving behavior e.g., larger reaction times, perception errors, etc. [Ivanchev et al., 2019]. In addition, it might not always be possible to receive information from neighbouring vehicles in unreliable communication environments due to the presence of communication failures, thus leading to varying information flow topologies. The *information flow topology (IFT)* specifies the vehicles from which a CAV uses information to make decisions depending on its sensing and communication range [Navas and Milanés, 2019, Qin et al., 2019, Li et al., 2017]. Various IFTs are available and each of these is described in detail in the background chapter (Section 2.3.3).

Most existing studies, however, have assumed fixed information flow topologies and may not handle changes in information flow topologies due to communication failures or the presence of HDVs [Rahman et al., 2021, Ding et al., 2022, Avedisov et al., 2022]. A few CAV car-following control algorithms that can handle dynamic information flow topologies occurring due to mixed traffic, have been developed in recent years, but they have only been validated in very limited scenarios for a very small number of vehicles (with a fixed sequence of CAVs and HDVs) and assuming perfect communication [Yu et al., 2023, Rahman et al., 2021, Zhou et al., 2023]. These studies, moreover, usually consider only very simplified vehicle models and perfect V2V communication. Therefore, it is essential to study car-following control strategies of CAVs in mixed traffic and unreliable communication scenarios, identify the challenges and develop control strategies that can address these challenges.

1.2 Challenges

This section presents the challenges to CAVs driving behaviour due to unreliable communication links in the first instance, then the challenges due to mixed traffic scenarios, and finally the challenges due to the combination of the two.

1.2.1 Challenges due to Unreliable Communication

The previous section introduced the capability of CACC to improve both traffic safety and efficiency. However, the effectiveness of CACC heavily depends on the availability of information from surrounding vehicles, and it might not always be possible to receive information in unreliable communication environments. Indeed in these environments, the information exchange is likely to suffer from packet losses or message reception delays due to limited transmission bandwidth, channel fading and interference, and therefore it is very **challenging to establish coordination and cooperation among surrounding vehicles** [O'Hara et al., 2015]. For instance, using the simplest predecessor-following (PF) IFT-based car-following control strategy where a CAV exploits information from its immediate leading vehicle only, a CAV typically **degrades its mode to sensor-based ACC** when it cannot establish a link with the previous vehicle due to communication failure, as shown in Figure 1.1. This results in reduced traffic efficiency due to the increased time headway in the ACC mode [Navas and Milanés, 2019]. In some situations, a CAV makes a **decision based on outdated information** when it cannot obtain the latest information about surrounding vehicles due to communication delays. This results in reduced traffic safety and efficiency [Santini et al., 2017].

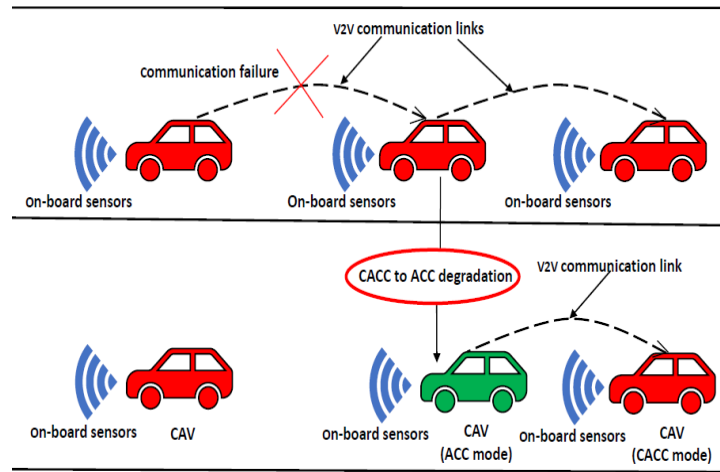


Figure 1.1: CAV longitudinal control degradation in the presence of communication failures.

In addition to exploiting information from the vehicle they immediately follow, CAVs can also use information from vehicles further ahead within their communication range in their car-following control decisions to enhance their performance [Li et al., 2023]. This

category of car-following control falls under the multiple-predecessor-following (MPF) IFT-based control. Most MPF IFT-based control strategies being proposed for CAV car-following assume fixed IFTs, implying perfect V2V communication for the IFT assumed. In practice, V2V communications are unreliable, **leading to varying IFTs**, thus making it challenging for the CAV car-following control algorithms designed based on fixed IFTs to improve traffic safety and efficiency.

1.2.2 Challenges due to Mixed Traffic

One major challenge in mixed traffic flow operation is the interaction of CAVs with human-driven vehicles due to the **uncertainty in human driving behaviour**. HDVs often exhibit large reaction times, so disturbances propagate and get amplified downstream into the string of vehicles following each other, which leads to traffic congestion and reduced traffic flow stability [Kesting and Treiber, 2006, Monteil et al., 2019, Ersal et al., 2020]. Another challenge is the **limited information availability** about surrounding vehicles and other traffic participants. For instance, as HDVs are typically not equipped with V2V, a CAV following a HDV cannot obtain information from its immediate leading vehicle via V2V communication. Instead, it needs to rely on its on-board sensors and **degrade their longitudinal driving mode to ACC**, as shown in Figure 1.2. Similarly, CAVs cannot exploit information from vehicles further ahead within their communication range, due to the random mix of CAVs and HDVs at different CAV penetration rates, resulting in **varying IFTs**. Therefore, it is very challenging to develop a car-following control strategy for CAVs in such traffic scenarios.

1.2.3 Challenges due to Mixed Traffic with Unreliable Communication

Most existing studies investigated the impact of CAVs at different penetration rates assuming perfect communication. Results show that CAVs have the potential to improve traffic safety and efficiency significantly, especially at high penetration rates [Guériau and Dusparic, 2020]. In practice, however, communication delays and packet drops might affect the results negatively [Ali et al., 2020]. Very few studies have analyzed the impact of CAVs on mixed traffic performance in the presence of communication impairments i.e., delays

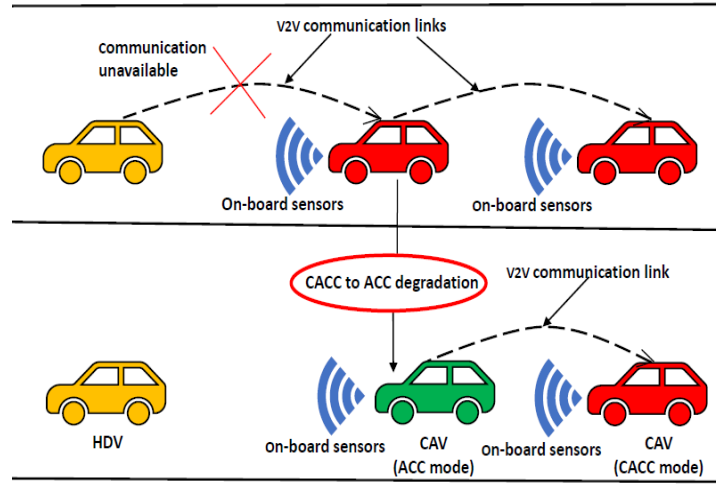


Figure 1.2: CAV longitudinal control degradation in mixed traffic.

and packet losses [Navas and Milanés, 2019, Di Vaio et al., 2019]. These studies report that while in reliable communication environments CAVs provide significant improvement in both traffic safety and efficiency as the penetration rate increases, this improvement is reduced in the presence of communication failures. Hence, the design of CAV car-following control strategies to improve traffic safety and efficiency becomes even more demanding when considering **the challenges of both mixed traffic and unreliable communication environments together**. Moreover, the limited information availability in mixed traffic with unreliable communication environment may trigger **a higher number of degradations from CACC to ACC** in the PF IFT-based control or **lead to varying IFTs** in the MPF IFT-based control and can further reduce traffic safety and efficiency [Yu et al., 2023].

1.3 Existing Approaches

While a number of studies on longitudinal control of CAVs have been reported in the literature in recent years, various control strategies based on different information flow topologies, as shown in Figure 1.3, have been developed considering pure CAV traffic only, where CAVs can exploit full information from their surrounding vehicles for their safe and efficient driving operations. These CACC control strategies have been widely used in both academia and industry because they have the possibility of multiple vehicles coordination and cooperation, thereby improving traffic safety and efficiency significantly. However, in mixed traffic

and unreliable communication environments, it is very challenging to establish coordination and cooperation among surrounding vehicles due to the presence of HDVs and packet drops/communication delays.

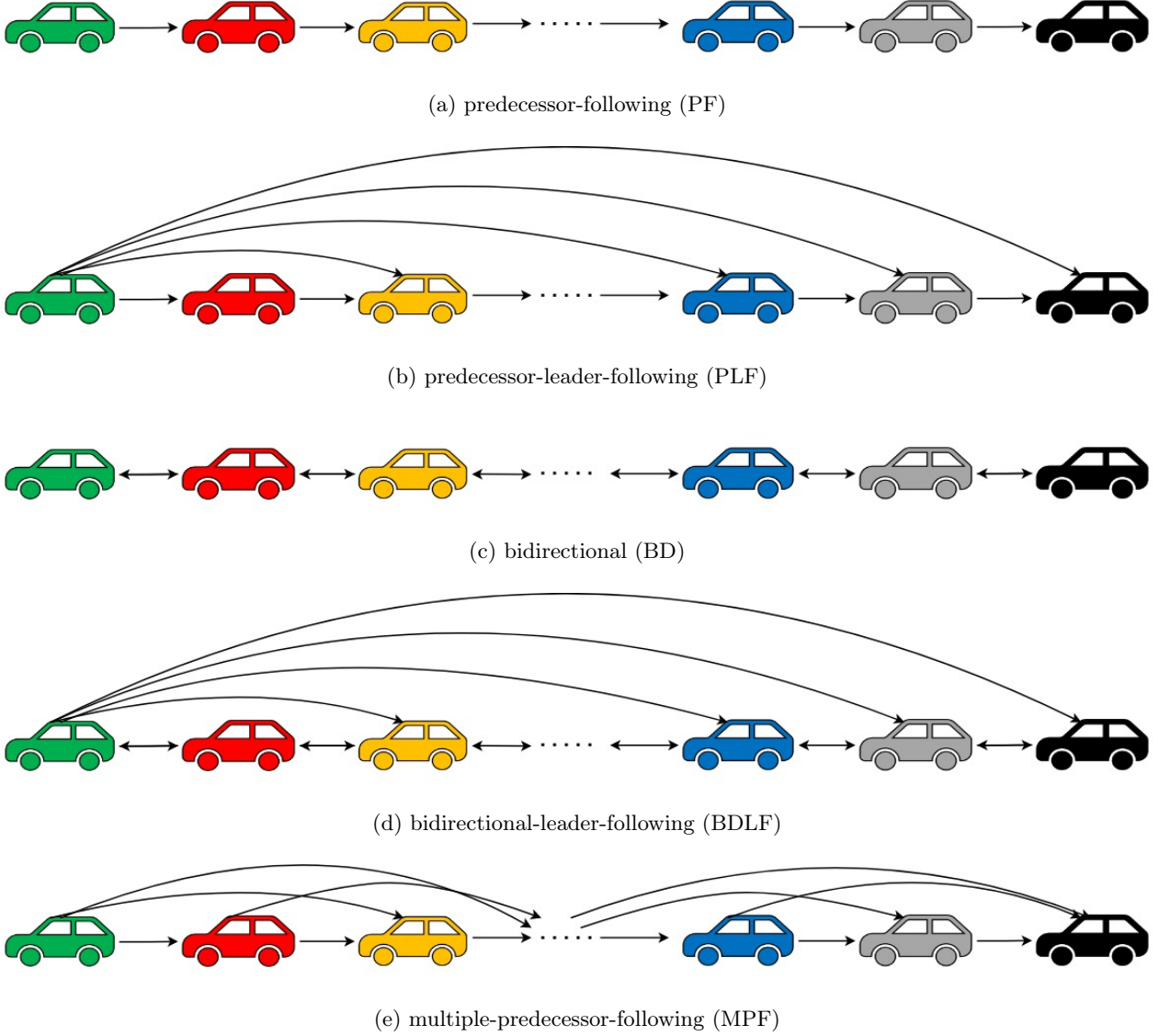


Figure 1.3: Various Information Flow Topologies (IFTs) for a string of vehicles performing car-following.

A few attempts have been made to develop car-following control strategies for CAVs by considering the uncertainties and stochastic driving behaviour of HDVs as well as communication delays and packet losses for their operation in mixed traffic and unreliable communication environments [Navas and Milanés, 2019, Di Vaio et al., 2019]. Most of them, however, have been designed based on the simple PF IFT only (as shown in Figure 1.3a), and degrade CAVs' control mode to ACC if information is not available from the preceding vehicle due

to communication failures or it being a HDV, thereby resulting in decreased traffic safety and efficiency [Tu et al., 2019, Qin et al., 2019]. Although traffic safety can be achieved by increasing the time headway, this is at the expense of reduced traffic efficiency [Yao et al., 2020]. As most control strategies are based on the PF IFT only, they cannot harness the full potential of CAVs by communicating with multiple surrounding vehicles rather than a single vehicle, and have not been explored in large-scale traffic scenarios i.e., with a large number of vehicles due to their high computational cost and complexity [Zhang, 2018, Chen et al., 2021b]. Previous studies considering large-scale traffic scenarios, however, usually consider the car-following models simplifying the vehicle dynamics and ignoring realistic V2V communication, to control the CAV car-following behaviour. This could result in inaccurate performance evaluation of CAVs for their operation in realistic scenarios in terms of imperfect communication, mixed traffic, vehicle modelling, and real traffic networks.

In recent years, a few researchers have attempted to develop car-following control algorithms based on the MPF IFT (as shown in Figure 1.3e), i.e., considering information from more than one leading vehicle rather than the immediate leading vehicle only i.e., PF IFT, for CAVs operation in unreliable communication and/or mixed traffic environment [Zhang, 2018, Chen et al., 2021b]. Most of these studies, however, have assumed fixed IFTs and may not handle changes in information flow topologies due to communication failures or the presence of HDVs [Rahman et al., 2021, Ding et al., 2022, Avedisov et al., 2022]. A few robust car-following control algorithms that can handle dynamic information flow topologies occurred due to mixed traffic, have been developed in recent years, but they have only been validated in very limited scenarios for a very small number of vehicles (with a fixed sequence of CAVs and HDVs), assuming perfect communication [Yu et al., 2023, Rahman et al., 2021]. These studies, moreover, usually consider the car-following models simplifying the vehicle dynamics and ignore realistic V2V communication, to control the CAV car-following behaviour.

Existing car-following controllers have been evaluated only with either perfect communication, pure CAVs traffic, simple PF IFT or traffic scenarios. This precludes their applicability to CAVs deployment on roads in the near future. Therefore, the objective of this work is to design a CAV car-following control algorithm exploiting information from one or more surrounding CAVs that is able to: i) handle varying IFTs in mixed traffic

and unreliable communication, and ii) support the deployment of CAVs on motorways in the near future. These two key functions have not been well considered and investigated simultaneously, in existing research.

1.4 Research Questions

Considering the uncertainties of human-driven vehicles in mixed traffic, the unreliability of wireless communication networks, and high traffic demands in realistic traffic scenarios, this thesis explores whether and to what extent the use of an adaptive car-following control strategy designed for connected autonomous vehicles can improve traffic safety and efficiency in realistic scenarios on a motorway. This yields the following main research question:

- **Research Question:** How to design CAV car-following control strategies to improve mixed traffic safety and efficiency in realistic scenarios in terms of traffic composition (mixed traffic), communication (not assumed to be reliable) and road network (large-scale and real network)?

In particular, the above overarching research question can be broken down in the three following research questions:

- RQ1: Can CAVs improve both mixed traffic safety and efficiency in mixed traffic and unreliable communication environments on large-scale road networks?
- RQ2: Does exploiting information from multiple leading vehicles within their communication range give an advantage to CAVs (compared to single-vehicle information-based control) in terms of traffic safety and efficiency?
- RQ3: Can a CAV car-following controller designed based on multiple leading vehicles information further improves traffic safety and efficiency in the presence of the uncertainties of HDVs and communication failures?

Each of these research questions is discussed in detail in Section 3.4.

1.5 Thesis Approach

This work addresses each of the research questions in turn. It first investigates the impact of CAVs at different penetration rates on mixed traffic safety and efficiency in realistic scenarios (RQ1). To do so, it extends an existing PF IFT-based controller PLOEG [Ploeg et al., 2011] to operate in mixed traffic and unreliable communication environments, by degrading to ACC controller and adopting larger time headway in the presence of communication failures or when the preceding vehicle is a HDV. Although traffic safety can be improved by increasing the CAV time headway, this is at the expense of a reduction in traffic efficiency. Thus, a balance between traffic safety and efficiency needs to be considered while choosing the time headway parameter. Moreover, though the adjustment of desired time headways of CAVs is the most effective means of improving both traffic safety and efficiency, the optimal headway value depends on the different set of parameters such as control gain parameters, sensor and actuator delays, wireless network condition, penetration rate, traffic demand and road network type, that can affect traffic safety and efficiency. Due to the large number, and complexity, of these factors, existing studies generally focus on a subset of them only, e.g., only a single type of time headway is evaluated, the impact of CAVs on traffic safety and efficiency is evaluated only on one type of controller parameters, safety and efficiency are evaluated separately, or simplifying assumptions about the traffic scenario are made. This thesis extends existing studies by investigating the impact of CAV control based on both single leading vehicle information and multiple leading vehicles information on both traffic safety and efficiency, in realistic V2V communication and traffic flow scenarios at different CAV penetration rates and time headways, using real traffic data of an Irish motorway (the M50 motorway, in Ireland).

To investigate the effects of exploiting information from multiple leading vehicles, this work proposes the first MPF IFT-based controller for mixed traffic with unreliable communication (RQ2). Furthermore, it shows how tuning the controller parameters (control gains and time headways) can mitigate the detrimental effects of the uncertainties of HDVs and communication failures and based on the analysis, how to select the optimal control gains and time headway parameters to improve traffic safety without compromising efficiency. Moreover, a specially-designed adaptive weights assignment approach is proposed for the

MPF IFT-based controller design that can maximize CAVs' ability to cope with the varying IFTs due to the uncertainties of HDVs and communication failures associated with CAVs operation in mixed traffic and unreliable communication environment, to answer the third research question RQ3.

1.6 Contributions

The main contribution of this thesis is the design of CAV following control algorithms that enable CAVs to cope with varying IFTs resulting due to the presence of HDVs and communication failures, and then investigating the impact of CAVs on mixed traffic safety and efficiency in realistic scenarios, including imperfect communication, large-reaction time, vehicle modelling, and large-scale traffic scenario. All the algorithms are evaluated using simulation studies at different CAV penetration rates in a realistic communication environment, using real traffic data of an Irish motorway (the M50 motorway, in Ireland) under different traffic conditions. The results in this work thus represent a significant step towards the deployment of CAVs on motorways in the near future. Overall, the contributions of this thesis are as follows:

1. C1: Cautious car-following approach in CAV PF IFT-based control

Most CAV car-following control algorithms designed in previous research that consider both mixed traffic and unreliable communication are based on the PF IFT only, and degrade to sensor-based control (i.e., ACC) in the presence of communication failures or when the leading vehicle is a HDV. ACC allows vehicles to follow their preceding vehicles with a large time headway by enabling the ego vehicle to receive information from its preceding vehicle through on-board sensors only. On the one hand, previous studies claim that traffic safety improves significantly due to larger time headways in the ACC mode [Qin et al., 2019]. On the other hand, some previous studies show that degrading to ACC when following a HDV or in the presence of packet drops might create traffic congestion due to the speed variations in creating those large time headways in the ACC mode, thereby affecting both traffic safety and efficiency negatively [Tu et al., 2019]. To reduce the detrimental effects of such longitudinal

mode degradation, an adaptive CAV time headway approach i.e., adopting a more cautious car-following strategy is proposed in this thesis for CAVs operation in mixed traffic and unreliable communication environment, so that a CAV need not to increase its time headways significantly when it degrades to sensor-based ACC mode in the absence of information from its preceding vehicle due to communication failures or it being a HDV.

While the impact of CAVs on traffic safety and efficiency at different market penetration rates (MPRs) has been studied extensively, CAVs have typically been assumed to operate in realistic traffic scenarios with perfect communication. The few studies that consider imperfect communication include only a very small number of vehicles in the platoon formation with a designated leader and follower vehicles. This thesis extends existing studies by investigating the impact of CAVs on both traffic safety and efficiency, in realistic V2V communication and traffic flow scenarios at different CAV penetration rates and time headways, using real traffic data of an Irish motorway (the M50 motorway, in Ireland), which lays the foundation for deploying CAVs on motorways in the near future.

This contribution resulted in one conference and one journal paper. The conference paper [Garg et al., 2021] was presented at the 24th IEEE International Conference on Intelligent Transportation Systems (ITSC 2021), and its extended journal version [Garg and Bouroche, 2023a], published in the IEEE Transactions on Intelligent Transportation Systems. These two publications investigated the impact of CAV PF IFT-based car-following strategy on mixed traffic safety and efficiency in realistic scenarios in terms of imperfect communication, large-reaction time, vehicle modelling, and large-scale traffic scenario.

2. C2: MPF IFT-based control design for CAVs in mixed traffic and unreliable communication environments

A CAV typically adapts its speed based on information from the vehicle it follows. CAVs can also use information from vehicles further ahead within their communication range, and this results in improved traffic safety and efficiency. In mixed traffic and unreliable communication scenarios, however, this may not always be possible

due to the presence of human-driven vehicles without communication capabilities or communication failures, leading to varying IFTs. Therefore, this thesis focuses on first designing a MPF IFT-based car-following control strategy for CAVs, and then tuning CAV controller parameters (control gains and time headways) to improve the resilience of CAV control algorithm against the uncertainties of HDVs and communication failures for CAVs operation in mixed traffic and unreliable communication environments. This controller allows the incorporation of multiple leading vehicles information (only if they are CAVs) without assigning a designated leader and follower vehicles, thereby making it more flexible and scalable for its implementation in realistic traffic scenarios.

The publication that mostly encompasses the design of the first MPF IFT-based controller proposed in this thesis is in [Garg and Bouroche, 2023b], published in the proceedings of the 35th IEEE Intelligent Vehicles Symposium (IV 2023).

3. C3: Adaptive information weights assignment in the MPF IFT-based control

CAV controller parameters tuning is a promising approach to make CAVs resilient against the uncertainties of HDVs and the presence of communication failures. Under the MPF control strategy, existing distributed control algorithms assign the same weight assignment to all leading vehicle information or assign fixed information weights to leading vehicles, which seems pertinent in a fully connected environment with fixed IFT only. However, in mixed traffic and unreliable communication scenarios, which leads to varying IFTs, a CAV controller should not make use of all leading vehicle's information with the same weighting. Thus, a novel distance-based adaptive control approach is proposed for distributed control of CAVs that assigns different information weights to multiple leading vehicles to make more safer and efficient use of all exchanged information, thereby further improving traffic safety and efficiency.

The finding of this contribution is expected to be submitted soon as a journal paper entitled "Improving Mixed Traffic Safety and Efficiency in Realistic Scenarios by Tuning CAV Controller Parameters" in a reputed journal: Transportation Research Part C.

1.7 Scope

The scope of this thesis is limited to:

1. V2V longitudinal control of CAVs

Though this work investigates car-following along a motorway with multiple lanes, it only considers longitudinal control dynamics of vehicles to be significant and does not consider the many existing efforts on various lateral control strategies. Note that as V2I communication-based infrastructure might not be extensively deployed, this thesis focuses on the V2V communication-based longitudinal control of CAVs only, and does not address many existing efforts on control methods based on V2I communication. Furthermore, only rear-end conflicts are considered in the traffic safety evaluation as the focus of this thesis is car-following.

2. Independent vehicles

All existing studies on longitudinal control design of CAVs have assumed a platoon formation with a designated leader and follower vehicles. Among them, only a few studies focus on how vehicle platooning can be applied in large scale road networks, by grouping vehicles into a series of platoons driving along the road, but these studies assume reliable communication only. Vehicle platooning, however, imposes additional challenges to establish coordination among CAVs, especially in mixed traffic and unreliable communication environments. In mixed traffic, CAVs and HDVs are mixed on the road, and CAVs need to perform a lot of merging/diverging and lane-changing maneuvers to form a platoon, which might affect traffic safety and efficiency negatively [Deng, 2016, Mena-Oreja and Gozalvez, 2018]. In addition, the unreliability of wireless communication networks might further deteriorate traffic safety and efficiency due to packet loss or delay during the information exchange between the platoon leader and follower vehicles [Balador et al., 2022]. Therefore, the vehicle platooning concept is not applied in this thesis work, and the CAVs are considered to act independently of a leader.

3. Non-connected HDVs

In contrast to CCC strategies [Avedisov et al., 2022, Ge and Orosz, 2017] that exploits information from HDVs (who have communication capabilities, namely connected HDVs) for the CAV car-following control design, in this thesis work, it is assumed that HDVs do not have communication capabilities and therefore, cannot send/receive information via V2V communication. Furthermore, from the wireless networks point of view, different contention mechanisms have been proposed to reduce the probability of communication failures. But, this thesis work is limited to address the unreliability of communication failures from the control theory perspective only.

4. Constant driver reaction time

In this thesis, the human-driver car-following behavior is modelled using the well-known IDM car-following model, which has been proven to give realistic stop-and-go speed profiles. For human-driven vehicles that are completely operated by a human driver, drivers' reaction time is the primary source of time delay in their car-following driving behavior [Sun et al., 2018]. Human drivers generally exhibit large reaction times and perception errors in their driving decision making [Treiber et al., 2006]. Therefore, in this work, both small and large reaction times are considered to compare the effects of large reaction time on traffic performance. Despite human-driver reaction time being a varying parameter depending on different driving conditions, a constant human-driver reaction time is incorporated in the IDM car-following model. Furthermore, from recent studies, there is a growing realization that the interactions between HDVs and CAVs are more subtle, but also more important than often assumed [Avedisov et al., 2022]. However, in this work, because the focus is on car following only, it is assumed that human drivers react to CAVs in the same way that they react to other HDVs.

1.8 Organization

The remainder of this thesis is organized as follows: Chapter 2 provides background information on connected and autonomous vehicles technologies. Chapter 3 presents the related work for CAVs operation in the presence of unreliable communication links and human-driven vehicles. It discusses the different control strategies to mitigate the effects

of unreliable communication links, mixed traffic uncertainties and mixed traffic with unreliable communication. Vehicle modeling is discussed in Chapter 4. Chapter 5 presents the design of a CAV controller to operate in the presence of unreliable communication links and human-driven vehicles. Chapter 6 presents the simulation setup and the implementation of proposed car-following control strategies for CAVs. Chapter 7 first presents the evaluation objectives, traffic scenarios and performance metrics. Then it presents the simulation results of different scenarios and discusses them in detail. Finally, Chapter 8 concludes the thesis and presents potential future work.

1.9 Summary

This chapter outlined the motivation, goals and scope of the work described in this thesis - essentially, a car-following controller design approach for a connected autonomous vehicle that enables improved traffic safety and efficiency in mixed traffic and unreliable communication scenarios despite unreliable V2V communication links and uncertainties of human-driven vehicles. The chapter began by presenting the motivation for the work described in this thesis, i.e., the deployment of CAVs is expected to improve traffic safety and efficiency, though it is unclear to what extent this has been evaluated in realistic scenarios. The problem was defined in more detail by presenting the limitations of CAVs operation in mixed traffic and unreliable communication scenarios on a large-scale road network. The main challenges that arise from this problem were outlined, and a brief overview of existing studies demonstrated that all of these challenges have never been tackled simultaneously. Finally, the chapter concluded by detailing the approach of this work, and the contributions of this thesis, as well as the areas that are outside the scope of the work.

2 Background

This chapter first provides an overview of automation and communication technologies in connected autonomous vehicles. Then it presents the hierarchical longitudinal and lateral control architectures for CAVs. Section 2.1 illustrates the different levels of autonomous vehicles and Section 2.2 provides some background information about different wireless communication technologies used for vehicular networking. Section 2.3 presents an overview of longitudinal control of CAVs, including longitudinal control architecture, spacing policies and information flow topologies. In addition, Section 2.4 briefly presents an overview of lateral control of CAVs.

2.1 Levels of Automation

Technological advancements in the automation industry, especially in sensors technology, facilitated the automation in vehicles [Galvani, 2019]. The National Highway Traffic Safety Administration (NHTSA) classified automated vehicles into five levels in 2013 and this was superseded when the Society of Automotive Engineers (SAE) [Committee, 2021] categorized them into six levels i.e. from Level 0 (no automation) to Level 5 (full automation) in 2014, see Figure 2.1. As per the classification by SAE International, the different automation levels are described as follows. In Level 0, i.e., No Automation, the human driver is responsible for all the driving tasks, while Level 1 (Driver Assistance) provides driving assistance to a human driver with simple tasks such as steering and braking using the Advanced Driver Assistant System (ADAS). Level 2, a.k.a. Partial automation, takes over the control of steering and breaking under some circumstances under the full attention of a human driver, and the rest of the driving tasks are performed by a human driver. In Level 3 (Conditional Automation), an automated driving system in the vehicle can perform all driving tasks under

some circumstances on motorways and a human driver must be ready at all times to take back the vehicle control if asked to do so. Level 4 (High Automation) allows an automated driving system to perform all driving tasks while capturing and detecting the surrounding environment, though only in certain circumstances such as in geofenced metropolitan areas where human drivers need not to pay attention at all. Finally, Level 5, full automation, allows automated driving systems to perform all the driving tasks under all conditions, without any intervention of a human driver.

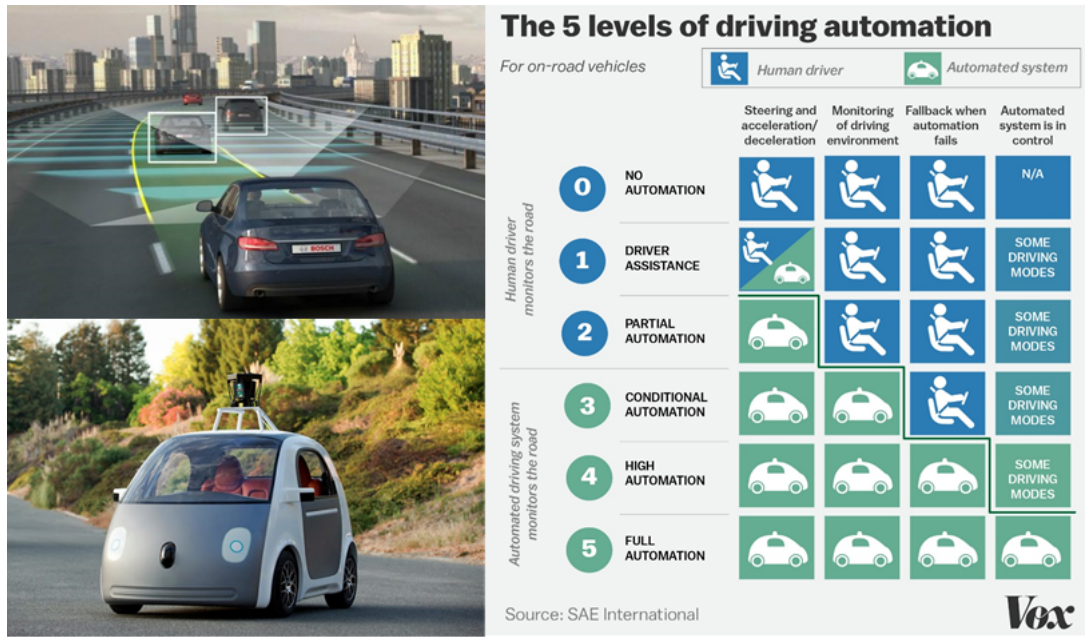


Figure 2.1: Automated driving levels [Galvani, 2019].

2.2 Communication Technologies

Leveraging an autonomous vehicle to become more aware of its surrounding environment and enhance its ability to respond has become possible due to vehicle-to-everything (V2X) communication technologies [Wang et al., 2019b]. These wireless technologies allow autonomous vehicles to perceive information about their environment, including other vehicles or infrastructure, via vehicle-to-vehicle (V2V) or vehicle-to-infrastructure (V2I) communication, jointly known as V2X communication. On the one hand, though V2V communication can provide situational awareness of surrounding traffic via exchanging information with neighbour vehicles, leveraging the surrounding traffic information has limited benefits to some traffic applications, such as route choice, journey planning and overall traffic congestion mit-

igation. On the other hand, V2I communication can provide global traffic information as the deployment of communication networking infrastructures as roadside units progresses [Jia and Ngoduy, 2016a, Shet and Yao, 2021]. Therefore, vehicles can adapt their behaviour to the downstream traffic flow conditions, thereby improving overall traffic safety and efficiency.

The establishment of a reliable, robust and secure wireless communication network is a big challenge while implementing CAV technology [Singh et al., 2019]. On-Board Unit (OBU) and Road Side Unit (RSU) are the two main components of a wireless vehicular network [Sarakis et al., 2016]. OBUs are equipped with communication devices and sensing devices to collect and exchange information with other vehicles and potentially RSUs within communication range. An RSU is a static device installed generally at a road intersection, in a traffic light tower or busy road area to accomplish various functions such as forwarding data to vehicles that are out of V2V communication range, running traffic management applications, providing internet access to vehicles for infotainment applications etc. [Sarakis et al., 2016].

There are many radio access technologies (RATs) proposed in the literature for V2X communication such as WiFi, Bluetooth, DSRC, LTE-A, and 5G. WiFi and Bluetooth are mainly used for non-safety applications due to their high latency and weak reliability [Viitala et al., 2013, Singh et al., 2019]. Conversely, DSRC and C-V2X promise to deliver sufficient quality of service (QoS) performance in terms of latency, reliability, availability and data throughput for most safety critical applications [Chekkouri et al., 2015]. Dedicated Short Range Communication (DSRC), which operates on 5.85-5.925GHz in the United States and 5.855-5.905GHz in Europe (75 MHz bandwidth), is a standard vehicle communication protocol for V2V communication among CAVs [Singh et al., 2019]. Although it enables various short-range safety-critical applications e.g., warning message dissemination, collision avoidance, etc., it cannot support a variety of non-safety-critical applications e.g., multimedia sharing, tooling, etc. that demand high bandwidth and high data rate [Singh et al., 2019]. A good number of previous studies has used DSRC technology for V2V communication in CAVs to perform cooperative car-following control e.g., in [Avedisov et al., 2022, Beregi et al., 2021, Gong et al., 2019]. Furthermore, DSRC has been successfully tested and deployed in real world scenarios by numerous stakeholders, such as in [Avedisov et al., 2022, Balador et al., 2022, Guanetti et al., 2018]. However, in recent years, C-V2X

has been promoted by the 5G Automotive Association and Qualcomm, as an alternative to DSRC [Ahangar et al., 2021, Yu et al., 2023, Wang et al., 2019b]. Initial field experiments on C-V2X show that it provides a longer transmission range than DSRC and allows for re-transmission of lost packets, unlike DSRC. Furthermore, C-V2X can support a much wider range of services from low-bandwidth safety applications such as collision warning message dissemination to high-bandwidth non-safety applications such as passenger information/entertainment [Siegel et al., 2018]. Moreover, because pedestrians and cyclists generally have cellular phones, C-V2X can potentially enable CAVs to exchange information with them in addition to surrounding vehicles and infrastructure.

2.3 Car-following Control

Adaptive cruise control (ACC) and *cooperative adaptive cruise control (CACC)* are two major car-following control systems employed in connected and autonomous vehicles for their autonomous driving behavior in the longitudinal direction [Santini et al., 2017]. ACC allows vehicles to follow their preceding vehicles based on sensors-only perception, while CACC allows vehicles to follow their preceding vehicles with a shorter time headway by enabling wireless communication perception in addition to sensors perception (Figure 2.2). This has the potential to provide improved traffic safety and efficiency [O'Hara et al., 2015]. This section introduces the general longitudinal control architecture (2.3.1), spacing policies (2.3.2), and information flow topologies (2.3.3) to be used for designing CAV car-following control algorithms in Chapter 5.

2.3.1 Control Architecture

The longitudinal control of CAVs is typically organised in a hierarchical control architecture, where the upper-level control determines the desired acceleration to maintain inter-vehicle distance for each vehicle through information (e.g., position, speed, and acceleration) obtained by on-board sensors and V2V communication, and the lower level control generates the throttle and braking commands to track the reference speed commands as determined by the upper-level control [Montanaro et al., 2019], as shown in Figure 2.3.

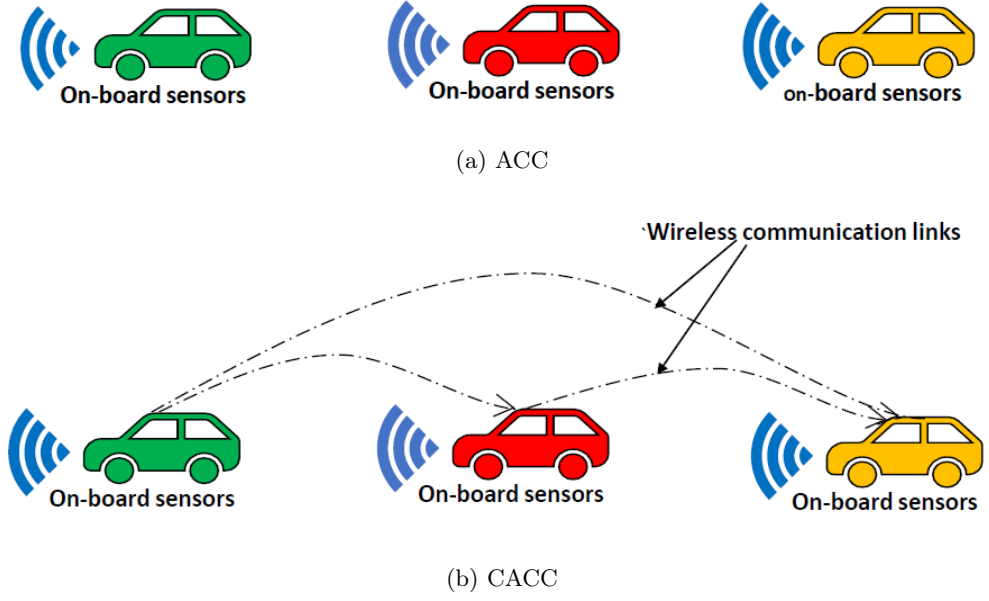


Figure 2.2: Car-following control systems.

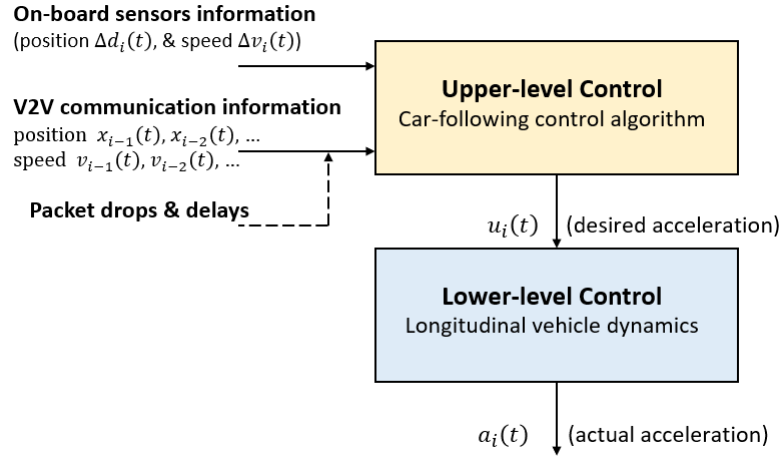


Figure 2.3: Hierarchical longitudinal control architecture.

Longitudinal motion control at upper-level e.g., Adaptive Cruise Control (ACC) and Cooperative ACC (CACC), is described using *car-following models* that determine the acceleration/deceleration of a vehicle while taking input information such as the position, speed and acceleration of the preceding vehicles. To regulate the inter-vehicle distance and speed error to a minimum value, a CACC controller takes the acceleration of the preceding vehicle as the feedforward signal and the distance and speed error as the feedback signals [Wang et al., 2018]. First and second order vehicle dynamics have been employed for low-level longitudinal control [Montanaro et al., 2019]. These, however, assume that the control input is applied instantaneously to vehicle dynamics. Third order vehicle dynamic

models have been proposed to model delays and time lags in engine response, sensors and actuators [Rajamani, 2006].

A generic car-following control system is shown in Figure 2.4. This control system is designed based on the linear feedback control method to regulate each CAV close to its desired state i.e., inter-vehicle distance. The design of a CACC control system contains three key components: spacing policy, information flow topology and controller [Milanés and Shladover, 2014]. CACC controllers are usually designed based on either the Proportional-Derivative (PD) control or Model Predictive Control (MPC) [Shi et al., 2023]. PD control regulates the error between the actual gap and the desired gap, based on proportional and derivative terms of the error. MPC for CACC controls the process of actual gap changes while satisfying a set of constraints. In general, PD control is adopted more widely since it is more computationally efficient than MPC [Lai et al., 2020].

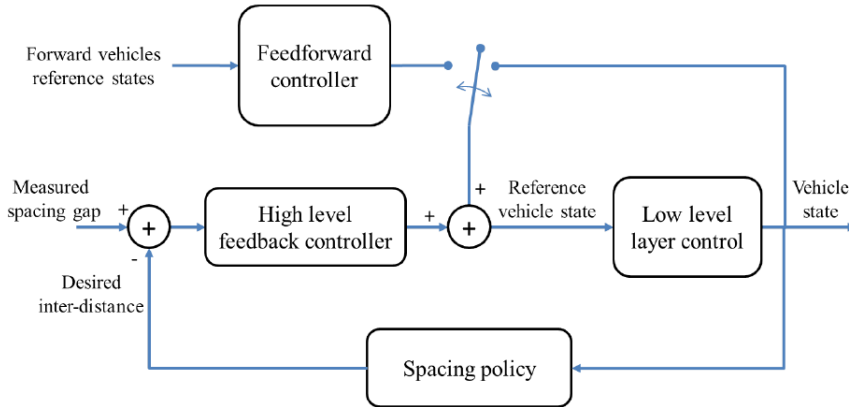


Figure 2.4: General Car-following Control Structure [Milanés and Shladover, 2014].

2.3.2 Spacing Policies

Several spacing policies for car following control have been proposed in the literature [Zeng et al., 2019]. In the *constant distance (CD)* policy, the desired distance between two consecutive vehicles is fixed, and independent of each vehicle's velocity. In the *constant time headway (CTH)* policy, the desired time-headway is fixed, however, the desired inter-vehicle distance varies with the vehicle velocity. Furthermore, the *variable time headway (VTH)* policy, in which the desired time-headway is varying with respect to the vehicle speed, has been investigated to design a car-following control algorithm in a complex and dynamic traffic environment [Wu et al., 2020]. A group of tightly coupled vehicles that travel to-

gether on the road with a small spacing between them is called a *platoon* [Rajamani et al., 2000]. Vehicle platooning and CACC are similar concepts from the high-level point of view. However, CACC focuses only on the longitudinal control of vehicles, while platooning focuses on both longitudinal and lateral control to group CAVs in strings. Vehicle platooning comprises of three stages: stage I (formation stage) during which vehicles approach each other to form a platoon, stage II (maintaining stage) during which vehicles maintain a desired inter-vehicle distance to improve traffic efficiency, and stage III (separation stage) in which vehicles start leaving the platoon to reach their destinations [Hall and Chin, 2005].

2.3.3 Information Flow Topologies

The *information flow topology (IFT)* describes the information exchange within the platoon (see Figure 2.5) depending on the sensing and communication range [Li et al., 2017]. These include *predecessor-following* (each vehicle receives messages from the vehicle in front of it), *predecessor-leader-following* (assumes a platoon formation, and each vehicle receives messages from the platoon leader and the vehicle in front of it), *multiple-predecessor-following* (each vehicle receives messages from multiple vehicles in front of it), *bidirectional* (each vehicle receives messages from the vehicle in front and the vehicle in back of it) and *bidirectional-leader-following* topology (assumes a platoon formation, and each vehicle receives messages from the vehicle in front and the vehicle directly behind it, as well as from the platoon leader).

2.4 Lateral Control

Lateral control consists of two control problems: lane keeping and lane changing. Lane-keeping can be performed efficiently by AVs using their own sensors in most conditions [Marino et al., 2011, Bevely et al., 2016, Chu et al., 2018, Hu et al., 2019, FENICHE and MAZRI, 2019, Ersal et al., 2020]. In contrast, lane changing is a very complex problem and it has a strong impact on traffic safety and efficiency due to the number of manoeuvres that rely on it: vehicle overtaking, obstacle avoidance, on-ramps merging and off-ramps diverging, intersection management, vehicle platooning, etc., [Hegde and Bouroche, 2022].

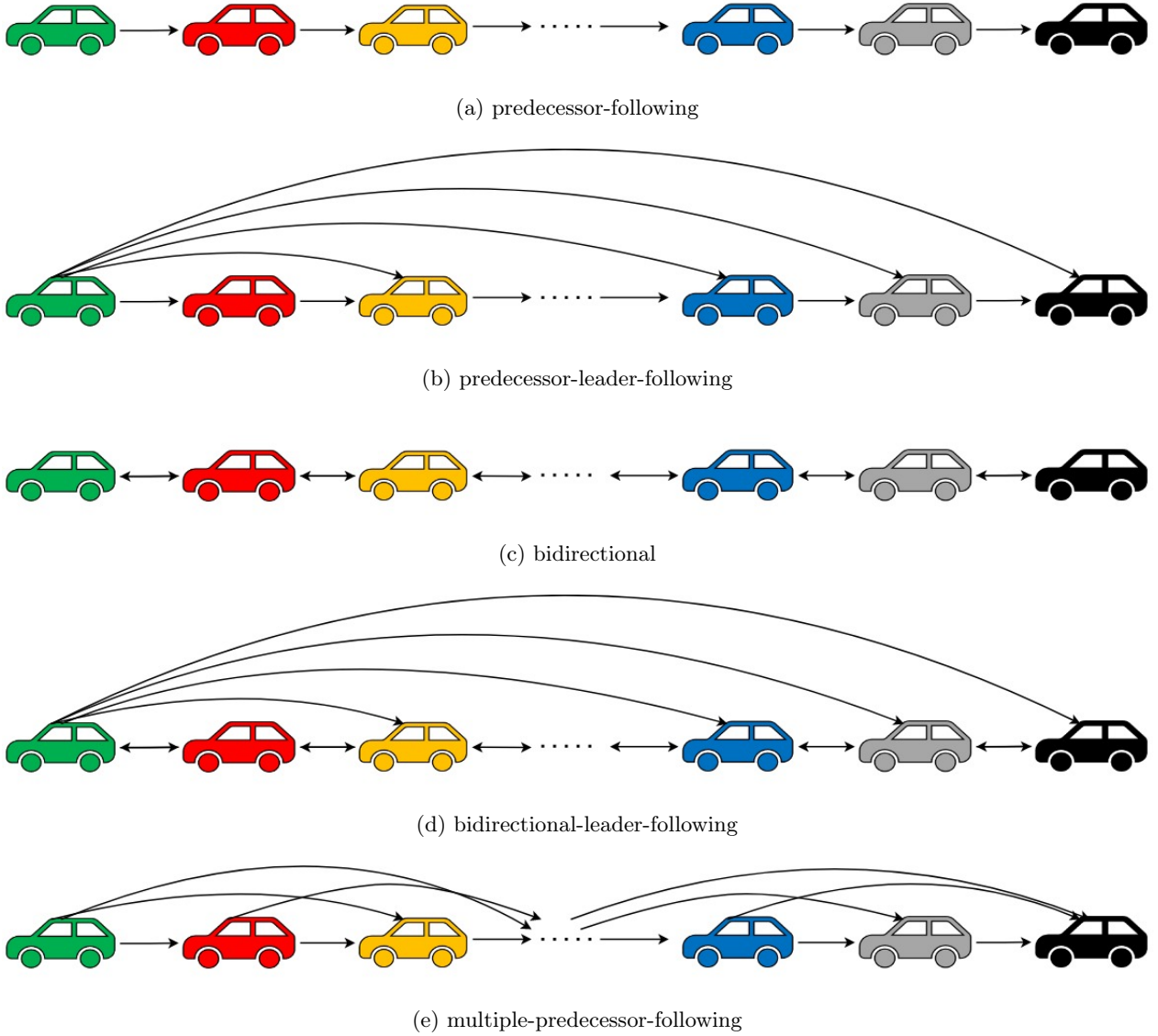


Figure 2.5: Various Information Flow Topologies (IFTs) for a string of vehicles performing car-following.

Lateral control has a multi-level control architecture: behavioral decision making, path planning and motion control levels, as shown in Figure 2.6 [Paden et al., 2016, Bevy et al., 2016]. The *behavioral decision making* and *path planning* levels decide when, where and how to perform lane changing using available information, considering traffic safety and efficiency. The *motion control* level determines the steering command to track the trajectory generated by the path planning module to implement a lane change maneuver [Xu and Peng, 2020]. Lane-changing decision making is described using *lane-changing (LC) models* that take input information of the adjacent vehicles and decide whether the subject vehicle should change lane. LC models have been proposed based on the Gipps model, utility theory,

cellular automata, Markov process and Fuzzy logic [Zheng, 2014, Kesting et al., 2007]. A lane change can be *mandatory (MLC)* when it is essential due to imposed traffic rules or the designated route, or *discretionary (DLC)* when it is voluntary to improve the travel speed or the driving experience [Moridpour et al., 2010].

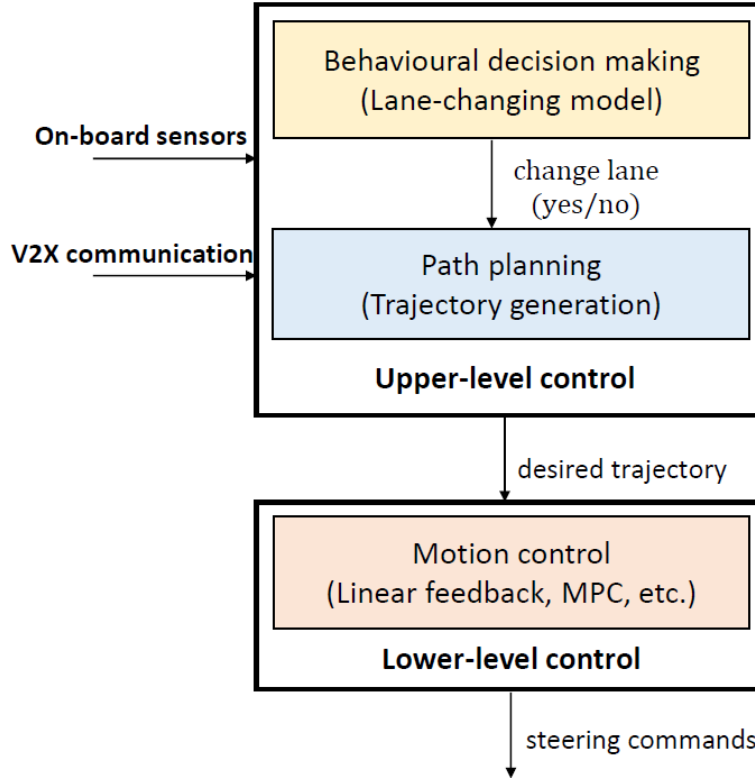


Figure 2.6: Hierarchical lateral control architecture.

In this work, a widely used LC2013 lane-changing model is used that considers the intention of changing lanes using a decision-tree algorithm [Erdmann, 2015]. In the LC2013 lane-changing model, a vehicle decides to change its lane for various reasons such as to reach a specific destination, to overtake a slow vehicle, to cooperate with other vehicles, or to follow local traffic regulations. Furthermore, if a vehicle changes its lane, a follower CAV detects the change in the speed of the leading vehicle whether it be CAV or HDV, and uses the car-following control algorithm proposed in this work to reduce the speed variations between the ego vehicle and follower vehicle.

2.5 Summary

This chapter first introduced the different automated driving levels and wireless communication technologies that have been developed for CAVs. Definitions and classifications related to spacing policy and information flow technologies notions are provided, which are fundamental for the CAV car-following control algorithm design. Afterwards, this chapter presented an overview of the CAV longitudinal and lateral control architectures, in order to provide the necessary background for understanding the existing work on CAV control strategies. In the next chapter, we review the existing work on CAVs in realistic scenarios with a focus on the longitudinal control strategies to address the challenges in unreliable communication and mixed-traffic environments.

3 Related Work

CAVs encounter challenges in their operation when they execute driving actions in realistic scenarios. Various control strategies have been proposed to address the potential challenges of communication impairments and uncertainties present in the driving behavior of human-driven vehicles in the realistic operational environment of CAVs. This chapter presents the existing work on CAV longitudinal control strategies to tackle detrimental effects of CAV's driving behaviour due to unreliable communication links in the first instance (Section 3.1), then due to mixed traffic scenarios (Section 3.2), and finally due the combination of the two (Section 3.3). Section 3.4 presents the open research challenges and research questions based on this related work. Lastly, Section 3.5 presents the closest and relevant baseline approach selection.

3.1 Control Strategies to Address Unreliable Communication

CAVs receive information from surrounding vehicles and RSU-equipped infrastructure, and incorporate this information to design cooperative control strategies [O'Hara et al., 2015, Sarker et al., 2020]. In order to qualitatively and quantitatively evaluate the detrimental effect of unreliable communication links, the notion of string stability is often used. *String stability* ensures that fluctuations in leading vehicle behavior (acceleration/deceleration caused due to scenarios such as stop and go, hard brake, cut-in, cut-out) do not propagate downstream into the string [Nowakowski et al., 2015, Feng et al., 2019].

A number of studies have investigated the effect of communication delays and packet losses on the robustness of the string stability i.e., CAVs' driving behavior. When the communication is not perfect, string stability deteriorates drastically when a vehicle cannot establish a communication link with its preceding vehicle and therefore degrades its mode

to ACC or makes a decision based on the outdated information. This section describes control strategies designed to provide robustness against the challenges in the operation of CAVs despite unreliable communication. Firstly, we present existing car-following control strategies developed to ensure string stability despite unreliable communication for homogeneous CACC systems. Then, existing control strategies are presented for heterogeneous CACC systems in unreliable communication environments.

3.1.1 Homogeneous CACC Systems

Car-following control systems in which all vehicles in the string have identical dynamics (e.g., vehicle size, actuator lags, driveline parameters) are called *Homogeneous CACC Systems*. When communication is not perfect, packet losses can halt information transfer, whereas packet delays might delay it. This section presents existing control strategies catering for packet losses, followed by control strategies catering only for delays.

Packet losses

The estimation algorithm/observer design has been widely adopted to preserve string stability at the desired time-headway despite packet losses. In this approach, when no acceleration information from the preceding vehicle is available via V2V, it is estimated instead. For example, Ploeg *et al.* proposed a graceful degradation of a CACC system into a degraded-CACC rather than ACC [Ploeg et al., 2015]. In this approach, an estimator (Kalman filter) is designed using on-board sensors measurements to estimate the acceleration of the preceding vehicle in the predecessor-following IFT. The degraded CACC system outperforms the ACC system in terms of string stability performance at reduced time-headway, but shows a degraded string stability performance compared to a CACC system with reliable V2V communication because of a significant time-lag in the estimated acceleration with respect to the desired acceleration. To further reduce the string stable time-headway, Acciani *et al.* studied string stability properties using a third-order longitudinal dynamic model with actuator delay (internal delay of the system) over an unreliable communication network [Acciani et al., 2018]. They designed two different controllers, a local controller (feedback control) and a cooperative controller (feedforward control). The objective of each local controller is to

stabilize the individual vehicle based on the information obtained through onboard sensors, i.e., local measurements and the cooperative controllers stabilize the platoon operation in terms of string stability by estimating the acceleration information of the preceding vehicle using an observer. While most existing traditional estimation methods rely on onboard sensors (e.g., radar and lidar) that can estimate the information of the preceding vehicle in case of communication failures, data-driven model-based estimation methods such as long short-term memory neural network, recurrent neural network have also been used recently to estimate the lost information [Tian et al., 2021].

The aforementioned studies consider the predecessor-following information flow topology only. In practice, CAVs can obtain information from multiple predecessors within their communication range to further reduce time-headway while ensuring string stability. In particular, Zhao *et al.* investigated string stability using multiple-predecessor-following information flow topology [Zhao et al., 2021]. They found that string stability is improved when information is available from multiple leading vehicles without any packet losses, however, the presence of packet losses increases the minimum string-stable time-headway. To ensure string stability in such situation, historical information of multiple-leading vehicles is used in the controller design [Zhao et al., 2021]. This study assumes a fixed information flow topology. In practice, however, the information flow topology (IFT) varies dynamically due to communication failures e.g., some vehicles may have two-predecessor-following IFT and some may have one-predecessor-following IFT due to one link failure in the same platoon. These dynamic IFTs convert a homogeneous CACC system into a heterogeneous CACC system due to the presence of different IFTs in the same platoon, and impose new challenges in the CACC control design, compared to using fixed-IFTs. These are discussed in Section 3.1.2.

Communication delays

Beyond the problem of packet losses in wireless communication, packet delays is another important issue, as unreliable communication links can destabilize the CACC system behavior [Wang et al., 2020b]. Different control methods are reported in the literature to address the effect of constant and time-varying delays in the communication network on

the robustness of string stability. In the majority of the existing literature, string stability is investigated using the predecessor-following IFT. In addition, disseminating the leader vehicle information to all following vehicles will increase the robustness of the controller (predecessor-leader following IFT). For example, Peters *et al.* demonstrated that if we transmit velocity information of the platoon leader and position information of predecessors to all following vehicles, string stability can be achieved in the presence of a certain amount of latency in the communication links [Peters et al., 2014]. They considered a linear second-order vehicle dynamic model in which each vehicle is described as a point mass with state variables: vehicle position and velocity. Due to consideration of the drag force in the system dynamics, this second order model behaves as a linear mass-damper system with vehicle acceleration as a control input. In addition to stabilizing the system in the presence of communication delays, the platoon control using leader information can also mitigate the negative effects of unmodeled nonlinear dynamics, parameter uncertainties and disturbances present in the system in realistic scenarios. Transmitting leader information to all vehicles without large delays and packet losses is a challenging task however. To address this problem, platoon control can supplement lost information due to unreliable communication links with information from its own sensors. This approach was successfully implemented using a bidirectional information flow topology [Hao and Barooah, 2013]. This topology, however, suffers from high sensitivity to the platoon length.

The aforementioned approaches are only applicable in the presence of small and constant communication delays. To achieve string stability in the presence of large and time-varying communication delays, Biron *et al.* proposed an estimation algorithm using two Luenberger' observers and a delay estimator, in which the delay estimator estimates the communication delay and uses it to compensate the mean value of the delay in the designed observer [Biron et al., 2017]. Another observer is used to estimate the state of the preceding vehicle in normal conditions, i.e., without communication failure, to know the communication status using non-zero output error. This estimation algorithm provides better CACC controller performance, i.e., very close to the CACC performance without communication failures.

In essence, the aforementioned studies design car-following control algorithms without incorporating communication delays and they therefore can achieve string stability only with large time headways [Gómez et al., 2014]. While string stability is maintained, it

is at the expense of reduced traffic efficiency. In order to achieve the full potential of CACC in terms of both string stability and traffic efficiency, communication delays must be considered into the controller design. For example, [Xing et al., 2020] studied the effect of communication delays on string stability and designed a Smith predictor to compensate delays in the CACC controller. A Smith predictor cannot be applied directly to compensate time delays in CACC as delays are generally present in the feed-forward loop, not in series with the process. Xing *et al.*, therefore, proposed a master-slave control strategy to relocate the CACC controller so that the communication delays model is in series with the process to be controlled. The master-slave control strategy employs bidirectional communication with a predecessor-following IFT to establish V2V communication. In this master-slave strategy, the preceding vehicle ($i-1$) acts as a master and the following vehicle (i) serves as a slave. The follower vehicle controller is relocated into the preceding vehicle and the desired acceleration of the follower vehicle is computed in the preceding vehicle as shown in Figure 3.1. The proposed scheme performs well by reducing the string-stable time gap in the presence of uncertain delays. This scheme, however, is only applicable to homogeneous CACC systems as the control function of the following vehicle is executed on the preceding vehicle. In recent work, Zhang *et al.* proposed an alternative approach to explicitly consider communication delays into the CACC control algorithm in the form of an adaptive spacing policy based on the semi-CTH spacing policy [Zhang et al., 2020]. The proposed control scheme uses historical information of the preceding vehicle behavior instead of its current information to compensate communication delays and ensure the string stability with a smaller time headway than the CACC system designed based on current information. Unfortunately, this approach is also only applicable to homogeneous CACC systems.

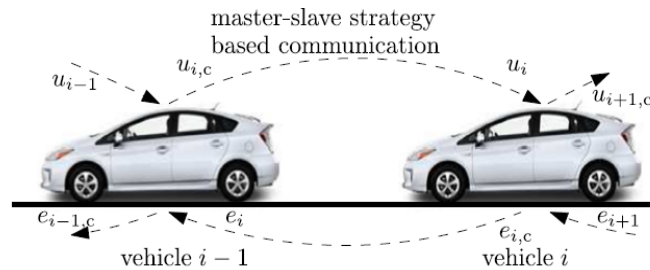


Figure 3.1: Master-slave based CACC operation, where e_i and $u_{i,c}$ are the inter-vehicle distance error, and desired acceleration of the vehicle i (computed in the preceding vehicle $i-1$) respectively [Xing et al., 2020].

Table 3.1 summarizes the different car-following control strategies for homogeneous

Table 3.1: Summary of the different car-following control strategies for homogeneous CACC systems in unreliable communication environments

Reference	Spacing policy	IFT	Longitudinal vehicle dynamics	Car-following control method	Methodology	Communication imperfections	String stability	Simulation/Experimentation
[Ploeg et al., 2015]	CTH	Predecessor-following	3^{rd} order	CACC	degraded-CACC (dCACC) by estimating the preceding vehicle acceleration	Long delays and packet losses	Yes	Both simulation & experimentation
[Biron et al., 2017]	CTH	Predecessor-following	2^{nd} order	CACC	Modified CACC algorithm using two Luenberger's observers and a delay estimator	Time-varying delays	No	Simulation
[Acciani et al., 2018]	CTH	Predecessor-following	3^{rd} order	CACC	Observer design to estimate the preceding vehicle's states	Packet losses	Yes	Simulation
[Zeng et al., 2019]	CD	Predecessor-following	3^{rd} order	CACC	Joint optimization of controller parameters and maximum tolerable delays	Short delays	Yes	Simulation
[Xing et al., 2020]	CTH	Predecessor-following	3^{rd} order	Master-slave CACC	Smith predictor design	Time-varying delays	Yes	Simulation
[Zhang et al., 2020]	Semi-CTH	Predecessor-following	3^{rd} order	Delay-compensating CACC	Uses historical information instead of the current information	Time delays	Yes	Simulation
[Hao and Barooah, 2013]	CD	Predecessor-following and bi-directional	2^{nd} order	Linear and nonlinear controllers	Proportional-derivative (PD) controller	Time delays	Yes	Simulation
[Peters et al., 2014]	CD	Predecessor leader-following	2^{nd} order	Linear position and speed control	Proportional-derivative (PD) controller	Time delays	Yes	Simulation
[Navas and Milanés, 2019]	CTH	Multiple predecessor-following	2^{nd} order	Advanced-CACC	Use of two CACC controllers with different time headways	Packet losses	Yes	Both simulation & experimentation
[Zhao et al., 2021]	CTH	Multiple predecessor-following	3^{rd} order	CACC	Markov jump linear systems theory	Packet losses	Yes	Simulation

vehicles strings in the presence of unreliable communication links (both communication delays and packet losses). It shows that most studies have chosen the constant time-headway spacing policy with the predecessor-following IFT to design a car-following control system, while ensuring string stability. Adopting multiple-predecessors-following IFTs instead of the predecessor-following IFT seems to be a promising approach to ensure string stability at smaller time-headway, and needs to be further explored in imperfect communication environments. Furthermore, none of the studies have included non-linearity in longitudinal vehicle dynamics.

3.1.2 Heterogeneous CACC Systems

In practice, vehicles may have different dynamic models (e.g., non-identical driveline dynamics time constant, actuator delays and parameter uncertainties) or different IFTs in the same string [Wang et al., 2020b] and CACC systems supporting such strings of vehicles are called *heterogeneous CACC systems*. Identical distributed controllers cannot stabilize the string operation in this case as they do in the case of homogeneous CACC systems. Therefore, car-following controller must be designed considering heterogeneity in vehicle dynamics and/or information-flow topologies [Zhu et al., 2019]. This section first presents existing control strategies designed based on one-vehicle ahead information only, followed by control strategies based on information from multiple preceding vehicles.

Based on the predecessor-following IFT

One possible approach to deal with heterogeneous CACC systems is to first impose uncertainties on homogeneous CACC systems and then apply robust control methods to achieve string stable behavior [Wang et al., 2020b]. Using this approach, Harfouch *et al.* investigated string stability performance in the presence of heterogeneity in vehicle dynamics and unreliable V2V communication links [Harfouch et al., 2018]. The model reference adaptive control (MRAC) augmentation method was used to design the control input to ensure the string stable behavior of a heterogeneous platoon, and a switching control strategy was adopted to transition from CACC to ACC in the case of communication failures. This approach, however, ensures string stability at the expense of traffic efficiency due to the large time-headway in the ACC mode. To achieve string stability at a reduced time-headway in the presence of communication failures, Nunen *et al.* proposed a model predictive control (MPC) approach to increase robustness in terms of string stability by sharing the vector of predicted accelerations over a finite time horizon via V2V communication [van Nunen et al., 2019]. The predicted acceleration vector can compensate communication failures for a short period of time to maintain stable CAV driving behaviour. This approach shows good robustness in terms of string stability in the presence of packet losses, though only under the assumption that packet loss are restricted to a short time period. Similarly, a recent study [Sawant et al., 2020] proposed a disturbance observer-based sliding mode control tech-

nique to achieve string stability in a heterogeneous CACC system when information is not available from the preceding vehicle due to communication network failures. The proposed approach ensures string stability thanks to an accurate estimation of the preceding vehicle's acceleration and its inclusion in the designed control law. A disturbance observer is designed to estimate the uncertainties present in vehicle dynamics and acceleration of the preceding vehicle as a lumped disturbance, and a sliding-mode controller ensures the string stability of a platoon using the estimated information. This robust control approach, however, assumes limited deviations from homogeneous vehicle dynamics and may not guarantee string stability in all scenarios.

In the aforementioned approaches, the heterogeneity in vehicle dynamics is not directly considered, but is instead imposed as uncertainties/disturbances on homogeneous CACC systems. These approaches assume limited parameters uncertainties and disturbances, which may not be valid assumptions in realistic scenarios. To address this problem, some researchers proposed explicit control methods to consider the heterogeneity in vehicle dynamics directly in the controller design. Such explicit control methods, however, require a more complex IFT than the predecessor-following IFT to achieve string stability. Different control methods for heterogeneous CACC systems based on complex IFTs are discussed in the following.

Based on the multiple-predecessors-following IFT

Most CACC systems have been studied based on a simple IFT (i.e., predecessor-following topology). A number of recent studies address delays and packet drops in information exchange based on complex IFTs rather than the simple predecessor-following IFT [Liangye et al., 2019, Gong et al., 2019, Wang et al., 2020a, Li et al., 2021, Santini et al., 2017, Oliveira et al., 2021]. This section presents existing control strategies catering for communication delays, followed by control strategies catering only for packet losses.

Communication delays: Most studies focus on investigating the upper bound on information delays and stability conditions analytically under different IFTs and then designing a robust car-following control algorithm to ensure string stability of a platoon in the presence of bounded communication delays [Santini et al., 2017, Oliveira et al., 2021, Li

et al., 2021]. For example, Santini *et al.* proposed a consensus-based control approach that considers the platoon a high-order consensus problem with the goal of coordinating all vehicles to reach an equal inter-vehicle gap, representing a non-fixed information flow topology with time-varying delays [Santini et al., 2017]. The idea was to design a decentralized control algorithm so that the emerging platoon information flow topology, depending on the communication links, is asymptotically stable without the need to pre-establish (with respect to the controller design) the topology. The proposed approach turns the information flow topology into a design parameter that dynamically re-configures the controller. In addition, the controller automatically compensates for outdated information caused by heterogeneous communication delays. Both analytical and simulation results showed that the controller can stabilize a vehicle platoon with different information flow topologies, in the presence of various disturbances and bounded delays. However, this controller is designed based on the leader-predecessor-following IFT and applicable to the platoon structure (i.e., with a designated leader vehicle) only. Furthermore, Li *et al.* proposed a generalized car-following model considering generic information flow topologies, with heterogeneous time delays that can be configured according to the V2V information flow topology [Li et al., 2021]. In this way, the proposed model can also be combined with the switching IFT in the case of unstable communication to describe the dynamic behavior of traffic flow. It is assumed that the switching topology among the three fixed topologies follows the direction of predecessor-following, bidirectional-leader-following, two-predecessor-leader-following, then again predecessor-following, bidirectional-leader-following, ..., and the switching period is 25s. Results show that CAVs traffic flow under two-predecessor-leader-following topology possesses better traffic performance than bidirectional-leader-following and predecessor-following topologies at the same time delay value. This approach is, however, implemented in a traffic flow scenario with a small number of vehicles and needs further investigation in realistic traffic scenarios.

According to the literature and IVC standards, the frequency at which each vehicle has to broadcast its data must be no lower than 10 Hz [Ploeg et al., 2011], which is a value that imposes tight communication constraints, stresses the channel (shared by all vehicles), but finds its justification in the vehicle's dynamics and, thus, can be considered a hard physical requirement. With the need to provide reliability to vehicular networks, solutions emerge

to offer a guaranteed message delivery service through a control mechanism so that vehicles behavior can dynamically adapt to the network conditions. For example, Oliveira *et al.* proposed the *AddP-CACC* approach that combines the AddP reliable communication protocol with the consensus-based control strategy to achieve string stability of a vehicle platoon in the presence of various disturbances and time-varying delays, especially in congested traffic scenarios [Oliveira et al., 2021]. A reliable communication protocol is used to meet the network reliability requirements of platoon control applications [Oliveira et al., 2021] and the consensus-based control strategy has shown robustness in the presence of disturbance in the leader vehicle dynamics and communication failures [Santini et al., 2017]. Results show that the AddP-CACC approach performs better in achieving string stability compared to the commonly-used fixed frequency standard. Though this was the first study combining network load control mechanism with the car-following control, it lacks analytical proof in checking the string stability conditions.

Packet losses: Compared to the aforementioned studies considering heterogeneous delays only during the information exchange, some studies also address string stability in the presence of packet drops. Liangye *et al.* proposed considering multiple unidirectional IFTs such as predecessor-following, predecessor-leader following, two-predecessor-following and two-predecessor-leader following, among vehicles in the same platoon in the presence of communication failures [Liangye et al., 2019]. A distributed model predictive control (DMPC) algorithm was developed in which a local receding horizon open-loop optimal control problem was formulated to design the control input of each nonlinear vehicle model in a platoon under state and input constraints. The proposed approach has been validated in terms of string stability using the CD spacing policy with a desired inter-vehicle distance of 3m. This approach assumes a fixed IFT. In practice, however, IFTs vary dynamically due to communication failures e.g., some vehicles may have a two-predecessor-following IFT and some may have a one-predecessor-following IFT due to one link failure in the same platoon. To address this, Gong *et al.* proposed a two predecessors-following IFT-based platoon control strategy, where the subject vehicle gets the acceleration information of its two predecessors via V2V communication, and the position, and speed of its immediate predecessor using onboard sensors [Gong et al., 2019]. If its V2V communication link with either or both predecessors fails, the controller switches to CACC/ACC depending on the

degeneration scenarios. An adaptive PD controller with two acceleration feed-forward filters is designed to achieve string stability in a CAVs platoon. This approach provides minimum string stable time-headway, though, it might not perform well in congested traffic scenarios due to the high probability of packet losses and subsequent degradation in traffic efficiency in the ACC mode.

To address dynamic IFTs in congested traffic scenarios, a CACC-OIFT strategy (IFT optimization model) was proposed to obtain the optimal IFT to maximize string stability [Wang et al., 2020a]. Communication failures mainly occur in a platoon of CAVs when more than one vehicle sends information via the same channel at the same time. Therefore, the CACC-OIFT strategy aims to control in real-time the number of platoon vehicles with send functionality activated, according to ambient traffic conditions and platoon size, to reduce the probability of V2V communication failures and achieve maximized platoon performance in terms of string stability. An adaptive PD controller was designed to track the car-following behavior under the two-predecessors-following topology. The proposed CACC-OIFT strategy shows better platoon performance in the presence of unreliable communication links than CACC with fixed-IFTs. Furthermore, these dynamic IFTs impose additional challenges in the CACC control design, compared to using fixed-IFTs because the topology switching process causes damage to the smoothness of CAVs traffic flow [Li et al., 2021]. For instance, compared with the acceleration curves of CAVs under fixed topologies, topology switching leads to an obvious sudden change in velocity, velocity error and acceleration curves when CAVs move under switching topology. This problem highlights the need to design a robust car-following model for CAVs operation under switching topology. In addition, the authors highlighted the need for further research on this topic, not only with respect to safe degradation from CACC to ACC but also on how to switch back to CACC once communication is reestablished.

The aforementioned studies show that both packet loss ratio (PLR)¹ and message transmission frequency, i.e., the information exchange rate, have a strong influence on the reliability of communication links in a connected environment [Bevly et al., 2016, Bischoff et al., 2020]. A higher message transmission frequency represents a higher possibility of obtaining updated information from other CAVs, but there is a trade-off between the mes-

¹PLR is the ratio of the number of lost packets to number of sent packets.

sage transmission frequency and the number of vehicles sending messages due to the limited transmission bandwidth. For this reason, in dense traffic conditions, CAVs will send information at a low frequency and may, therefore, have to control their driving actions based on outdated information, resulting in delayed response to traffic conditions. Driving actions taken using outdated information about surrounding vehicles can severely affect traffic safety and efficiency [Wang et al., 2019c]. To address this problem, Sybis *et al.* investigated multi-channel operations with the use of dual radio transceivers [Sybis et al., 2019]. They investigated multi-channel operations using two IEEE 802.11p transceivers in a vehicle instead of channel switching in a single transceiver, with each vehicle transmitting its information to other vehicles using two channels e.g., channel CH172 to send basic safety messages (BSMs)/cooperative awareness messages (CAMs) and a different service channel to send CACC messages only. Thanks to the use of dual radio transceivers, message transmission frequency can be increased, providing the CACC controllers with fresher information from other vehicles and therefore enabling the use of shorter inter-vehicle distance and improving traffic performance in congested traffic.

Table 3.2 summarizes the different car-following control strategies for heterogeneous vehicle strings in unreliable communication environments. While implicit control methods address the heterogeneity as uncertainties and/or disturbances imposed on homogeneous CACC systems, explicit control methods address heterogeneity directly in their control design. In unreliable communication environments, the CAVs' driving mode is degraded from CACC to ACC when information is not available for a long time, resulting in string stability at the expense of a large time-headway. Although these car-following control strategies have shown robustness against uncertainties in vehicle dynamics and communication failures, they have only been applied considering limitations such as limited deviations in the heterogeneity of vehicles, simple IFTs, or longitudinal vehicle dynamics without considering the time lags in engine response.

3.2 Control Strategies to Address Mixed Traffic

By utilizing information of multiple surrounding vehicles obtained via V2V communication in their car-following controller, connected autonomous vehicles are widely expected to

Table 3.2: Summary of the different car-following control strategies for heterogeneous CACC systems in unreliable communication environments

Reference	Spacing policy	IFT	Longitudinal vehicle dynamics	Car-following control method	Implicit/Explicit control	Methodology	Communication imperfections	String stability	Simulation/Experimentation
[Harfouch et al., 2018]	CTH	Predecessor-following	3^{rd} order	CACC with adaptive switched control strategy	Implicit	Model reference adaptive control (MRAC) augmentation	Packet losses	Yes	Simulation
[van Nunen et al., 2019]	CTH	Predecessor-following	3^{rd} with actuator delays order	CACC	Implicit	Model predictive control (MPC)	Packet losses and time delays	Yes, nominal conditions	Both simulation & experimentation
[Sawant et al., 2020]	CTH	Predecessor-following	3^{rd} order	CACC	Implicit	Disturbance observer based sliding-mode control	Packet losses	Yes	Simulation
[Santini et al., 2017]	CTH	Predecessor, Predecessor-leader, Two predecessors and Bi-directional following	3^{rd} order	CACC	Explicit	Consensus-based control algorithm	Time-varying delays	Yes, better than fixed IFTs	Simulation
[Liangye et al., 2019]	CD	Multiple uni-directional predecessor-following	3^{rd} order nonlinear	CACC	Explicit	Distributed model predictive control (DMPC)	Short delays	Yes	Simulation
[Gong et al., 2019]	CTH	Two predecessor-following	2^{nd} order	CACC with dynamic IFT	Explicit	Adaptive PD control	Packet losses	Yes, better than fixed IFTs	Simulation
[Wang et al., 2020a]	CTH	Two predecessor-following	2^{nd} order	CACC with optimized IFT	Explicit	Adaptive PD control	Packet losses	Yes, better than fixed IFTs	Simulation
[Sybis et al., 2019]	CTH	Predecessor-following	3^{rd} order	Modified CACC	Explicit	Use of dual-radio transceivers	Packet losses	Yes	Simulation
[Oliveira et al., 2021]	CTH	Predecessor, Predecessor-leader and Bidirectional-following	3^{rd} order	CACC	Explicit	AddP reliable communication protocol with the consensus-based control	Time-varying delays	Yes, better than fixed IFTs	Simulation
[Li et al., 2021]	CD	Predecessor, Predecessor-leader and Bi-directional	3^{rd} order	Generalized-CACC	Explicit	Fixed and switching-based IFT	Time-varying delays	Yes, better than fixed IFTs	Simulation

improve traffic safety and efficiency [Bian et al., 2019, Abolfazli et al., 2022]. In mixed traffic scenarios, however, it may not always be possible for a CAV to obtain information from surrounding vehicles that do not have communication capabilities and are beyond its line of sight. This results in hindering CAVs in utilizing their full potential, especially at low penetration rate of CAVs [Rahman et al., 2021, Ding et al., 2022]. *Connected Cruise Control (CCC)* is a popular car-following control strategy for CAVs operation in mixed traffic. CCC allows a CAV to exploit information from surrounding connected HDVs (HDVs with communication capabilities) to control its longitudinal motion. CCC is an effective control strategy at CAV low penetration rates as it can provide significant improvement in traffic performance by retrofitting communication devices to more and more HDVs, in contrast to CACC which can only provide significant benefits at high penetration rates of CAVs [Zhang and Orosz, 2016].

Firstly, this section presents existing car-following control strategies designed based on the predecessor-following IFT, followed by control strategies based on the multiple-predecessor-following IFT. Then, it describes managed lane and platooning strategies to further improve mixed traffic performance.

3.2.1 Predecessor-Following IFT-based Control

CACC technology allows vehicles to travel with reduced spacing between adjacent vehicles, resulting in improved traffic efficiency [Arnaout and Arnaout, 2014, Liu et al., 2018]. Simulation studies show that at low penetration rates (usually less than 25%), CAVs have a negative impact on traffic efficiency, while at medium-to-high high penetration rates (usually 40% or more) they would provide a significant improvement [Calvert et al., 2017, Do et al., 2019, Guériau and Dusparic, 2020]. Simulation studies, however, are very sensitive to the car-following models chosen to describe the driving behaviour of both CAVs and HDVs [Horcas et al., 2017, Monteil et al., 2019, Liu and Fan, 2020]. To improve traffic efficiency at low penetration rates, it was proposed to equip HDVs with V2V communication devices (turning them into connected vehicles) [Shladover et al., 2012, Di Vaio et al., 2019]. Therefore, connected HDVs will now have capabilities of sending and receiving information via V2V communication just like CAVs, thereby resulting in improved traffic safety and

efficiency [Rahman et al., 2021]. But the advantages of connected vehicles in improving mixed traffic performance would also depend on the human-driver compliance factor with the received information [Sharma et al., 2019]. When the traffic information is obtained by a connected HDV, the driver of that vehicle can either respond according to the received information or completely (or partially) ignore it.

While most studies focus on analyzing the impact of CAVs on traffic efficiency only, a few recent studies have investigated traffic safety aspects explicitly [Ye and Yamamoto, 2019, Papadoulis et al., 2019]. They found that a low market penetration rates of CAVs (level 4) was sufficient to improve safety (e.g., 12-47% reduction in safety conflicts at 25% MPR) as most road accidents occur due to human perception errors and large reaction times [Papadoulis et al., 2019]. A recent study, however, shows that level 2 CAVs actually have a negative impact on traffic safety (around 10% increase in safety conflicts at 25% MPR) [Gu  riaux and Dusparic, 2020]. Such safety conflicts can be reduced with the use of conservative time headway settings but this is at the expense of traffic efficiency [Ye and Yamamoto, 2019]. Providing communication capabilities in HDVs is shown to further improve traffic safety [XIAO, 2020]. Simulation results, however, are very sensitive to the car-following models chosen to describe the driving behaviour of CAVs, similarly to efficiency. Indeed, a recent study shows that CAVs actually have a negative impact on traffic safety while using the CACC car-following model, and improve it significantly when the IDM car-following model is used [Mahmud et al., 2019].

While simulation platforms are very useful to evaluate CAV control strategies, they need to be tested and validated in experimental studies. For example, the TransAID project [Mitsakis et al., 2019] by the CERTH - HIT conducted simulation studies to study the impact of different penetration rates of CAVs, HDVs, connected HDVs on traffic safety, efficiency and fuel consumption under different traffic levels. Additionally, it investigated the effects of transitions of control and minimum risk manoeuvres at transition areas such as road works, accident zone and on/off-ramps merging zone, etc., using infrastructure-based control methods, and developed the real world prototypes for field testing.

Table 3.3 summarizes the different control strategies based on information from one-vehicle ahead only and the impact of CAVs (of different automation levels) on traffic per-

Table 3.3: Comparative study of the control strategies based on the predecessor-following IFT for CAVs operation in mixed traffic and their impact on traffic performance

Reference	Vehicle types	MPR (%)	Car-following model	Time headway settings	Control strategy	Road network	Traffic scenario	Traffic efficiency	Traffic safety	Traffic flow stability
[Shladover et al., 2012]	CAVs, HDVs, Connected HDVs	10, 20, 30, 40, 50, 60, 70, 80, 90	CAV-MIXIC model, HDV-NGSIM oversaturated freeway flow model	1.48-1.8s (HDVs), 1.1-2.2s (ACC mode), 0.5s (CACC mode)	CACC	Single-lane 6.5-km long highway	Over-saturated	✓	✗	✗
[Arnaout and Arnaout, 2014]	CAVs, HDVs	0, 20, 40, 60, 80, 100	IDM with different parameters	0.8-1s (HDVs), 0.5s (CACC mode)	CACC	Four-lane 6-km long highway	Moderate, saturated & over-saturated	✓	✗	✗
[Talebpour and Mahmassani, 2016]	CAVs, AVs, Connected HDVs	10, 25, 50, 75, 90	CAV-MIXIC model, HDV-IDM	1-1.5s	CACC	Single lane highway	Free flow	✓	✗	✓
[Ye and Yamamoto, 2019]	CACC, HDVs	0, 20, 30, 40, 50, 60, 70, 80, 90	Cellular automation (CA) model	0.5-1.1s	CACC	Two-lane 10-km long highway	Free-flow	✓	✓	✗
[Papadoulis et al., 2019]	CAVs, HDVs	0, 25, 50, 75, 100	CAV-User-defined control algorithm, HDV-Wiedemann 99	0.6s (CACC mode)	Platooning strategy based on local co-ordination	Three-lane 44.27-km long motorway	Free-flow, saturated & over-saturated	✓	✓	✗
[Liu and Fan, 2020]	CAVs, HDVs	0, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100	CAV-Revised IDM, HDV-Wiedemann-99	-	CACC	Four-lane highway	Over-saturated	✓	✗	✗
[Guériau and Dusparic, 2020]	CAVs, HDVs	0, 2.5, 7, 20, 40, 70	CAV-Field-tested ACC, CACC model (PATH) and IDM, HDV-Krauss	1.2-1.5s (HDVs), 0.6-0.8s (CACC mode)	CACC	Urban, national and motorway	Free-flow, saturated, over-saturated	✓	✓	✗
[Jie et al., 2020]	AVs, HDVs, Connected HDVs	-	IDM with different parameters	0.8s, 1s, 1.5s, and 2s	CACC	A very long single-lane highway	String of twenty, forty, sixty, eighty, one-hundred vehicles	✗	✗	✓

✓: considered, ✗: not considered.

formance, for different penetration rates and traffic scenarios. It shows that different studies have chosen different time headway values. As the time-headway plays a major role in mixed traffic performance, its value should be chosen based on field-experiments performed in realistic scenarios. Furthermore, it is reported that CAVs provide a significant improvement in traffic efficiency when human-driven vehicles are equipped with communication devices turning them into connected vehicles, especially at low CAV penetration rates.

3.2.2 Multiple-Predecessor-Following IFT-based Control

Most studies use CAVs' car-following control algorithms using information from their immediate preceding vehicle only, and employ the same IFT for all CAVs. CAVs, however, can exploit information from multiple preceding vehicles within their communication range, thereby enhancing the resilience of their control algorithms, contributing to better traffic safety and efficiency than the predecessor-following IFT-based control [Rahman et al., 2021, Ding et al., 2022, Avedisov et al., 2022]. In mixed traffic, however, some vehicles are human-driven vehicles that do not broadcast information and some are CAVs that broadcast information to other vehicles within their communication range. CAVs can only exploit information from multiple preceding vehicles when they all are equipped with wireless communication devices [Di Vaio et al., 2019, Wang et al., 2021, Zhang et al., 2018, Cui et al., 2021]. So equipping HDVs with communication devices would allow designing CAVs' control algorithms based on information from multiple preceding vehicles [Zhang et al., 2021]. To demonstrate the advantages of providing communication capabilities to HDVs and exploiting from multiple preceding vehicles, Cui *et al.* investigated the impact of CAVs on mixed traffic (comprising of CAVs, HDVs and connected HDVs) when they utilize information received from multiple preceding vehicles in their controller design [Cui et al., 2021]. It is concluded that the information of multiple preceding vehicles helps CAVs to achieve better mixed traffic stability. The parameters of the HDV, connected HDV, and CAV car-following models have not been calibrated by driving simulation, however. Avedisov *et al.* performed experiments with real vehicles on a 3-vehicles fully connected network (i.e., 1 CAV and 2 connected HDVs). Experimental results are used to establish a simulation study based on 100-vehicles network. The study uses the OVM car-following model for simulation study, where car-following model parameters are tuned based on experimental results of 3-vehicles

network [Avedisov et al., 2022]. Simulation results show that exploiting information from multiple preceding vehicles has the potential to further improve traffic efficiency as compared to using information from the immediate preceding vehicle only. Overall, on the one hand, it is accurately claimed that connectivity can help CAVs to achieve better traffic safety and efficiency. On the other hand, several studies reported that multiple-vehicles exchange information does not necessarily provide better traffic safety and efficiency [Li et al., 2020, Zheng et al., 2018]. The more information is transmitted, the higher the likelihood of communication delays, packet losses, etc., due to the congestion of communication channels. Therefore, the advantages of using multiple leading vehicles information rather than a single vehicle information in the CAV controller design need to be investigated further.

The aforementioned control approaches based on equipping HDVs with communication devices are being applied for CAV low penetration rates only. Conversely, a few studies investigated CAVs' control algorithms designed based on complex IFT other than the simple predecessor-following IFT, without equipping communication devices in HDVs [Zhang, 2018, Chen et al., 2021b]. In particular, [Zhang, 2018] studied a CACC system exploiting information from multiple-preceding vehicles in mixed traffic, and a strategy is designed to determine whether the data received from other vehicles is incorporated into the CACC control algorithm. However, this study was limited to a platoon of 8 vehicles only, with a fixed sequence of HDVs and CAVs. Furthermore, Chen *et al.* developed a consensus-based control model for mixed-vehicles platoon using the variable time-headway policy and leader-predecessor-following IFT, assuming the platoon leader to be a CAV only [Chen et al., 2021b]. The stability conditions of the mixed vehicle platoon system are derived through analytical study, and simulation experiments are conducted under different penetration rates, vehicle ordering and reaction times. Results show that the car-following control model designed based on the VTH spacing policy is better in terms of string stability of a mixed vehicle platoon than the control based on the CTH policy. Moreover, the effects of different penetration rates, vehicle ordering and reaction times on mixed platoon stability are shown through simulation studies. Results indicate that increasing the penetration rate of CAVs in the mixed vehicles platoon has a positive impact on the platoon stability. Simultaneously, CAVs in front of HDVs can help HDVs to better track the leader's state changes. Increasing the reaction-time delay has a negative impact on mixed platoon sta-

bility. Another study claims that for a mixed vehicles platoon with multiple-predecessor following IFT, the optimal platoon control performance is obtained when all HDVs move behind all CAVs [Jia et al., 2019]. These studies, however, have assumed fixed IFTs, which seems quite unrealistic due to the the presence of HDVs with communication capabilities in mixed traffic environment. Considering the occurrence of variations in IFTs in mixed traffic environment, Yu *et al.* [Yu et al., 2023] proposed an adaptive CAV controller, called mixed AV-CAV vehicle (MACV) to avoid the CAV car-following mode degradation to ACC in the absence of information coming from leading vehicles, thereby improving traffic safety and efficiency. This work has been performed in a very limited traffic scenario i.e., with a small number of vehicles, assuming perfect communication.

To further improve mixed traffic flow operations, different parameter estimation methods have been proposed in recent years that may be used to identify the dynamics of human-driven vehicles in mixed traffic environments [Ge and Orosz, 2016, Wang et al., 2023b]. They help CAVs to implement car-following control algorithms based on information from multiple leading vehicles, including HDVs. While most existing traditional estimation methods rely on onboard sensors (e.g., radar and lidar) that can estimate information of leading human-driven vehicles within the line of sight (i.e., the immediate leading HDV only), data-driven model-based estimation method can be used to monitor the vehicles beyond the line of sight. This has the potential for further improving traffic safety and efficiency [Ding et al., 2022, Zhou et al., 2023]. In particular, [Ding et al., 2022] presented a neural network-based estimation method for CAVs to estimate the speed of human-driven vehicles (HDVs) that are beyond the line of sight. First, an Elman neural network (ENN) model was built using a large amount of real car-following data to estimate speed information of two preceding HDVs with model parameters optimized using the sparrow search algorithm (SSA). Then, this neural network model was integrated with the multi-anticipative IDM car-following model for analyzing the impact of CAVs on traffic safety and efficiency. Another study in [Zhou et al., 2023] presented a deep neural network-based estimator and predictor to estimate the number of HDVs between two CAVs and their kinematic states in mixed traffic flow. Then, the multi-anticipative IDM car-following model was integrated with the model-guided deep deterministic policy gradient algorithm (DDPG), thereby resulting in improved traffic safety and efficiency at different CAV MPRs. The improvement in traffic stability

was shown at smaller time headways as compared to when the multi-anticipative IDM car-following model was used for evaluating the impact of CAVs on traffic flow stability, demonstrated the advantages of the extended intelligent driving model-guided DDPG over the model-free DDPG algorithm. The model training was, however, performed in very limited scenarios for a mixed platoon with a maximum of five HDVs between two adjacent CAVs due to the highly complex and computationally expensive nature of those advance machine-learning based estimation algorithms. Furthermore, to reduce the model training dimension and alleviate computation cost for CAVs operation in mixed traffic flow since the sequencing of CAVs and HDVs are random, Shi *et al.* proposed decomposing a whole mixed traffic flow into multiple small subsystems where each subsystem is comprised of a leader HDV followed by multiple CAVs, and then developing a deep reinforcement learning-based longitudinal control algorithm for CAVs to learn the leading HDV's behaviour [Shi et al., 2021]. However, this study assumes a fixed IFT. In addition, it is very challenging to organize the traffic in such a manner that each HDV is followed by multiple CAVs, and might also include a lot of lane-changing, which has not been investigated in this research. All these studies assume fixed IFTs, which seems quite unrealistic considering the unavailability of information in mixed traffic and unreliable communication environments.

Table 3.4 summarizes the different control strategies based on information from multiple vehicles ahead, and the impact of CAVs (of different automation levels) on traffic performance, for different penetration rates and traffic scenarios. It shows that different IFTS such as predecessor-following (PF), two-predecessor-following (TPF), bidirectional (BDL), multiple-predecessor following (MPF) have been implemented for CAVs' controller design, but with a small number of vehicles only [Zheng et al., 2016, Li et al., 2020, Bian et al., 2019]. Furthermore, it shows that exploiting multiple predecessors' information in the car-following control design allows CAVs to guarantee string stability even at smaller time headways, which results in better traffic efficiency. These studies were, however, limited to perfect communication. Furthermore, most existing work on CACC, CCC, and other control strategies has been performed with a small number of vehicles to demonstrate the advantages of CAVs and assume fixed IFTs. The effects of such control strategies in realistic traffic scenarios (i.e., with a large number of vehicles) considering both mixed traffic and unreliable communication, however, has not been extensively studied yet.

Table 3.4: Comparative study of the car-following control strategies based on the multiple-predecessor-following IFT for CAVs coordination in mixed traffic and their impact on traffic performance

Reference	Vehicle types	MPR (%)	Time headway settings	Control strategy	Road network	Traffic scenario	Traffic efficiency	Traffic safety	Traffic flow stability
[Zhang, 2018]	CAVs, HDVs, Connected HDVs	-	1 and 1.2s	Selective multiple-predecessor-following IFT-based CACC	A string of 8 vehicles	-	✗	✓	✓
[Rahman et al., 2021]	CAVs, AVs, CVs, HDVs	0, 20, 40, 60, 80, 100	1.1s (HDVs), 0.6s (AVs and CAVs)	Multiple-predecessor-following IFT-based CACC	14-miles long freeway	Congested	✓	✓	✗
[Cui et al., 2021]	CAVs, HDVs, Connected HDVs	10, 20, 80, 90	1s	Multiple-predecessor-following and multi-time step-based CACC	A platoon of 12 to 16 vehicles	Congested	✗	✗	✓
[Chen et al., 2021b]	CAVs, HDVs	0, 2, 4, or 6 HDVs	1.2s (HDVs), 1s (CAVs)	Leader-predecessor-following IFT-based adaptive consensus control	A platoon of 8 vehicles	Free-flow	✗	✗	✓
[Wang et al., 2021]	CAVs, Connected HDVs	-	5m	Multiple-predecessor and successor IFT-based LCC	A platoon of 6 vehicles	-	✗	✗	✓
[Zhang et al., 2021]	Connected HDVs	-	4 to 6m	Multiple-predecessor-following IFT-based cruise control	A string of 20, 40, 60, 80, 100 vehicles	Congested	✗	✗	✓
[Avedisov et al., 2022]	CAVs, HDVs, Connected HDVs	25, 50, 75, 100	45-55m (for HDVs), 29-45m (CAVs)	Connected cruise control	A string of 100 vehicles	-	✓	✗	✓
[Ding et al., 2022]	CAVs, HDVs	0, 20, 40, 60, 80, 100	1.5s (for HDVs), 0.6, 1.1, 1.5, 2s (for CAVs)	SSA-ENN combined with multi-anticipative IDM	A String of 20 and 40 vehicles	Free-flow, moderate and congested	✓	✓	✗
[Zhou et al., 2023]	CAVs, HDVs	0, 30, 50, 70, 90, 100	2s (for HDVs), 1.2556s (for CAVs)	DDPG combined with multi-anticipative IDM	A String of 80 vehicles	Free-flow and moderate	✓	✓	✓
[Shi et al., 2021]	CAVs, HDVs	0, 20, 40, 60, 80, 100	1s (for CAVs), 1.12s (for HDVs)	DPPO DRL (CAV), IDM (HDV)	A single lane with 6 vehicles platoon	Free-flow	✓	✓	✓
[Yu et al., 2023]	CAVs, HDVs, Connected HDVs	20, 40, 60, 80	0.8s (for CAVs), 1.1s (for HDVs)	MACV (CAV), FVDM (HDV and connected HDV)	A single lane with 30 vehicles	Free-flow	✓	✓	✗

✓: considered, ✗: not considered.

3.2.3 Managed Lane and Platooning Strategies

The *managed lane strategy* i.e., having dedicated lanes for CAVs, is a promising solution to improve traffic safety and efficiency for CAVs operation on multi-lane freeways in mixed traffic. This strategy, however, can only improve traffic efficiency with high penetration rates of CAVs [Liu et al., 2018, Razmi Rad et al., 2020]. In a four-lane freeway, for example, each lane can accommodate 25% of the total vehicles on the road. If the CAV penetration rate is smaller than this, allocating one lane exclusively to CAVs means that the dedicated lane will not be used fully. To overcome this limitation, Zhong *et al.* proposed four types of managed lane strategies for CACC-equipped vehicles and analyzed their impact on traffic performance [Zhong and Lee, 2019]. A *High Occupancy Vehicle (HOV) lane* strategy allows vehicles with a high number of occupants (usually two or more than two) e.g., carpools, buses, etc. to travel on that lane, while the *Mixed Managed lane* allows CACC-equipped vehicles to use the HOV lane along with high occupancy vehicles, which can improve traffic efficiency significantly at low penetration rates. The *Dedicated CACC lane* allows only CACC-equipped vehicles to use that lane and finally a *Dedicated Lane with Access Control* allows CACC vehicles to join or leave the dedicated lane at designated locations only. With penetration rates of CAVs higher than 25% on a four-lane freeway, there would be one or more lane dedicated to CAVs and the remaining general purpose lanes would have mixed traffic. In general purpose lanes, however, a CAV will degrade to an AV when following a HDV or when it cannot establish a communication link with the preceding vehicle. The optimal number of dedicated CACC lanes can be calculated to maximize the traffic efficiency in different traffic scenarios e.g., free-flow, saturated, over-saturated [Hussain et al., 2016].

Another strategy to improve mixed traffic performance is *vehicle platooning* [Liu et al., 2018]. There are three types of clustering strategies for CAVs coordination to form a platoon of vehicles: - Ad Hoc, Local and Global coordination (see Figure 3.2) [Nowakowski et al., 2015]. In *ad hoc coordination*, CAVs operate in ACC mode except when following a CACC-equipped vehicle. In this scheme, the probability of a platoon formation highly depends on the market penetration rate of CAVs, but as the vehicle sequence is random, it is relatively low. This coordination scheme is comparably simpler to implement but it cannot harness the full potential of CACC vehicles [Zhong et al., 2020]. Whilst in the *local coordination*

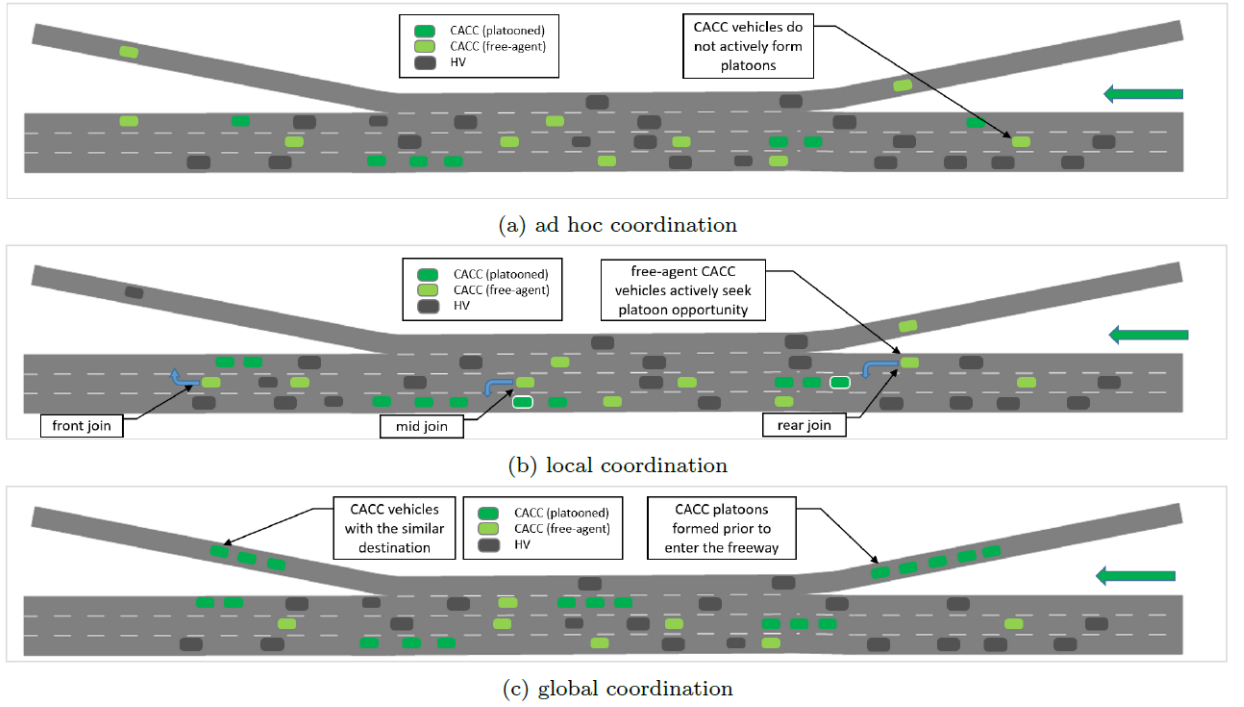


Figure 3.2: CACC Clustering Strategies [Zhong et al., 2020].

strategy, CAVs send messages to other CAVs in their surroundings to actively form a platoon. They coordinate with each-other to facilitate clustering through catch-up/slow-down and lane changing actions [Zhong et al., 2020]. The *global coordination strategy* involves advance planning to establish coordination among CAVs based on vehicles, source and destination before the CAVs even enter the highway [Nowakowski et al., 2015].

For vehicle platooning operations, a vehicle performs lane changing maneuvers to either merge into a platoon or diverge from the platoon [Liu et al., 2018]. The merging vehicle sends a merging request to its surrounding vehicles and adjusts its speed to find a safe gap in the target lane. The following vehicle sends back an acknowledgment to the merging vehicle and maintains a gap with the leading vehicle if the merging request has been accepted by the leading and following vehicles in the target lane. The leader vehicle allows a new vehicle to join the platoon, unless the platoon has reached its maximum size, in which case the newly joined vehicle will be designated as the leader of a new platoon. A recent study investigated a control method to generate optimal trajectories while minimizing the fuel consumption and travel time to improve traffic efficiency in addition to safety and passenger comfort [El Ganaoui-Mourlan et al., 2021]. They measured the improvement in fuel efficiency

and travel time due to platooning and lane-changing under different traffic loads (free-flow, moderated and congested roads) and concluded that vehicle platooning can provide better fuel efficiency than normal car-following, as well as car-following with optimal control model and lane-changing, if platoon members remain tightly coupled as part of the platoon for a long period i.e., long-term platoon operation with lane-changing avoidance. Furthermore, Ghiasi *et al.* investigated the impact of combining managed lanes and CAVs platooning strategies on mixed traffic efficiency at different penetration rates, and assuming different time headways values depending on the vehicle types (a CAV following another CAV, a CAV following a HDV, a HDV following a CAV, a HDV following another HDV) [Ghiasi et al., 2017]. Results reveal that at a given penetration rate, there are different possible cases of CAVs platooning (i.e., platoon sizes) depending on clustering strategies, and each of them provides different traffic performance due to the difference in their time-headways. Thus, CAVs platoon size has a strong influence on mixed traffic efficiency [Badnava et al., 2021]. Moreover, Yao *et al.* investigated the impact of maximum platoon size on mixed traffic performance such as, traffic efficiency, safety, fuel consumption and traffic flow stability [Yao et al., 2023]. Results show that traffic efficiency increases with the increase in platoon size, while traffic stability, safety, and fuel consumption are decreased. This reveals that maximum platoon size should be carefully chosen to maintain a good trade-off between traffic efficiency and traffic safety.

While vehicle platooning has the potential to provide significant improvements in traffic performance, its application presents some challenges in terms of platoon size, merging/diverging and lane-change maneuvers. Firstly, the CAV platoon size is limited by the communication range, so platoon management strategies need to decompose a long platoon into many small platoons [Jia and Ngoduy, 2016b, Ruan et al., 2022]. After this decomposition, not only the vehicles within the same platoon are required to establish coordination among themselves, but cooperation among small platoons is also required to ensure safe and efficiency CAVs operation [Jia and Ngoduy, 2016b]. Secondly, merging/diverging and lane changing might affect the traffic safety and efficiency adversely due to changes in the driving behavior of neighbouring vehicles [Yang et al., 2019]. This highlights the need for lane changing algorithms to adopt an anticipatory strategy rather than rely on mandatory lane changes that are more likely to create conflicts with neighbouring vehicles [Liu et al., 2018]. Fur-

thermore, in a mixed traffic environment comprising of both CAVs and HDVs, CAVs will be distributed randomly in realistic traffic scenarios. This brings additional challenges for practical application of vehicle platooning due to the possibility of a lot of lane-changing maneuvers (merging/diverging, joining/leaving) in forming a CAV platoon [Li et al., 2022].

Table 3.5 summarizes the study of the different managed lane and platooning strategies of CAVs and their impact on traffic performance, for different penetration rates and traffic scenarios. Studies show that the general-purpose-lane strategy, with mixed vehicles in each lane is the best suited for CAVs at low penetration rates. For medium CAV penetration rate (usually 30-55%), dedicated CAV lanes can further improve traffic efficiency by enabling strings of CACC-equipped vehicles with reduced time headways. Nevertheless, CAVs clustering strategies for dedicated lanes and the impact of clustering on HDVs needs to be explored further. In managed lane strategies, CAVs actively coordinate to form platoons by sending messages within their communication range. In particular, the effect of communication delays and packets drops during platoon formation needs to be analysed and quantified.

3.3 Control Strategies to Address Mixed Traffic with Unreliable Communication

In mixed traffic scenarios with unreliable communication, when a CAV cannot establish a communication link with its immediate leading vehicle (including when the leading vehicle is a HDV), its car-following mode fall-backs to ACC, resulting in reduction in both traffic safety and efficiency [Tu et al., 2019]. Consecutively, a recent study shows that CAVs can provide significant improvement in mixed traffic safety in the presence of unreliable communication links by adopting a more cautious car-following strategy (i.e., larger time headways), however, this improvement is at the cost of a slight reduction in traffic efficiency [Yao et al., 2020]. To improve traffic efficiency in imperfect communication environments, Navas *et al.* proposed an advanced-CACC approach (ACACC), based on Youla-Kucera (YK) parameterization, to design a CACC system where the ego-vehicle does not need to degrade to ACC when it does not get information from the preceding vehicle [Navas and Milanés, 2019]. The system exhibits car-following behavior between CACC and ACC when information is

Table 3.5: Comparative study of the managed lane and platooning strategies for CAVs operation in mixed traffic and their impact on traffic performance

Reference	Vehicle types	MPR (%)	Time headway settings	Control strategy	Road network	Traffic scenario	Traffic efficiency	Traffic safety	Traffic flow stability
[Hussain et al., 2016]	CAVs, HDVs	0, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100	0.3-0.45s (CACC mode), 1.2-1.8s (ACC mode), 1.8s (HDVs)	Dedicated CACC lane	Two, four and six lanes highway	Free-flow & over-saturated	✓	✗	✗
[Ghiasi et al., 2017]	CAVs, HDVs	0, 50, 75, 100	Stochastic headways	Managed CACC lane and platooning	One, two, three, four and five lanes highway	Free-flow, saturated & over-saturated	✓	✗	✗
[Liu et al., 2018]	CAVs, HDVs, Connected HDVs	0, 20, 40, 60, 80, 100	1.4s (HDVs), 0.6s (CACC mode)	Dedicated CACC lane	Four-lane 18-km long highway	Free-flow & over-saturated	✓	✗	✗
[Zhong and Lee, 2019]	CAVs, HDVs	0, 10, 20, 30, 40, 50, 60	1s (CACC mode), 1.2s (ACC mode)	Managed CACC lane and platooning	Four-lane 8-km long highway	Free-flow, saturated & over-saturated	✓	✓	✗
[Zhong et al., 2020]	CAVs, HDVs	0, 10, 20, 30, 40	0.6s (CACC mode), 0.9s (ACC mode)	Ad-hoc and local coordination-based platooning	Four-lane 8-km long highway	Free-flow, saturated & over-saturated	✓	✓	✗
[El Ganaoui-Mourlan et al., 2021]	CAVs, HDVs	-	-	Platoon formation control	A platoon of 7 vehicles	Free-flow, saturated & over-saturated	✓	✗	✗
[Yao et al., 2023]	AVs, CAVs, HDVs, Connected HDVs	0, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100	0.6s (CACC mode), 1.5s (ACC mode), 1.6s (HDVs)	Maximum platoon size control	A string of 100 vehicles	Free-flow, saturated & over-saturated	✓	✓	✓

✓: considered, ✗: not considered.

available from any vehicle ahead except the preceding vehicle, to achieve string stability at shorter time-headways. The ACACC system consists of two proportional derivative (PD) based-CACC controllers with different time-headways: a CACC controller with a shorter time-headway when information from the preceding vehicle is available, and another CACC controller with a larger time-headway when information from the preceding vehicle is not available, but some is from other vehicles ahead. YK parameterization is used to provide

a stable interpolation between these two controllers. The proposed approach has shown improved traffic efficiency with different types of preceding vehicles such as HDV, ACC-equipped vehicle, etc. Furthermore, a recent experimental study based on a driving scenario of only two vehicles (i.e., a CAV following a connected HDV on the Mcity test track) highlighted that despite the negative effects of delays and losses in V2X communication, CAVs can improve the resilience of autonomous vehicles against on-board sensors malfunctioning in bad weather conditions, and properly tuning the control gains can increase CAV controller robustness against delays [Beregi et al., 2021].

The aforementioned studies adopt CAVs' car-following control algorithms designed based on information from their immediate preceding vehicle only. However, CAVs can exploit information from multiple preceding vehicles within their communication range if those vehicles have communication capabilities, thereby enhancing the resilience of CAV control algorithms against communication impairments [Di Vaio et al., 2019, Zhang et al., 2018]. In practice, this may not always be possible due to the presence of human-driven vehicles that do not have communication capabilities, especially at low penetration rates of CAVs. Furthermore, as wireless vehicular networks are unreliable, information from other vehicles can be delayed or lost, which brings more challenges for CAVs in utilizing information from multiple preceding vehicles. Connected cruise control (CCC) is a widely used strategy in the literature to address these challenges, by first retrofitting HDVs with wireless communication devices to provide them communication capabilities, and then designing the CAV longitudinal controller that is robust against communication failures. The advantages of CCC strategy in improving mixed traffic performance in the presence of communication imperfections have been studied in [Zhang et al., 2018, Zhang and Orosz, 2016]. In particular, Zhang *et al.* proposed a hierarchical control framework to design CAV longitudinal controller in the presence of communication delays. At the upper-level control, CCC strategy is employed which exploits information received from multiple preceding vehicles ahead via V2V communication. Consecutively, an adaptive sliding-mode controller is designed as the low-level controller. Simulations were performed using a four-vehicles network to demonstrate the capabilities of a hierarchical control framework in achieving string stability in the presence of fixed communication delays and uncertainties in vehicle dynamics [Zhang et al., 2018].

On one hand, when a small percentage of HDVs are retrofitted with communication devices, a CAV either uses the CCC strategy when it has connected HDVs within its communication range to take information from via V2V communication or uses an ACC strategy when all preceding vehicles within its communication range are HDVs only. On the other hand, when all HDVs are retrofitted with communication devices, thereby resulting in a fully connected environment, a CAV can exploit information from all preceding vehicles within its communication range. For a fully connected environment, [Zhang and Orosz, 2016] presented a CCC strategy for a string of only one CAV at tail in mixed traffic and unreliable communication scenario while considering different information flow topologies. Results show that CAVs can further improve traffic efficiency by exploiting information from multiple leading vehicles rather than a single leading vehicle, but only if CAV controller gains are properly tuned. Furthermore, the study presented in [Di Vaio et al., 2019] developed a multiple predecessors information-based cooperative control strategy for CAVs to enhance mixed traffic flow dynamics in the presence of time-varying delays in the V2V communication links and human-driver reactions. They showed that CAVs can achieve improved traffic efficiency by exploiting information from multiple preceding vehicles even in the presence of communication imperfections as compared to the single vehicle information. Although above CAV longitudinal controllers are able to improve CAVs performance in mixed traffic and unreliable communication environment, they do not consider the heterogeneity in HDVs' driving behavior. To deal with HDVs stochastic behaviours in mixed traffic flow, authors in [Shi et al., 2023], proposed decomposing a mixed traffic flow into multiple subsystems such that each subsystem has one CAV to be the leader and last follower, while all consecutive HDVs in the middle are considered as an aggregated HDVs (i.e., AHDV), and then developing a deep reinforcement learning-based longitudinal control algorithm for CAVs to learn the AHDV's behaviour. All these studies assume fixed IFTs, which seems quite unrealistic considering the unavailability of information in mixed traffic and unreliable communication environments.

Table 3.6 summarizes the study of the different control strategies for CAVs in mixed traffic with unreliable communication and their impact on traffic performance. It can be seen that very few studies have investigated the impact of CAVs in realistic communication and traffic scenarios. Most studies assume perfect communication with large-scale road

networks, while others investigate the effect of imperfect communication links on traffic performance considering only a small number of vehicles in the string. In particular, the effects of communication latency and packet losses on CAV longitudinal control need to be characterised by detailed simulation studies, including the co-simulation of vehicular traffic (e.g., with SUMO) and communication network protocols (e.g., with OMNET++).

Table 3.6: Comparative study of the control strategies of CAVs coordination in mixed traffic with unreliable communication and their impact on traffic performance

Reference	Vehicle types	MPR (%)	Time headway settings	Control strategy	Road network	Traffic scenario	Traffic efficiency	Traffic safety	Traffic flow stability
[Zhang and Orosz, 2016]	CAVs, HDVs, Connected HDVs	-	5-35m	Connected cruise control	Single-lane	A four-vehicles network with different IFTs	✗	✗	✓
[Zhang et al., 2018]	CCC-equipped, Connected HDVs	-	3 and 4m (CAVs), 38 and 40m (HDVs)	Multiple vehicles ahead information-based connected cruise control	Single-lane	A platoon of four vehicles	✗	✗	✓
[Navas and Milanés, 2019]	CAVs, HDVs	-	1.5s (HDVs), 0.6s (CACC mode)	Advanced-CACC based on Youla-Kucera (YK) parameterization	Single-lane	INRIA experiment platform with three cycabs	✓	✗	✓
[Di Vaio et al., 2019]	CAVs, HDVs	-	Distance headway-20m	Multiple vehicles ahead information-based CACC	Single-lane	String of three, eight and twenty vehicles	✓	✗	✓
[Beregi et al., 2021]	CAVs, Connected HDVs	-	5-50m	Connected cruise control (CCC)	Mcity test track	Experiment with a string of two vehicles	✗	✓	✓
[Shi et al., 2023]	CAVs, HDVs	0, 20, 40, 60, 80, 100	1s (for CAVs), 1.12s (for HDVs)	DPPO DRL (CAV), Newell (HDV)	A single lane with 6 vehicles platoon	Congesed	✓	✓	✓

✓: considered, ✗: not considered.

3.4 Knowledge Gaps Analysis and Research Questions

A significant number of CAV longitudinal control strategies and their impact on traffic performance have been reported in the literature in recent years. We presented an extens-

ive survey of longitudinal control of CAVs, focusing on the existing car-following control strategies developed to address the potential challenges of CAVs operation in mixed traffic and unreliable communication environments. Based on the state-of-the-art survey, it identifies research gaps and formulates research questions for the operation of CAVs in realistic scenarios in terms of mixed traffic, unreliable communication, large-scale traffic scenarios, etc.

This section presents the research gaps identified after reviewing the related work and discusses research questions arising from the research gaps. The literature survey shows that a significant number of studies on longitudinal control of CAVs have been reported in the literature in recent years. Most of them, however, have assumed CAVs operation in unrealistic scenarios such as perfect communication, pure CAVs traffic and a platoon formation of a small number of vehicles. The design of CAV car-following control algorithms while considering realistic scenarios such as unreliable communication, mixed traffic flow, large-scale road networks simultaneously is a big research gap that needs to be addressed before the deployment of CAVs on roads in the near future.

- **Research Question:** How to design CAV car-following control strategies to improve mixed traffic safety and efficiency in realistic scenarios in terms of traffic composition (mixed traffic), communication (not assumed to be reliable) and road network (large-scale and real network)?

Research question 1 (RQ1)

The literature review (Section 3.2) shows that a significant number of studies has investigated the impact of CAV technology on traffic safety and efficiency, at different penetration rates and traffic scenarios. It can be seen in Table 3.3 that different studies have chosen different car-following models for CAVs and HDVs. Their results show that car-following models have a significant influence on traffic safety and efficiency results. Therefore they must be chosen carefully after calibration and validation performed based on field-experiments in realistic scenarios [Xiao et al., 2017, Rahman et al., 2021]. Most previous studies have investigated the impact of CAVs on traffic safety and efficiency separately, and only a few recent studies have investigated the impact of CAVs on traffic safety and efficiency jointly [Guériau

and Dusparic, 2020, Rahman et al., 2021].

While a lot of research has investigated the impact of CAVs on traffic safety and efficiency at different penetration rates, all have assumed either perfect communication or very simple scenarios (i.e. a small number of vehicles) with imperfect communication. Previous studies considering large-scale traffic scenarios, however, usually consider the car-following models by simplifying the vehicle model and ignore realistic V2V communication, which could result in inaccurate performance evaluation for CAVs operation in realistic scenarios in terms of imperfect communication, mixed traffic, vehicle modelling, and real traffic networks. In practice, the presence of communication delays and packet losses means that CAVs might receive only partial information from surrounding vehicles, and this can have detrimental effects on their performance [Xie et al., 2023]. **The deployment of CAVs is expected to improve traffic safety and efficiency, though it is unclear to what extent this has been evaluated in realistic scenarios.** This leads to the follow research question:

- **RQ1:** Can CAVs improve both mixed traffic safety and efficiency in mixed traffic and unreliable communication environments on large-scale road networks?

Research question 2 (RQ2)

As discussed in Section 3.1, cooperative adaptive cruise control (CACC) is a widely used car-following control strategy for CAVs that has the potential to improve traffic safety and efficiency significantly by exploiting information from one or more preceding vehicles via V2V communication and on-board sensors [Guanetti et al., 2018]. A number of CACC strategies based on both traditional model-based control algorithms such as PID control, model predictive control and consensus-based control, and advanced learning-based control algorithms such as reinforcement learning, deep learning and fuzzy logic has been proposed in recent years. These control strategies have been developed considering pure CAVs traffic where CAVs can exploit full information from their surrounding vehicles. Besides the widely used CACC strategy, in recent years, the connected cruise control (CCC) strategy was especially developed for CAVs operation in mixed traffic scenarios by assuming connected HDVs [Avedisov et al., 2022, Ge and Orosz, 2017]. These studies mostly focus on designing the CCC strategy with a single CAV exploiting information from one or more connected

HDVs in the platoon. On one hand, at least a proportion of HDV owners will not be interested in bearing the cost of retrofitting HDVs with communication capability [Zhou et al., 2023]. On the other hand, HDVs offer a lot of uncertainties and stochastic driving behaviour, and therefore it does not seem pertinent to totally rely on HDVs information for the CCC strategy design to improve traffic safety and efficiency.

As both CACC and CCC strategies used in CAVs heavily depends on the availability of information from their neighbors (CAVs or connected HDVs), they do not perform well in mixed traffic and unreliable communication scenarios where it might not always be possible to receive information from preceding vehicles without communication capabilities. While a few car-following control strategies have been proposed for CAVs operation in mixed traffic and unreliable communication environments without equipping HDVs with communication devices, most of these existing control strategies are based on PF IFT only, which could not harness full potential of CAVs by communicating with multiple surrounding vehicles rather than a single vehicle. Furthermore, existing simulation studies for both CACC and CCC have been performed with small numbers of vehicles to demonstrate the effects of CAVs. Adopting such control strategies on large-scale traffic networks in integration with realistic V2X communication, however, has not been thoroughly investigated due to the fact that such simulation studies suffer from very high computational complexity and communication overhead in establishing inter-vehicle communication and then updating the CAV control algorithm at each time step.

- **RQ2:** Does exploiting information from multiple leading vehicles within their communication range give an advantage to CAVs (compared to single-vehicle information-based control) in terms of traffic safety and efficiency?

Research question 3 (RQ3)

In recent years, a few researchers have attempted to develop car-following control algorithms based on the multiple-predecessor-following IFT, i.e., considering information from more than one preceding vehicle, for CAVs operation in unreliable communication or mixed traffic environment [Rahman et al., 2021, Ding et al., 2022, Avedisov et al., 2022]. Most of these studies, however, have assumed fixed IFTs and may not handle changes in information

flow topologies due to communication failures and the presence of HDVs together. A few robust car-following control algorithms that can handle dynamic information flow topologies occurred due to mixed traffic, have been developed in recent years, but they have only been validated in very limited scenarios for a very small number of vehicles (with a fixed sequence of CAVs and HDVs), assuming perfect communication [Yu et al., 2023, Zhou et al., 2023].

Some previous studies [Rahman et al., 2021, Beregi et al., 2021, Zhou et al., 2023] show that CAV controller parameters tuning is a promising approach to make CAVs resilient against the uncertainties of both HDVs and communication failures. However, they have assumed the same control gains for all leading vehicles, which seems unrealistic in mixed traffic and unreliable communication scenarios due to the presence of HDVs without communication capability and communication failures. **Leveraging adaptive controller parameters tuning to improve mixed traffic safety and efficiency in realistic scenarios has not been investigated yet.** This is captured in the following research question:

- **RQ3:** Can a CAV car-following controller designed based on multiple leading vehicles information further improves traffic safety and efficiency in the presence of the uncertainties of HDVs and communication failures?

3.5 Baseline Approach

This section builds on the analysis of the state of the art to identify an appropriate baseline for our work. It first outlines the requirements for the baseline approach and then compares existing control strategies based on these requirements, before motivating the choice of the CACC car-following model [Xiao et al., 2017] as a relevant baseline.

The set of requirements for the baseline are as follows:

- **Suitable spacing policy and simple information flow topology:** it must be designed using constant time headway spacing policy because CTH policy is most suitable for congested traffic scenarios. Moreover, the simplest information flow topology, the one-vehicle ahead (i.e., predecessor following IFT) is the most widely used IFT for CAVs operation in mixed traffic and unreliable communication environments.

- **Control method:** a variety of PF and MPF IFT-based car-following control algorithms are available for longitudinal control of CAVs, that are designed based on various control methods such as linear and non-linear control, MPC control, sliding mode control, and machine learning control. Among them, linear feedback control methods have been widely used for CAV car-following control due to their simple but accurate enough control architecture in contrast to advanced control methods.
- **Realistic communication modeling:** we need to choose a baseline car-following control algorithm for CAVs within the context of modelling realistic vehicle dynamics and realistic V2V communication networks simultaneously i.e., information exchange via V2V communication links during simulation run-time.
- **Low computational cost and complexity:** to evaluate CAVs in realistic scenarios, a car-following model is required that on the one hand assumes a realistic vehicle dynamics model, and on the other hand is amenable to large-scale traffic simulations. A car-following model assuming a 2nd order vehicle dynamics and using linear feedback control makes it a good candidate to use in large-scale traffic scenarios due to low computational cost and complexity.

Table 3.7: Summary of various existing baseline approaches

Reference	IFT	Spacing policy	Control method	Car-following model	Traffic scenario	Realistic communication modelling	Computational complexity
[Ploeg et al., 2011]	PF	CTH	Linear feedback PD control	PLOEG controller	Small number of vehicles	✓	Low
[Navas and Milanés, 2019]	PF	CTH	Linear feedback PD control	CACC car-following model	A string of 3 vehicles where ego vehicle receives information either from first or second leading vehicle	✓	Low
[Guériau and Dusparic, 2020]	PF	CTH	Linear feedback PD control	CACC and IDM car-following model	Large-scale	✗	Low
[Rahman et al., 2021]	MPF	CTH	Linear feedback PD control	IDM car-following model	Large-scale	✗	Low
[Ding et al., 2022]	MPF	CTH	SSA-ENN (machine learning)	IDM car-following model	String of 20 and 40 vehicles	✗	High

✓: considered, ✗: not considered.

Table 3.7 shows that most CAV control strategies are designed for a small number of vehicles e.g., a platoon control with a fixed leader of the platoon and several following vehicles, where a CAV takes information from the platoon leader and other follower vehicles only. Therefore it is not possible to apply these control strategies in large-scale traffic scenarios i.e., with a large number of vehicles. Previous studies considering large-scale traffic scenarios, however, usually consider car-following models simplifying the vehicle dynamics and ignore realistic V2V communication modeling, to control the CAV car-following behaviour. IDM is a widely used car-following model in both academia and industry to simulate CAVs due to its realistic stop-and-go behaviour. Another car-following model widely used for CAVs is the CACC car-following model whose parameters were calibrated and validated based on data collected during field tests in realistic traffic scenarios [Xiao et al., 2017]. Both IDM and CACC car-following models are suitable baselines, but we preferred to use the CACC car-following model developed in [Xiao et al., 2017] due to its better applicability for simulating CAVs.

3.6 Summary

This chapter presented an extensive literature survey on longitudinal control of CAVs to identify research gaps and formulate research questions for the operation of CAVs in mixed traffic and unreliable communication scenarios. A good number of CAV longitudinal control strategies (ACC, CACC, CCC) and their impact on traffic performance have been reported in the literature. These control strategies are developed based on both traditional model-based control algorithms such as PID control, model predictive control and consensus-based control, and advanced learning-based control algorithms such as reinforcement learning, deep learning and fuzzy logic. Most control strategies have been developed considering pure CAVs traffic where CAVs can exploit full information from their surrounding vehicles and establishes cooperation among them. A few control approaches that address the potential challenges of communication impairments and uncertainties present in the driving behavior of human-driven vehicles in mixed traffic environment assume fixed IFTs, which seems unrealistic due to the uncertainties of HDVs and communication failures. Furthermore, previous studies considering large-scale traffic scenarios, however, usually consider

the car-following models by simplifying the vehicle dynamics and ignore realistic V2V communication, to control the vehicle car-following behaviour, which could result in inaccurate performance evaluation for CAVs operation in realistic scenarios in terms of imperfect communication, mixed traffic, vehicle modelling, and real traffic networks.

Therefore, the gaps in the studies on car-following control of CAVs in mixed traffic and unreliable communication environment remain in the following two major aspects. Firstly, existing CAV car-following control strategies typically struggle to cope with varying IFTs in mixed traffic and unreliable communication environments. Furthermore, it is not well explored how to optimize mixed traffic safety and efficiency considering the random mix of CAVs and HDVs at different CAV penetration rate. Mixed traffic flow with different CAV penetration rate have diverse characteristics in terms of diverse IFTs, making it challenging to develop a car-following control strategy for CAVs, especially in realistic scenarios. Secondly, existing car-following controllers have been evaluated only with either perfect communication, pure CAVs traffic, simple PF IFT or traffic scenarios. This precludes their applicability to CAVs deployment on roads in the near future.

4 System Model

Vehicles of different automation levels and communication capabilities have different driving behaviors in both longitudinal and lateral directions. Therefore, to evaluate the impact of these vehicles on road traffic performance, it is necessary to model them differently. Various car-following and lane-changing models are typically used to describe the driving behavior of different vehicle types such as HDVs, Connected HDVs, AVs, CAVs etc. The car-following and lane-changing models used in this work are described in detail in this chapter. These particular models were chosen after reviewing related work [Arnaout and Arnaout, 2014, Navas and Milanés, 2019, Wang et al., 2019a, Yao et al., 2020] performing traffic mobility simulations in realistic traffic scenarios.

Firstly, this chapter presents the car-following and lane-changing models used for HDVs and CAVs in Sections 4.1 and 4.2, respectively. Then it briefly describes the assumptions behind controller design choices in Section 4.3.

4.1 Car-following Models

Car-following models describe the way a vehicle maintains the time/distance headway with the preceding vehicle on the road. Generally, car-following models are used to describe the human driving behaviour i.e., acceleration/deceleration when driving on the road and oversimplify the realistic vehicle dynamics by assuming the second order longitudinal control model and perfect V2V communication, therefore omitting the network-level evaluation by integrating both vehicle dynamics and V2V communication. Different car-following models such as Intelligent Driver Model (IDM), Enhanced Intelligent Driver Model (E-IDM), Gipps Model, Krauss Model, Wiedemann Model, Field-tested CACC and ACC model have

been presented and used in the literature to describe the driving behavior of HDVs, CAVs, degraded CAVs¹ in simulation studies [Ivanchev et al., 2019].

This section now discusses in turn the HDV car-following model (Section 4.1.1), CACC car-following model (Section 4.1.2), and then the ACC car-following model (Section 4.1.3).

4.1.1 HDV Car-following Model

The car-following behavior of HDVs is significantly different from that of CAVs and AVs due to human's large reaction time and likelihood of perception errors, requiring larger time headway, minimum safety gap, etc, and therefore should be modeled differently. This study uses the IDM car-following model with reaction time and perception errors for modeling the driving behavior of a human-driven vehicle in the longitudinal direction. The IDM is a widely used model to perform simulation studies due to its realistic stop-and-go behavior modeling [Wang et al., 2019a]. Furthermore, incorporating the driver's reaction time and perception errors explicitly in the driving behavior makes the model more realistic.

The IDM model is represented as [Treiber et al., 2006]:

$$\dot{v}(t + T_r) = a \left[1 - \left(\frac{v(t)}{v_f} \right)^4 - \left(\frac{s(t)^*(v(t), \Delta v(t))}{s(t)} \right)^2 \right] \quad (4.1)$$

where v and $\dot{v}$ represent the speed and acceleration of the ego vehicle, respectively; T_r is the reaction time; v_f is the free flow speed; a is the maximum acceleration; s^* and s are the estimated and actual distance between adjacent vehicles, respectively; and Δv is the speed difference between adjacent vehicles.

The estimated distance between adjacent vehicles is given as:

$$s(t)^*(v(t), \Delta v(t)) = s_0 + \max \left[0, v(t)T + \frac{v(t)\Delta v(t)}{2\sqrt{ab}} \right] \quad (4.2)$$

where T represents the time headway; s_0 is the minimum gap at standstill; and b is the desired deceleration. The IDM model parameters are presented in Table 4.1 [Yao et al., 2020]. The time headway parameter value of 1.5 s is chosen, according to related work

¹a CAV degrading its longitudinal driving mode from CACC to ACC in the presence of communication failures or when its immediate leading vehicle is a HDV, is called a degraded CAV

using the same car-following model [Tu et al., 2019, Navas and Milanés, 2019, Yao et al., 2020].

Table 4.1: Car-following model parameters for simulated HDVs

Parameters	Value
Maximum acceleration a	1.0 m s^{-2}
Desired deceleration b	2.0 m s^{-2}
Time headway T	1.5 s
Free flow speed v_f	33.3 m s^{-1}
Minimum gap s_0	2.0 m
Imperfection σ	0.5

Humans' reaction time and perception errors: Human drivers generally exhibit large reaction times and perception errors in their driving decision making [Treiber et al., 2006]. To artificially simulate these reaction times and perception errors as the uncertainties in human's driving behavior, a driver state device (DSD) is added to each HDV using parameters listed in Table 4.2 according to [Mitsakis et al., 2019, Andreotti et al., 2020]. DSD parameter values are chosen to model perception errors due to human drivers' perception of distance and speed differences between an ego vehicle and its immediate leading vehicle [Andreotti et al., 2020]. The human reaction time of 0.5 s is chosen according to [Sun et al., 2018].

Table 4.2: Driver state device parameters simulating drivers' imperfection

Parameter	Description	Value
actionStepLength	Driver reaction time in executing the decision logic	0.5 s
initialAwareness	Driver awareness	1.1
errorTimeScaleCoefficient	Time scale constant of the perception error process	100
errorNoiseIntensityCoefficient	Noise intensity constant of the perception error process	0.5
speedDifferenceErrorCoefficient	Scaling coefficient for the relative speed difference error	2
headwayErrorCoefficient	Scaling coefficient for the relative distance difference error	2
speedDifferenceChangePerceptionThreshold	Threshold value for the perception of changes in the speed difference	0.5
headwayChangePerceptionThreshold	Threshold value for the perception of changes in the distance difference	0.5

4.1.2 CACC Car-following Model

This work adopts an existing realistic CACC car-following model whose parameters were calibrated and validated based on data collected during field tests in realistic traffic scenarios [Xiao et al., 2017]. This CACC car-following model has four control modes: speed control, gap control, gap-closing control and collision avoidance mode, described in turn below, and Figure 4.1 shows how each control mode is triggered.

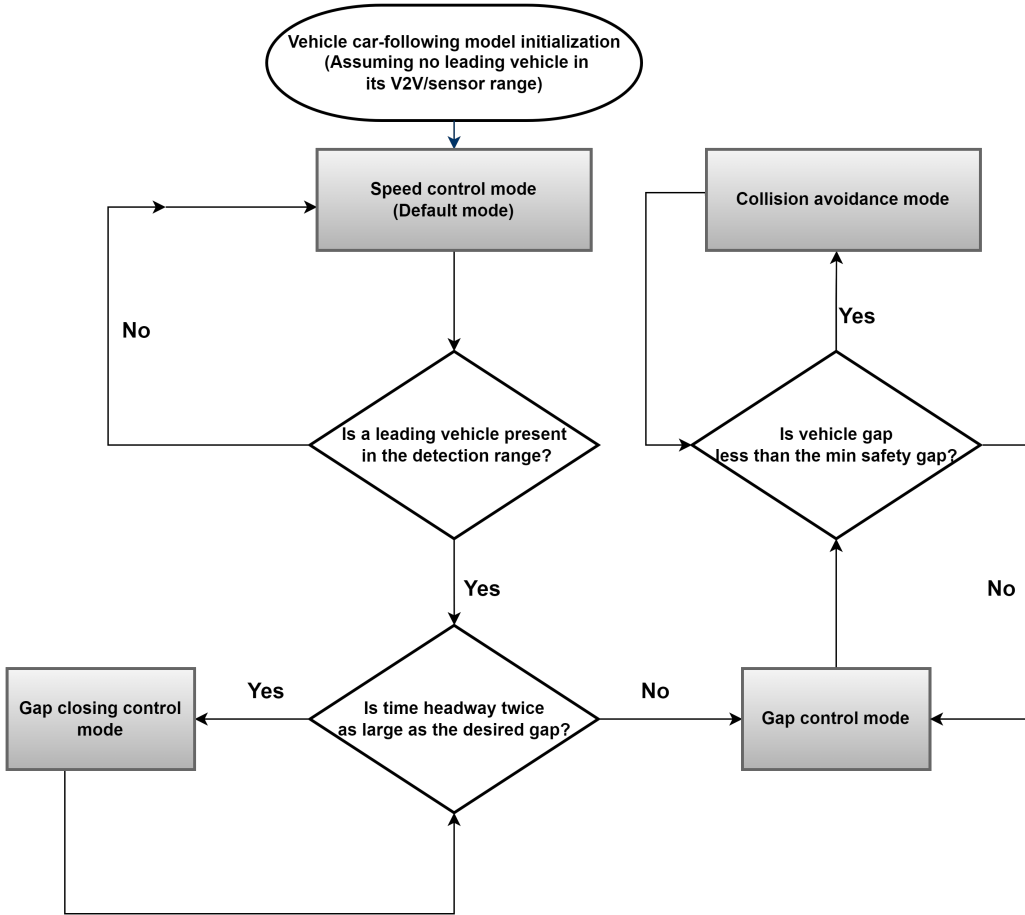


Figure 4.1: Flow chart of the different control modes of ACC-CACC car-following models.

Speed control mode: The objective of the *speed control mode* is to allow a vehicle to travel at its desired speed. A vehicle operates in this mode when it does not have a leading vehicle within the detection range of the radar (chosen to be 120m). To travel close to its desired speed, the acceleration of the vehicle at time $k + 1$ is modeled as:

$$a_{i,k+1} = k(v_d - v_{i,k}) \quad (4.3)$$

where v_d and $v_{i,k}$ are the desired speed and actual speed of the ego vehicle in the previous iteration, respectively; and k is the speed control gain. The value of $k=0.4 \text{ s}^{-1}$ is selected according to [Xiao et al., 2017].

Gap control mode: The objective of the *gap control mode* is to reduce the gap error and speed difference errors between adjacent vehicles. This mode is only activated in car-following scenarios when a leading vehicle is present in the detection range of the ego vehicle. To maintain a constant time headway with its leading vehicle, the speed of the ego vehicle at time $k + 1$ is modeled as:

$$v_{i,k+1} = v_{i,k} + k_p e_{i,k} + k_d \dot{e}_{i,k} \quad (4.4)$$

$$e_{i,k} = x_{i-1} - x_i - t_h v_i - l_{i-1} \quad (4.5)$$

where $e_{i,k}$ and $\dot{e}_{i,k}$ represent the gap error and gap error derivative between the leading vehicle $i-1$ and ego vehicle i , respectively; x_{i-1} and x_i are the position of the leading vehicle and the ego vehicle, respectively; k_p , k_d are the control gain parameters. $v_{i,k}$ is the speed at time k , the previous iteration, t_h is the desired time headway; l_{i-1} is the length of the leading vehicle. The values of $k_p=0.45 \text{ s}^{-2}$, $k_d=0.25 \text{ s}^{-1}$ and $t_h=0.6 \text{ s}$ are selected according to Xiao *et al.* [Xiao et al., 2017].

Gap-closing control mode: The objective of the *gap-closing control mode* is to switch control mode between the speed control and gap control mode when a leading vehicle is present but is still beyond the given threshold of the gap Control mode. This mode is derived by tuning the parameters k_p and k_d of the gap controller given in Equation (4.4). The new values of $k_p=0.01 \text{ s}^{-2}$ and $k_d=1.6 \text{ s}^{-1}$ are selected according to Xiao *et al.* [Xiao et al., 2017].

Collision avoidance control mode: The objective of the *collision avoidance mode* of the CACC model is to avoid rear-end collisions in car-following situations. The control logic is similar to the gap control mode, and the difference is the gain values which are $k_p=0.45 \text{ s}^{-2}$ and $k_d=0.05 \text{ s}^{-1}$, which are tuned in the TransAID project [Mitsakis et al., 2019].

4.1.3 ACC Car-following Model

This work uses the ACC car-following model to describe the driving behavior of a CAV when it cannot get the information from its preceding vehicle via V2V communication. The ACC car-following model also has four control modes: speed control, gap control, gap-closing control and collision avoidance mode [Xiao et al., 2017].

Speed control mode: The speed controller is identical for CAVs in either CACC or ACC mode, as the objective of the controller is to allow a vehicle to travel at its desired speed when there is no leading vehicle and hence additional V2V information does not play a role in vehicle cruising operation [Xiao et al., 2017]. The control model is given in Equation (4.3).

Gap control mode: The gap controller of the ACC car-following model is given as:

$$a_i = k_1(x_{i-1} - x_i - t_h v_i - l_{i-1}) + k_2(v_{i-1} - v_i) \quad (4.6)$$

where a_i represents the acceleration of the ego vehicle; x_{i-1} and x_i are the position of the leading vehicle and the ego vehicle, respectively; v_{i-1} and v_i are the speed of the leading vehicle and the ego vehicle, respectively; t_h represents the desired time headway; l_{i-1} is the length of the leading vehicle; and k_1 , k_2 are the position and speed error coefficients, respectively. Equation (4.6) shows that vehicle acceleration depends on both the inter-vehicle distance error and speed difference between an ego vehicle and its immediate leading vehicle. The time headway and gain parameters values $t_h=1.1$ s, $k_1=0.23$ s⁻², $k_2=0.07$ s⁻¹, are selected according to Xiao *et al.* [Xiao et al., 2017].

Gap-closing control mode: The gap-closing controller is derived by tuning the parameters k_p and k_d of the gap controller (see (4.6)), similarly to the CACC car-following model. The new values of $k_1=0.04$ s⁻² and $k_2=0.8$ s⁻¹ are selected according to Xiao *et al.* [Xiao et al., 2017].

Collision avoidance control mode: The objective of the collision avoidance mode of the ACC model is to avoid rear-end collisions in car-following situations. The control logic is similar to the gap control mode given by (4.6), and the difference is the gain values which are $k_1=0.8$ s⁻² and $k_2=0.23$ s⁻¹, which are selected according to the TransAID project [Mitsakis

et al., 2019].

The other car-following model parameters for CAVs are presented in Table 4.3. Different time headway settings are selected depending on whether a CAV is following a human-driven vehicle (1.1 s) or a CAV (0.6 s), according to studies using the same car-following model in realistic traffic scenarios [Milanés and Shladover, 2014, Xiao et al., 2017].

Table 4.3: Car-following model parameters for simulated CAVs

Parameters	Value
Speed deviation	0.05
Time headway	0.6 s, 1.1 s
Minimum gap	1.5 m
Max acceleration	2.9 m s^{-2}
Deceleration	7.5 m s^{-2}
Emergency deceleration	9 m s^{-2}

4.2 Lane-changing Models

Lane change decision making is described using *lane-changing (LC) models* that take input information of adjacent vehicles and decide whether the subject vehicle should change lane. LC models have been proposed based on the Gipps model, utility theory, cellular automata, Markov process and Fuzzy logic [Zheng, 2014, Kesting et al., 2007, Treiber et al., 2006]. In general, the subject vehicle is surrounded by a number of vehicles in the current lane as well as in the target lane, and needs cooperation while making lane-changing decisions. The gap acceptance model is utilized to compare the available gap in the target lane with the critical gap (minimum acceptable gap) and the subject vehicle changes lane only once a gap bigger than the critical gap is available in the target lane [Kesting and Treiber, 2006]. Generally, the size of the critical gap varies in accordance with the subject vehicle's speed with respect to the speed of the leading and following vehicles in the target lane. Once the subject vehicle detects a big enough gap in the target lane, it adjusts its speed to get aligned with this gap to execute a safe lane-change maneuver.

This work uses the most widely used LC2013 lane-changing model with different parameters to model the lane-changing behavior of HDVs and CAVs. These parameters are selected according to the TransAID project [Mitsakis et al., 2019]. The LC2013 lane-changing

model has three types of lane-changing: strategic, cooperative, and tactical [Kesting and Treiber, 2006].

Mandatory lane-changing: Vehicles execute strategic lane-changing when it is essential for them to avoid a dead-end lane because of road works, collision, the designated route, etc. In the LC2013 model, the `lcStrategic` parameter is used to model strategic lane-changing.

Cooperative lane-changing: Vehicles execute cooperative lane-changing to perform lane changing actions incorporating current and anticipated future movements of neighboring vehicles along with cooperation of the neighboring vehicles (such as adjusting their speeds to create a safe gap in the target lane). In the LC2013 model, the `lcCooperative` parameter is used to model cooperative lane-changing.

Tactical lane-changing: Vehicles execute tactical lane-changing to improve the travel speed or the driving experience by overtaking a slow leading vehicle. In the LC2013 model, the `lcSpeedGain` parameter is used to model tactical lane-changing.

To replicate different driving behaviors for different vehicle types (i.e., CAVs and HDVs), a sensitivity analysis with different parameters values was performed in the TransAID project [Mitsakis et al., 2019]. On top of this, several minor modifications are made in this work in order to model lane-changing behavior of CAVs and HDVs differently. The parameters `lcStrategic` and `lcSpeedGain` of the lane changing model of both HDVs and CAVs were left at their default values [Treiber et al., 2006] and `lcCooperative` parameter was changed from their default value of 1 to 0.5 to better replicate the lane-changing of HDVs according to [Gu  riaux and Dusparic, 2020].

4.3 Assumptions

This thesis focuses on CAV car-following controller design in mixed traffic and unreliable communication environments. The environment assumptions are given as follows:

- A CAV can obtain the kinematic state information (e.g., speed, position) of its immediate leading vehicle using both onboard sensors and V2V communication, and can

obtain information from vehicles further ahead via V2V communication only, in perfect communication conditions. However, unreliable V2V communication introduces packet losses/delays during that information exchange.

- Delays and packet losses in V2V communication links might be due to various factors such as channel congestion in dense traffic, communication interference, channel fading, etc. In this thesis, unreliable communication is mainly assumed due to communication channel congestion, and the Packet Error Rate (PER) condition dynamically determines the transmission status (fail/success) between any CAV pairs.
- Just like on-board sensors, only preceding vehicle's position and speed kinematic state information are exchanged via V2V communication. Though car-following behaviour can be improved by using acceleration information as well, but this is at the expense of increased complexity introduced from the 3rd order longitudinal control models.
- A CAV can receive its own real-time state information. Also, it is assumed that the information obtained from onboard sensors, and V2V communications contains no noise or falsified components.
- DSRC (also known as IEEE 802.11p communication standard) technology with a fixed communication range is assumed for each CAV for exchanging information with surrounding vehicles. Though some recent studies show that C-V2X can provide a longer transmission range as compared to DSRC and allows for re-transmission of lost packets in contrast to DSRC, it has not been tested and deployed in real world scenarios to the extent of DSRC. Therefore, the CAV control strategy developed in this thesis is based on assuming the DSRC technology for V2V communication.
- The beacon frequency is fixed, and the control strategy is implemented at each end of the control channel interval (CCHI).
- A CAV's real-time state information is sent to surrounding CAVs by vehicle-to-vehicle (V2V) communication. Vehicle position and speed are time-continuous in nature, and all vehicles are assumed to maintain a constant speed during each CCHI, that is, $v_i(t - \tau_i) \approx v_i(t)$, where τ_i is the information communication delay within each CCHI.

- In this thesis, we assume that HDVs have no communication capability. Furthermore, while some previous studies [Monteil et al., 2014, Monteil et al., 2016, Sharma et al., 2021a] assume that the driver of a HDV can perceive the information of multiple leading vehicles, a HDV is assumed to perceive information from its immediate leading vehicle only in this thesis. In addition, a HDV performs its car-following behaviour in the same way while following a HDV or a CAV. Studying human driver's psychological differences between HDVs and CAVs is an active research area and beyond the scope of this thesis.
- While CAVs can share kinematic state information i.e., position, speed and acceleration via V2V communication, only position and speed are exchanged due to the simplicity in designing control algorithms for second order longitudinal control models. In the presence of system uncertainties and physical limitations, including actuator lags and sensing delays, the vehicle dynamics will be modeled by a third-order system as below:

$$\begin{aligned}
 \dot{x}_i(t) &= v_i(t), \\
 \dot{v}_i(t) &= u_i(t), \\
 \dot{u}_i(t) &= \frac{-1}{\tau} [u_i(t) - a_i(t - \phi)],
 \end{aligned} \tag{4.7}$$

where x_i denotes the position of the rear bumper of vehicle i , v_i and u_i are the velocity and acceleration of vehicle i , respectively. The input a_i is the desired acceleration, whereas τ is the actuator lag of vehicle i in low-level control dynamics i.e., powertrain, and ϕ is the sensing delay.

- The second order vehicle dynamics model is considered, ignoring air drag, rolling resistance, and actuator delay. Since the main focus is on developing a high-level longitudinal control strategy for CAVs operation in large-scale traffic scenarios, the longitudinal control model is simplified by ignoring the air drag, rolling resistance, and actuator delay in the vehicle dynamics model. In contrast, a good number of analytical studies considered 3rd order longitudinal control model [Xing et al., 2020, Zhao et al., 2021, van Nunen et al., 2019, Oliveira et al., 2021]. Though these studies might

provide significant improvement over 2nd order model, the CAV car-following control strategies designed based on 3rd order model consume large computation time and are therefore barely feasible for large-scale traffic simulations [Jia et al., 2021].

4.4 Summary

This chapter presented the dynamics of the vehicles namely the human-driven vehicles, connected autonomous vehicles and the degraded connected autonomous vehicles in both longitudinal and lateral directions. All car-following models were mathematically described using second-order differential equations. Overall, while many car-following models have been used to study the impact of CAVs on traffic safety and efficiency, identifying the most accurate models for both CAVs and HDVs is a challenging task. While the delay in the human-driven vehicle mainly comes from human reaction times, the delay in the connected automated vehicle is primarily due to V2V communication. In this thesis, the CACC and IDM car-following models are chosen to describe the longitudinal behavior of CAVs and HDVs, respectively, due to their realistic acceleration profiles. The CACC model parameter values are left at their default values [Xiao et al., 2017]. In the existing IDM car-following model of a HDV, we added reaction time and perception error parameters to model humans' large reaction times and perception errors in their driving decision making, other IDM model parameters are selected according to [Wang et al., 2019a, Yao et al., 2020].

Although these empirical car-following and lane-changing models are best suited for microscopic mixed traffic simulation studies comprising of HDVs, CAVs and degraded CAVs in realistic traffic scenarios due to their car-following behaviour based on real vehicles, these driving models are still oversimplified to investigate the impact of CAVs on traffic safety and efficiency considering large-scale traffic scenarios in integration with realistic V2X communication. For example, the CACC car-following model developed in [Xiao et al., 2017] is a CAV's longitudinal control model that describes how a CAV follows another adjacent CAV on a motorway. This car-following model, however, simplifies a CACC controller and vehicle dynamics into a single model and thus lacks flexibility to develop and test different controllers. This simplification can thus compromise the authenticity of the simulation-based studies. Therefore, we need to develop a specific car-following control algorithm for CAVs

within the context of modelling realistic vehicle dynamics and realistic V2V communication network simultaneously. In the next chapter, we present the design of CAV car-following control algorithms for their operation in realistic scenarios including mixed traffic, unreliable communication and large-scale traffic scenarios.

5 Design

Based on the knowledge gaps analysis derived from the related work (Section 3.4), the objective of this work is to investigate whether mixed traffic safety and efficiency can be improved for CAVs operation in realistic scenarios by a CAV car-following controller exploiting information from one or more surrounding CAVs that is able to: i) handle varying IFTs in mixed traffic and unreliable communication, and ii) support CAV operations in large-scale traffic scenario. These two key functions have not been well considered and investigated simultaneously, in existing control approaches.

As discussed in Section 1.5, to answer the main research question considered in this thesis (see Section 3.4), two different categories of CAV car-following controllers are proposed: PF IFT-based control and MPF IFT-based control. The first category, the PF IFT-based control strategy, mainly focuses on extending the existing PF IFT-based PLOEG controller to investigate the impact of CAVs on mixed traffic safety and efficiency in realistic scenarios, to answer the first research question RQ1. Then, we present the main contribution of this thesis i.e., the first MPF IFT-based controller design that can improve CAV's ability in coping with the varying IFTs due to the uncertainties of HDVs and communication failures associated with CAVs operation in mixed traffic and unreliable communication environments, to answer the remaining two research questions (RQ2-RQ3).

Firstly, this chapter briefly discusses the motivation behind the controller design choices in Section 5.1. Then, it introduces *PLOEG*, an existing PF IFT-based CAV car-following controller, and explains how this controller is modified using a cautious car-following approach in this work to cope with communication failures and uncertainties of HDVs in mixed traffic and unreliable communication environments (Section 5.2). Section 5.3 introduces our proposed *MPF IFT-based controller* design to further improve CAVs behaviour

in mixed traffic and unreliable communication environments. This includes a specially-designed adaptive weights assignment approach. Finally, this chapter presents a summary in Section 5.4.

5.1 Motivation

The study of CAV car-following control strategies has attracted many researchers, though most of them have only focused on fully connected and automated environments. Moreover, most CAV car-following control algorithms designed in previous research that consider both mixed traffic and unreliable communication are based on the PF IFT only, and degrade to sensor-based control i.e., ACC controller in the presence of communication failures or when the leading vehicle is a HDV. A few MPF IFT-based control strategies for CAVs have been proposed in the literature, but they either assume a fully connected environment, where HDVs are equipped with communication devices, or assume fixed IFT in a perfect communication environment. However, these strategies typically struggle to cope with varying IFTs in mixed traffic and unreliable communication environments. Furthermore, they have not been investigated in large-scale traffic scenarios with realistic V2X communication. Therefore, the main contribution of this thesis is to propose a simple, but scalable CAV car-following control strategy exploiting information from one or more surrounding vehicles so that they can be aware of the surrounding traffic, and then tuning CAV controller parameters to make them resilient against varying IFTs due to the uncertainties of both HDVs and communication failures.

5.2 PF IFT-based Control

Using the simple PF IFT-based car-following control strategy, CAVs can supplement the information from their own sensors with information from their preceding vehicles via V2V communication, as shown in Figure 5.1. This has the potential to improve traffic safety and efficiency. A variety of PF IFT-based car-following control algorithms, namely CACC controllers, are available for longitudinal control of CAVs, that are designed based on various control methods such as linear and non-linear control [Gong et al., 2019], MPC control [van

Nunen et al., 2019], sliding mode control [Sawant et al., 2020], and machine learning control [Tian et al., 2021], discussed in detail in Section 3.1. Among them, linear feedback control methods have been widely used for CAV car-following control due to their simple but accurate enough control architecture in contrast to advanced control methods such as model predictive control (MPC) and long short term memory-based control (LSTM) [Shi et al., 2023]. Furthermore, although a few previous studies on PF IFT-based CAV control have investigated the CACC to ACC degradation in both mixed traffic and unreliable communication environments [Navas and Milanés, 2019, Qin et al., 2019, Tu et al., 2019], the detrimental effects of this degradation on CAV car-following behaviour have not been well explored. In addition, far too little attention has been paid to design control approaches to address the detrimental effects of this degradation on traffic safety and efficiency. To address this, we first adopt *PLOEG*, an existing PF IFT-based CAV control strategy, and then propose CACC to ACC degradation with a cautious car-following approach to cope with communication failures and uncertainties of HDVs in mixed traffic and unreliable communication environments.

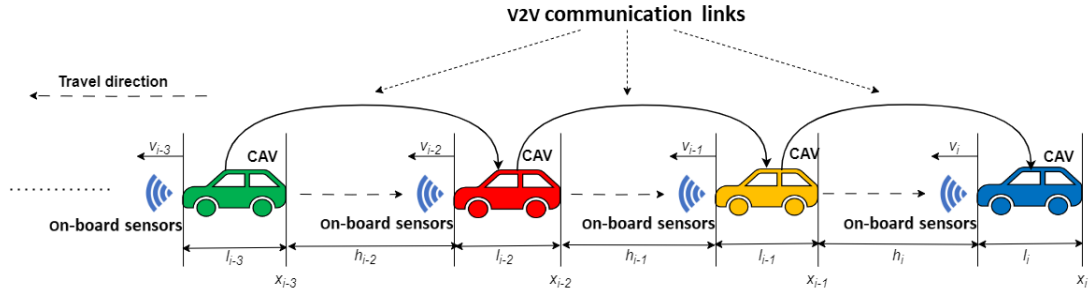


Figure 5.1: Predecessor-following-IFT-based control design.

This section now discusses in turn the PF IFT-based controller model (in Section 5.2.1), *PLOEG*, an existing PF IFT-based CAV car-following control algorithm (in Section 5.2.2), and how this controller is modified for CAVs operation in mixed traffic and unreliable communication environments (in Section 5.2.3), and then the proposed cautious car-following approach (in Section 5.2.4).

5.2.1 PF IFT-based Controller Model

In this section, we describe in brief the PF IFT-based CAV controller model, adopted from [Ploeg et al., 2011]. The longitudinal control dynamics of vehicle i are represented as

$$\begin{aligned} \dot{x}_i(t) &= v_i(t), \\ \dot{v}_i(t) &= u_i(t) = f_i(v_i(t), \Delta x_{i,i-1}(t), \Delta v_{i,i-1}(t)) \end{aligned} \quad (5.1)$$

where x_i denotes the position of the rear bumper of vehicle i , v_i and u_i are the velocity and desired acceleration of vehicle i , respectively. $\Delta x_{i,i-1}$ and $\Delta v_{i,i-1}$ are the position and velocity difference of vehicle i with respect to its immediate leading vehicle $i - 1$.

The main objective of each vehicle i is to follow its leading vehicle $i - 1$ at a desired distance $d_{i,i-1}$. The constant time headway (CTH) policy in the PF IFT-based control is denoted as

$$d_{i,i-1}(t) = h_i(t)v_i(t) + D \quad (5.2)$$

where h_i is the time headway and D is the minimum standstill distance.

The spacing error $e_i(t)$ is formulated as

$$e_i(t) = d_i(t) - d_{i,i-1}(t) = [x_{i-1}(t) - x_i(t) - L_i] - [h_i(t)v_i(t) + D] \quad (5.3)$$

where L_i is the vehicle length.

The control law can now be designed by formulating the error dynamics

$$\begin{bmatrix} e_{1,i} \\ e_{2,i} \end{bmatrix} = \begin{bmatrix} e_i \\ \dot{e}_i \end{bmatrix} \quad (5.4)$$

$$\begin{aligned} \dot{e}_{1,i} &= e_{2,i} \\ \dot{e}_{2,i} &= \ddot{e}_i \\ \dot{e}_{2,i} &= u_{i-1} - [h_i \dot{u}_i + u_i] \end{aligned} \quad (5.5)$$

with the new input

$$q_i \triangleq u_{i-1} - [h_i \dot{u}_i + u_i] \quad (5.6)$$

From Equation 5.6, it is observed that input q_i should stabilise the position and speed error dynamics while compensating for the input u_{i-1} of the immediate leading vehicle in order to obtain exact vehicle following, i.e.,

$$\lim_{t \rightarrow \infty} e_i(t) = 0$$

. Hence, the control law for q_i is designed as follows:

$$q_i = k \begin{bmatrix} e_{1,i} \\ e_{2,i} \end{bmatrix} + u_{i-1} \quad (5.7)$$

where $k = [k_p, k_d]$ are the control gains.

5.2.2 The PLOEG controller

To address RQ1, a controller is required that on the one hand assumes both realistic vehicle dynamics model and realistic communication, and on the other hand is amenable to large-scale traffic simulations. For this purpose, the existing PLOEG controller was extended in this work to propose the PF IFT-based CAV control strategy. This section presents first the existing PLOEG controller, then its limitations.

In this work, the existing PLOEG CACC controller, in which an ego vehicle receives information (i.e., position and speed) from only its immediate leading vehicle is adopted [Ploeg et al., 2011]. The PLOEG CACC controller aims to regulate the relative speed and distance between each vehicle and its predecessor, using the constant-time-headway spacing policy and the simplest information flow topology, the one-vehicle ahead (i.e., predecessor-following) [Ploeg et al., 2011]. This, in addition to assuming a 2nd order vehicle dynamics and using linear feedback control makes it a good basis for the proposed controller design approach for CAVs operation in realistic scenarios in terms of mixed traffic, unreliable communication and large-scale traffic scenarios.

This controller, however, is only designed for pure CAVs traffic assuming perfect communication only, where state information (i.e., position and speed) of the immediate leading vehicle can be obtained accurately via V2V communication. Therefore, the car-following control algorithm used in the PLOEG controller needs to be modified for CAVs operation in mixed traffic and unreliable communication environments, where it might not always be possible to get information via V2V communication links.

5.2.3 Extending the PLOEG Controller in Mixed Traffic and Unreliable Communication Environments

RQ1 asks whether CAVs can improve both mixed traffic safety and efficiency in mixed traffic and unreliable communication environments on large-scale road networks. A lot of research has investigated the impact of CAVs on mixed traffic safety and efficiency by using the PF IFT-based CAV car-following controller. However, an open question remains regarding the extent to which CAVs can improve traffic safety and efficiency in realistic scenarios in terms of imperfect communication, humans' large reaction time and perception errors, vehicle modelling and large-scale traffic scenarios. To address RQ1, we therefore propose modifying the PLOEG car-following control algorithm such that a CAV degrades its longitudinal driving mode from communication-based to sensor-based control i.e., car-following using on-board sensor information instead of information obtained via V2V communication, when it cannot establish a link with the previous vehicle either because it is a HDV or due to communication failures, as shown in Figure 5.2. Additionally, a CAV reverts back to the communication-based control i.e., CACC mode once the V2V communication link is established again. This degrading/reverting mechanism relies on the active monitoring of the status of the communication interface at each time step [Segata et al., 2022]. It is worth mentioning that before the degradation, a CAV follows its preceding vehicle in the CACC mode with a smaller time headway. When the degradation occurs, a CAV switches its longitudinal control mode to the ACC, with a much larger time headway compared to the CACC mode.

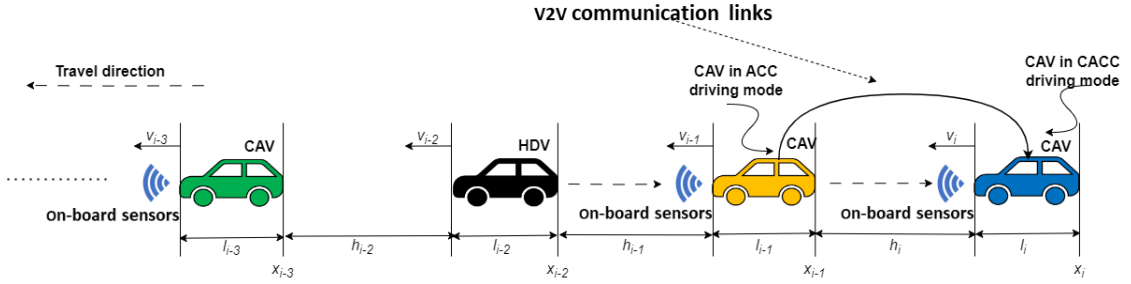


Figure 5.2: Predecessor-following-IFT-based control design for CAVs in mixed traffic environment.

5.2.4 Cautious Car-following Approach

Increasing the time headway during the CACC to ACC mode degradation might lead to CAVs accelerating abruptly, thereby affecting CAV car-following behaviour negatively [Wang et al., 2019a]. Different approaches such as estimator/observer design [Ploeg et al., 2015, Acciani et al., 2018, Tian et al., 2021], have been proposed to improve the robustness of CAVs behaviour against the delays/losses in V2V communication links. All these approaches estimate the kinematic states of the leading vehicle when no information from the preceding vehicle is available via V2V due to communication failures, to avoid large time headways in the ACC mode. While this state estimation approach might be suitable for pure CAVs traffic due to limited uncertainty in the driving behaviour of CAVs, it will not work well when the leading vehicle is a HDV due to the uncertainties and stochastic driving behaviour of HDVs [Shi et al., 2021, Shi et al., 2023].

Furthermore, a few previous studies (e.g., in [Tu et al., 2019, Qin et al., 2019, Wang et al., 2019a]) have considered degrading CACC to ACC for CAVs operation in both mixed traffic and unreliable communication environments, as described in detail in Chapter 3. These studies claim that traffic safety improves due to larger time headways in the ACC mode, but this is at the expense of decreased traffic efficiency [Qin et al., 2019, Tu et al., 2019]. Degrading to ACC when following a HDV or in the presence of packet drops, however, might create traffic congestion due to the speed variations to create these large time headways in the ACC mode, thereby affecting both traffic safety and efficiency negatively [Segata et al., 2022]. To reduce the detrimental effects of such longitudinal mode degradation, we propose a cautious car-following approach for CAVs i.e., adopting more conservative time headway for CAVs, for their operation in mixed traffic and unreliable communication environment, so that a CAV need not to increase its time headways significantly when it degrades to

sensor-based ACC mode in the absence of information from its preceding vehicle due to communication failures or it being a HDV. The proposed approach distinguishes itself from previous studies to construct smoother transitions in CAV longitudinal mode degradation from CACC to ACC controller.

Algorithm 1 enables the implementation of the proposed cautious car-following approach as the distributed control protocol for CAVs adopting larger time headways when they encounter information loss due to communication failure or the leading vehicle being a HDV. This approach can avoid intense speed fluctuations in increasing the time headway in the ACC mode, and thereby seems a promising solution to improve both traffic safety and efficiency. This cautious car-following strategy can essentially be used to not only improve traffic safety from reducing rear-end collisions by giving more time for vehicles to react to their leading vehicles, but it also can reduce cognitive loads on drivers.

Algorithm 1 Pseudo Code for cautious car-following approach for each CAV controller

```

1: Initialize: Vehicle car-following model parameters (e.g., speed, position, time headway)
2: Input: Position and velocity of a leading vehicle,  $x_{i-1}$ , and  $v_{i-1}$ 
3: Input: Increased time headway,  $h_i(t) + \Delta h \leftarrow h_i(t)$ 
4: if packet is lost or leading vehicle is a HDV then
5:   if a CAV is in the CACC mode then
6:     Perform CACC to ACC mode degradation
7:   else
8:     if a CAV is in the ACC mode then
9:       Revert back to CACC mode
10: end
11: Apply PF IFT-based control algorithm given in Equation (5.6) as a distributed control for CAVs
12: Output: Control input  $u_i$  for vehicle  $i$ 

```

To summarise, the PF IFT-based control strategy with a cautious car-following approach is simple enough for CAV controller implementation in large-scale traffic scenarios in integration with realistic inter-vehicle communication, and to investigate the impact of CAVs on mixed traffic safety and efficiency in realistic scenarios.

5.3 MPF IFT-based Control

To further improve traffic safety and efficiency, various MPF IFT-based CACC control algorithms [Di Vaio et al., 2019, Santini et al., 2017, Navas and Milanés, 2019, Jia et al., 2019, Bian et al., 2019, Abolfazli et al., 2022, Avedisov et al., 2022] have been proposed in the literature for pure CAVs traffic, as shown in Figure 5.3. These have been widely used in

both academia and industry because they have the possibility of adapting CAV car-following behaviour based on multiple vehicles information compared to the PF IFT-based control algorithms, thereby potentially improving traffic safety and efficiency significantly. These control algorithms are developed based on both (i) traditional model-based control such as PID control, model predictive control and consensus-based control, and (ii) advanced learning-based control such as reinforcement learning, deep learning, fuzzy logic, etc., to maintain the desired time headway while minimizing the relative speed difference and gap error, as discussed in detail in Section 3.1. However, in mixed traffic and unreliable communication environment, it is not always possible to adapt CAV car-following behaviour based on information from multiple leading vehicles due to the presence of HDVs without communication capability and communication failures, and therefore control algorithms need to be re-designed considering these factors.

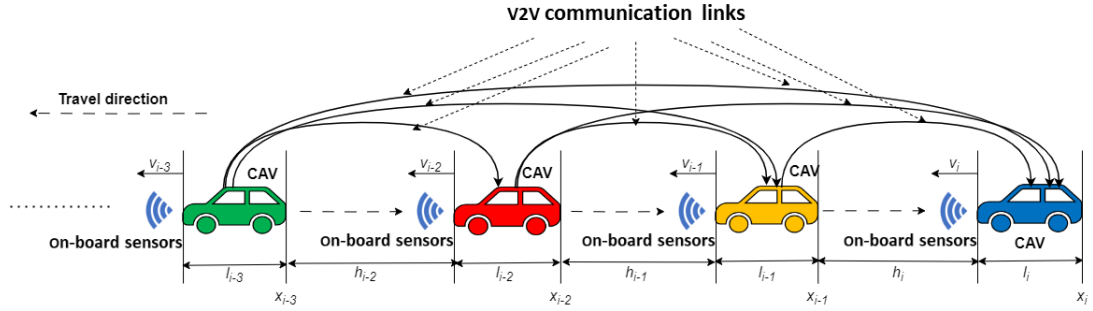


Figure 5.3: Multiple-predecessor-following-IFT-based control design.

Many car-following control approaches have been proposed in the literature to optimize CAV car-following behavior in the presence of HDVs and communication failures, though gaps in the studies on CAVs operation in mixed traffic and unreliable communication environments remain in the following two aspects. Firstly, most existing MPF IFT-based CAV car-following control strategies assume fixed IFTs and consider a predefined sequencing of CAVs and HDVs in a platoon. The distribution of vehicle types in the traffic flow depends on the penetration rate, but also varies over time and space, leading to diverse and varying IFTs, making it necessary to develop computationally efficient but adaptive car-following control strategies for CAVs considering varying IFTs, especially in large-scale traffic scenarios [Ge and Orosz, 2016, Ge and Orosz, 2017, Shi et al., 2023]. Secondly, a few existing MPF IFT-based CAV car-following control strategies that have been designed to handle varying IFTs but they either consider mixed traffic with perfect communication or pure

CAVs traffic with unreliable communication. These strategies therefore struggle to cope with variations in IFTs in both mixed traffic and unreliable communication environments. Furthermore, they have only been validated in very limited scenarios for a very small number of vehicles (with a fixed sequence of CAVs and HDVs).

To address RQ2 and RQ3, we propose a MPF IFT-based distributed CAV control strategy based on linear feedback control methods to enhance the robustness and practicality of the CAV car-following controller in realistic scenarios. Additionally, we have developed an adaptive tuning approach specially designed for the MPF IFT controller. The proposed control strategy offers significantly lower computational complexity than the advanced learning-based methods [Shi et al., 2021, Shi et al., 2023, van Nunen et al., 2019], as it is based on the linear closed-loop feedback control architecture and only considers 2nd order vehicle dynamics, making it suitable for large-scale traffic simulations. While 3rd order vehicle models might produce better car-following behaviour, we are favouring less complex models but accurate enough for CAVs performance evaluation in large-scale traffic scenarios. Furthermore, unlike other related work, the proposed CAV car-following control algorithm is able to cope with the uncertainties of HDVs and communication failures for CAVs operation in mixed traffic and unreliable communication environments with realistic traffic demands, thereby improving traffic safety and efficiency in realistic scenarios.

This section now discusses in turn the MPF IFT-based controller design (in Section 5.3.1), controller parameters (time headway and control gains) tuning (in Section 5.3.2), and then the adaptive weights assignment approach (in Section 5.3.3). Finally, stability properties of the proposed controller are discussed in brief in Section 5.3.4.

5.3.1 Controller Design

To address RQ2 "*Does exploiting information from multiple leading vehicles within their communication range give an advantage to CAVs (compared to single-vehicle information based control) in terms of traffic safety and efficiency?*", our proposed approach designs a first MPF IFT-based CAV car-following controller that incorporates information from multiple leading vehicles in its algorithm, for mixed traffic and unreliable communication scenarios with no fixed information flow topology, as shown in Figure 5.4. This controller

framework is adopted from works in [Jia et al., 2019, Jia and Ngoduy, 2016b] designing the MPF IFT-based control algorithm in pure CAV traffic. Jia et al. also consider information from multiple leading vehicles in the controller design, but in their solution, they consider a fixed information flow topology in a platoon with a designated leader and several follower vehicles. Their work is focused on designing a consensus-based car-following control algorithm for CAVs with the goal of coordinating all vehicles to follow the same speed, and is only applicable in pure CAVs traffic. Our work extends this work such that the proposed CAV controller allows the incorporation of multiple leading vehicles information (only if they are CAVs), thereby making it more flexible and scalable for its implementation in realistic traffic scenarios. In addition, the controller is designed such that it still functions in mixed traffic, including when all neighbour vehicles are HDVs that do not have communication capabilities. In that case, a CAV degrades its car-following control mode to ACC. Our proposed approach relies on the active monitoring of the status of the communication link to handle varying IFTs in mixed traffic and unreliable communication environments i.e., if we do not receive a frame via V2V communication within a time period, we can automatically and immediately understand that packet is lost/delayed.

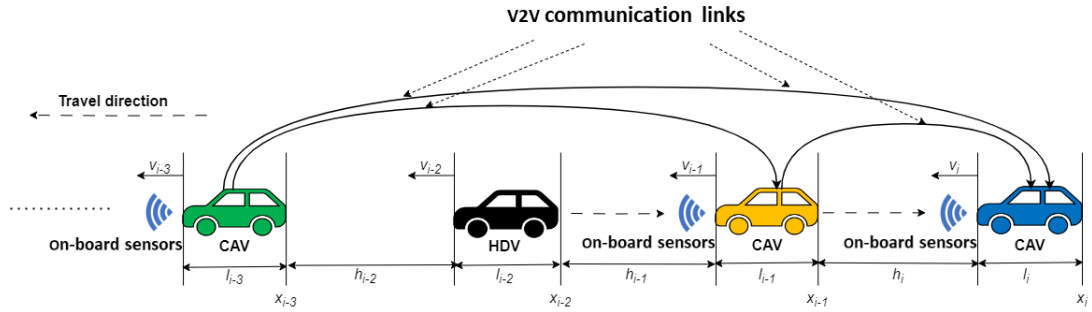


Figure 5.4: Multiple-predecessor-following-IFT-based control design for CAVs in mixed traffic environment.

The longitudinal control dynamics of vehicle i are represented as [Jia et al., 2019],

$$\begin{aligned}\dot{x}_i(t) &= v_i(t), \\ \dot{v}_i(t) &= u_i(t) = f_i^c(v_i(t), \Delta x_{i,j}(t), \Delta v_{i,j}(t))\end{aligned}\tag{5.8}$$

where x_i denotes the position of the rear bumper of vehicle i , v_i and u_i are the velocity and desired acceleration of vehicle i , respectively. $\Delta x_{i,j}$ and $\Delta v_{i,j}$ are the position and velocity difference of vehicle i with respect to its neighbour vehicle j .

In practice, the acceleration u_i is bounded by an upper bound $a_{\max,i} > 0$ and a lower bound $a_{\min,i} < 0$, where the magnitude of $a_{\min,i}$ denotes the maximum deceleration. Thus, the constraint $a_{\min,i} \leq u_i(t) \leq a_{\max,i}$ is imposed for all t .

The desired distance between vehicle i and its neighbour vehicle j in the CTH policy under MPF topology is formulated as,

$$x_{ij}^d = \sum_{j \in N_i^c} (h_{ij}v_{ij} + d_{ij}) \quad (5.9)$$

where $h_{ij} \geq 0$ and $d_{ij} > 0$ denote the time headway of vehicle i and desired standstill gap of vehicle i with respect to its neighbour vehicle j , respectively.

The MPF-based linear control algorithm under CTH policy following the approach in [Jia et al., 2019] is denoted as,

$$u_i^c(t) = \sum_{j \in N_i^c} a_{ij} \{ \alpha [x_j(t) - x_i(t) - x_{ij}^d(t)] + \beta [v_j(t) - v_i(t)] \} \quad (5.10)$$

where controller parameters (α, β) , the weight factors of kinetic information (position and speed), are feedback control gains that need to be properly tuned to achieve optimal traffic performance. N_i^c and a_{ij} denote neighbour set of CAVs under MPF topology and varying information flow topology (a_{ij} is 1 when information is available from j to i , otherwise 0), respectively. $N_i^c = \{i-j, i-j+1, \dots, i-1\}$ is defined as the set of j leading vehicles within the communication range of an ego vehicle i . In the subsequent sections, we describe the CAV controller parameters tuning approach that is performed in order to cope with varying IFTs in mixed traffic and unreliable communication environments, thereby resulting in improved traffic safety and efficiency in realistic scenarios.

5.3.2 Controller Parameters Tuning

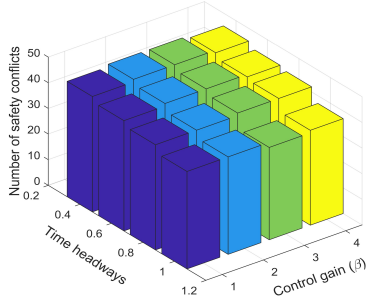
The generality of the impact of CAVs can be challenged by a different set of parameters such as time headway, control gain parameters, sensor and actuator delays, wireless network condition, penetration rate, traffic demand and road network type, that can affect traffic safety and efficiency. For this reason, controller parameters design is critical to the traffic performance. Therefore, this work investigates how the controller parameters affect the sys-

tem performance and based on the analysis, how to select the optimal (control parameters) values to enhance the traffic performance.

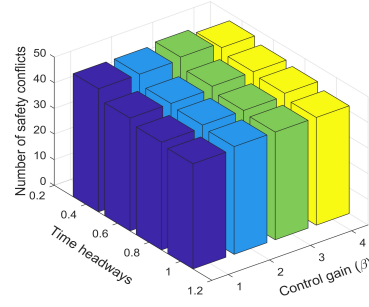
Furthermore, a key requirement for the CAV car-following controller design is to maximize CAV's ability to cope with the varying IFTs due to the uncertainties of HDVs and communication failures associated with CAVs operation in mixed traffic and unreliable communication environments. The controller parameters tuning approach is particularly proposed to take into account varying information flow topology and make the MPF IFT-based controller adaptive against the presence of HDVs as well as communication failures. Our proposed controller parameters tuning approach has a great generalization capability of improving resilience against varying IFTs due to communication failures and uncertainties of HDVs, fulfilling the car-following task more safely and efficiently under different CAV penetration rates and realistic traffic demands.

The experiment design of tuning the controller parameters (control gains and time headways) of CAVs is performed based on a validation network, at four different control gains configurations and different time headways, using the controller framework detailed in Section 5.3.1, then validated the tuned controller parameters on a realistic road network (the M50 motorway, in Ireland). In all control gains configurations, only the velocity error coefficient β is varied (between 1 and 4), while keeping the position error coefficient $\alpha > 0$ as constant and equal to 1, similarly to related work [Bian et al., 2019, Jia et al., 2019, Jia and Ngoduy, 2016b]. This is also due to the fact that in the CTH policy, the desired inter-vehicle distance varies according to the vehicle velocity only [Bian et al., 2019]. Furthermore, in all configurations, the time headway was varied between 0.4s and 1s in 0.2s increments. This range of headways between vehicles was chosen according to related work [Bian et al., 2019, Rahman et al., 2021]. An ACC time headway value of 1.1s is selected when all neighbour vehicles are HDVs, similarly to related work [Navas and Milanés, 2019, Di Vaio et al., 2019].

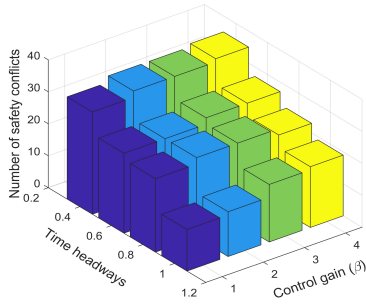
Figures 5.5 and 5.6 show the 3D plots of traffic safety (i.e., the number of safety conflicts) and efficiency (i.e., travel time) for different headways and control gains, at different CAV penetration rates, with and without packet drops. The x-axis indicates the control gain, y-axis represents the time headway, and z-axis shows the number of safety conflicts or



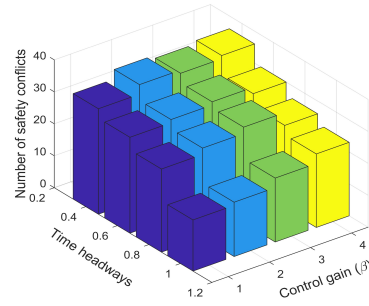
(a) MPR 20%, PER 0%



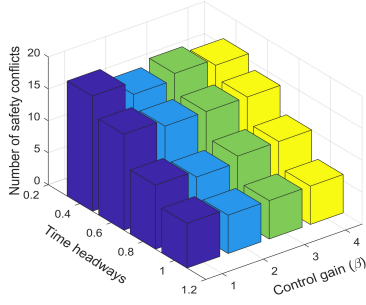
(b) MPR 20%, PER 70%



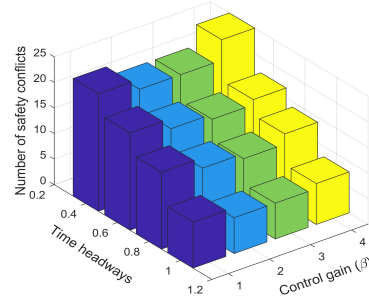
(c) MPR 40%, PER 0%



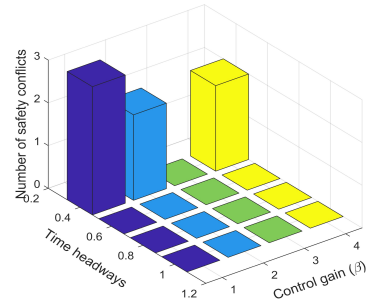
(d) MPR 40%, PER 70%



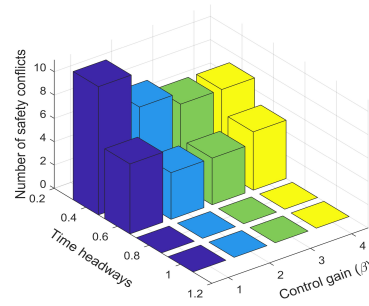
(e) MPR 70%, PER 0%



(f) MPR 70%, PER 70%

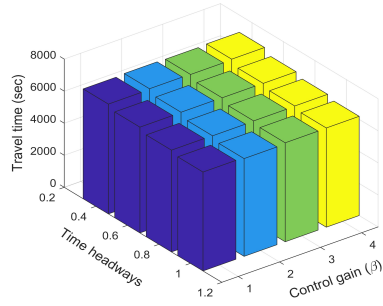


(g) MPR 100%, PER 0%

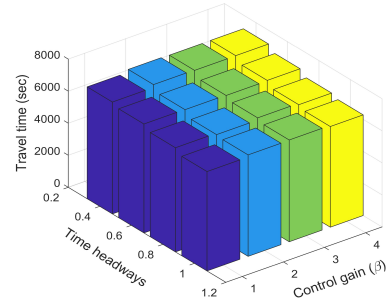


(h) MPR 100%, PER 70%

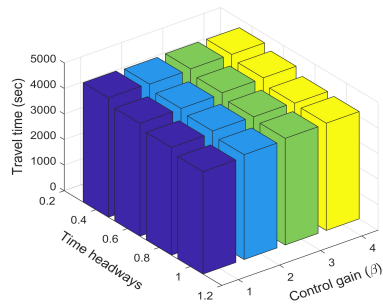
Figure 5.5: Controller parameters (time headway and control gains) tuning based on the number of safety conflicts at different penetration rates of CAVs (20%, 40%, 70%, 100%), with and without packet drops



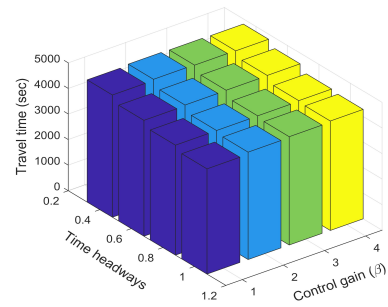
(a) MPR 20%, PER 0%



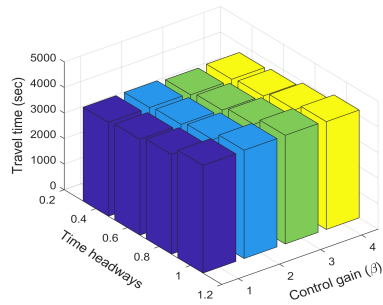
(b) MPR 20%, PER 70%



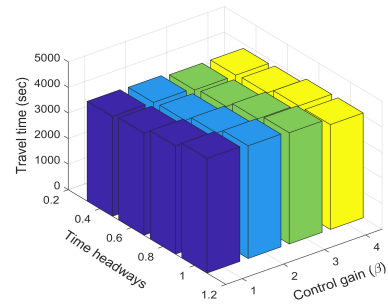
(c) MPR 40%, PER 0%



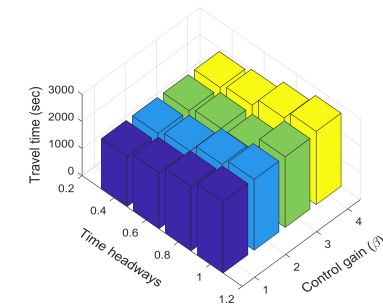
(d) MPR 40%, PER 70%



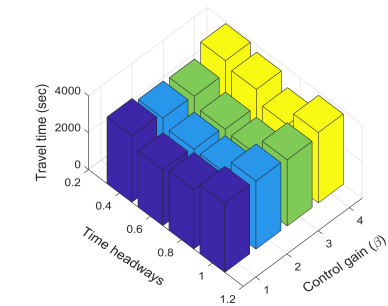
(e) MPR 70%, PER 0%



(f) MPR 70%, PER 70%



(g) MPR 100%, PER 0%



(h) MPR 100%, PER 70%

Figure 5.6: Controller parameters (time headway and control gains) tuning based on travel time at different penetration rates of CAVs (20%, 40%, 70%, 100%), with and without packet drops

travel time. In perfect communication environments, there is no significant effect of different control gains, but traffic safety is better at larger time headways, as shown in Figure 5.5 (a), (c), (e) and (g). This shows that traffic safety improves significantly when CAVs use more cautious car-following strategies i.e., larger time headways. This is, however, at the cost of a reduction in traffic efficiency, as shown in Figure 5.6 (a), (c), (e) and (g). Moreover, in imperfect communication environments, both control gains and time headways have significant effects on traffic safety and efficiency. Therefore, it is suggested that CAVs should choose different time headways and control gains specific to their penetration rate and packet error rate. For instance, the combination of larger time headways and smaller control gains provide better traffic safety and efficiency at low-to-medium penetration rates (i.e., 20% and 40%), as shown in Figure 5.5 (b, d) and 5.6 (b, d). In contrast, the combination of smaller time headways and higher control gains provide better traffic safety and efficiency at high penetration rates (i.e., 70% and 100%), as shown in Figure 5.5 (f, h) and 5.6 (f, h). Moreover, at high penetration rates, traffic efficiency improves significantly with higher gain values and smaller time headways, but this results in a higher number of safety conflicts i.e., reduced traffic safety. Although traffic safety can be improved by increasing the time headways, this is at the expense of a reduction in traffic efficiency. The above trade-off between traffic safety and efficiency can be resolved by selecting the control gains and time headways carefully. Therefore, we choose control gains ($\alpha=1$, $\beta=2$), time headway (1s)) for CAV low-to-medium penetration rates (i.e., 20% and 40%), and control gains ($\alpha=1$, $\beta=3$), time headway (0.8s)) for CAV high penetration rates (i.e., 70% and 100%). Using these combinations of time headways and control gains, CAVs do not need to massively increase the time headway in order to compensate for the effects of communication failures and the uncertainties of HDVs. These parameters are used in the proposed *MPR-tuned MPF IFT* controller for simulating CAVs.

5.3.3 An Adaptive Distance-based Control Approach for Controller Parameters Tuning

While CAVs exploiting information from multiple leading vehicles has the potential to improve both traffic safety and efficiency further compared to CAVs taking information from their immediate leading vehicle only, such MPF IFT-based control might lead to CAVs ac-

celerating when more distant CAVs accelerate, which may cause serious safety problems, especially when there are human-driven vehicles in-between. Figure 5.7 illustrates this pattern more clearly using the following example. Consider the scenario shown in this figure where vehicles $i - 3$ and $i - 2$ accelerate, vehicle $i - 1$ decelerates to turn towards the ramp, and vehicle i monitors the motion of vehicles $i - 3$ and $i - 2$ via V2V communication. If vehicle i exploits information from all leading vehicles and assigns the same weighting to each leading vehicle information, it may collide with vehicle $i - 1$, because the acceleration of vehicle $i - 3$ leads vehicle i to accelerate when vehicle i should decelerate to avoid a collision with vehicles $i - 1$. This is due to assigning the same weighting to all leading vehicles, without taking into consideration their position and sequence from the ego vehicle, thereby resulting in safety conflicts. Another challenge is the communication overhead that is generated by exploiting information from all leading vehicles within the communication range, significantly worsening vehicular network congestion conditions. Generally, some leading vehicles which are quite far, but within the communication range of an ego vehicle, will contain less relevant information for CAV controller design, but this will definitely increase the communication overhead problem. This problem inevitably deteriorates the communication channel congestion conditions and impacts the reliability of the exchange of information that is transmitted over the shared control channel. This condition can ultimately affect both traffic safety and efficiency negatively.

As discussed in Section 3.2.2, a few recent studies [Rahman et al., 2021, Ding et al., 2022, Yu et al., 2023] addresses this limitation by assigning different weights to different leading vehicles, but fixed weights, according to their sequence in the string. This study, however, only works well in a fully connected traffic environment with perfect communication. However, information exchange among vehicles can be interrupted in mixed traffic and unreliable communication environments, leading to varying IFT that can further deteriorate the CAV controller performance [Yu et al., 2023]. In order to better adapt to the varying IFTs in the mixed traffic and unreliable communication environment, for the first time, our work extends this work to adapt the CAV control gains according to the distance of leading vehicles from an ego vehicle, rather than requiring all leading vehicles to use the same control gains or assigning control gains according to leading vehicle's sequence only, which provides a novel way to design the MPF IFT-based car-following control strategy handling varying

IFTs more effectively. It is worth mentioning that the information weight factor between two close vehicles may cause a safety threat and has much higher importance than the information exchange between two far vehicles. Hence, illustrating information weighting as a function of transmitter-receiver distance will be more enlightening than only assuming the same weighting for the whole network. In this work, a *distance-based adaptive weights assignment* approach, which serves as a novel CAV controller parameters tuning approach is proposed that assigns different information weighting to multiple leading vehicles according to their distance from the ego vehicle. In contrast to previous studies assuming a fully connected environment with perfect communication and hence assigning fixed weights to information from leading vehicles according to their sequence, we assign adaptive weights to information from leading CAVs based on their distance from an ego vehicle. Consider the scenario described in Figure 5.7, using the distance-based adaptive approach for information weighting assignment, information from vehicle $i - 1$ is assigned the highest weighting and information from vehicle $i - 3$ is assigned the lowest weighting. Hence, vehicle i will make a priority decision to decelerate according to vehicle $i - 1$, as compared to accelerate according to vehicle $i - 3$ behaviour.

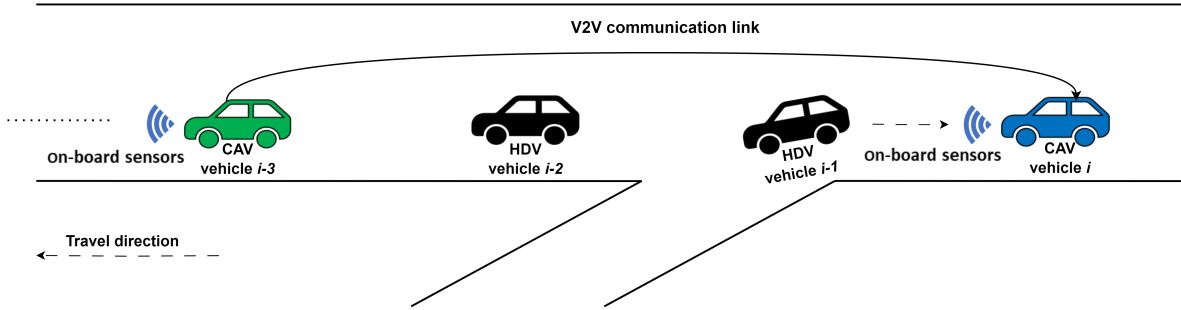


Figure 5.7: CAVs control using information from multiple leading vehicles in mixed traffic

$$\left[w_{i,i-1}, w_{i,i-2}, w_{i,i-3}, w_{i,i-4}, w_{i,i-5} \right] = \left[\frac{d_{i,i-1}}{d_{i,i-1}}, \frac{d_{i,i-1}}{d_{i,i-2}}, \frac{d_{i,i-1}}{d_{i,i-3}}, \frac{d_{i,i-1}}{d_{i,i-4}}, \frac{d_{i,i-1}}{d_{i,i-5}} \right] \quad (5.11)$$

where $d_{i,i-1}$, $d_{i,i-2}$, $d_{i,i-3}$, $d_{i,i-4}$, $d_{i,i-5}$ are the distance between an ego vehicle and first leading vehicle, the distance between an ego vehicle and second leading vehicle, the distance between an ego vehicle and third leading vehicle, the distance between an ego vehicle and fourth leading vehicle, the distance between an ego vehicle and fifth leading vehicle,

respectively. $w_{i,i-1}$, $w_{i,i-2}$, $w_{i,i-3}$, $w_{i,i-4}$, $w_{i,i-5}$ are the control gains assigned between an ego vehicle and first leading vehicle, distance between an ego vehicle and second leading vehicle, distance between an ego vehicle and third leading vehicle, distance between an ego vehicle and fourth leading vehicle, distance between an ego vehicle and fifth leading vehicle, respectively.

Using this adaptive information weighting assignment approach, the proposed MPF-based linear control algorithm is modified as,

$$u_i^c(t) = \sum_{j \in N_i^c} a_{ij} \{ \alpha \cdot w_{ij} [x_j(t) - x_i(t) - x_{ij}^d(t)] + \beta \cdot w_{ij} [v_j(t) - v_i(t)] \} \quad (5.12)$$

where controller parameters (α, β) , the weight factor of kinetic information (position and speed), are feedback control gains that needs to be properly tuned to achieve optimal traffic performance. $N_i^c(t)$ and a_{ij} denote neighbour set of CAVs under MPF topology and varying information flow topology (a_{ij} is 1 when information is available from j to i , otherwise 0), respectively. $N_i^c = \{i - j, i - j + 1, \dots, i - 1\}$ is defined as the set of j leading vehicles within the communication range of an ego vehicle i .

Algorithm 2 Pseudo Code for an adaptive distance based control gains tuning for MPF IFT-based Algorithm

- 1: Input: Position and velocity of neighbouring vehicles within the communication range of a vehicle i , x_j , and v_j
 - 2: **for** each vehicle j within the communication range **do**
 - 3: Calculate the distance of leading vehicles from an ego vehicle
 - 4: Calculate control gain coefficients according to given information weighting formula in Equation 5.11.
 - 5: Normalize the weights. $w_{i,j} = \frac{w_{i,j}}{\sum_{j \in N_i^c} w_{i,j}}$
 - 6: Apply MPF IFT-based control algorithm given in Equation 5.12 as a distributed control for CAVs
 - 7: Output: Control input u_i for vehicle i
 - 8: **end for**
-

Algorithm 2 enables the implementation of an adaptive distance-based approach for control gains tuning of the distributed control protocol proposed in this section. Note that we limit the number of leading vehicles to five, as previous studies show that looking at more than five leading vehicles does not yield significant improvement in traffic performance [Ge and Orosz, 2017, Avedisov et al., 2022, Zhou et al., 2023]. For each CAV, this algorithm will be used to achieve car-following control. The design steps of the algorithm are emphasized as follows: The first step of the proposed distance-based controller parameters tuning is to

measure the longitudinal position of each leading vehicle and then calculate the distance w.r.t. the ego vehicle within its communication range. It is assumed that each CAV considers information from five leading vehicles only if the number of leading vehicles within its communication range is more than five. Based on the calculated distances between an ego vehicle and multiple leading vehicles, the immediate leading vehicle information is assigned the highest weighting and the farthest vehicle is assigned the lowest weighting according to the formula given in Equation 5.11, which is the second step. The information from leading vehicles beyond the fifth leading vehicle is simply discarded from the calculations. In the third step, the MPF IFT-based CAV controller is used following this adaptive weight assignment approach. The control gain computation portion of the algorithm is invoked at each simulation time step.

5.3.4 Stability Analysis

Stop-and-go waves are a major cause of traffic congestion resulting in reduced traffic safety and efficiency, often triggered by instability in the car-following behaviour [Sun et al., 2018, Di Vaio et al., 2019]. The growth of disturbance (e.g., a spacing and speed deviation from a steady state) over time and space during car-following leads to the instability of traffic flow. Therefore, the main objective of traffic flow stability analysis is to consider the influence of random disturbances on traffic flow performance. When the disturbance is small, it gradually reduces and disappears in the traffic flow with time. In this case, the disturbance has little impact on the traffic flow. However, when the disturbance is significant, it spreads in the traffic flow, resulting in the reduction in traffic efficiency and increasing the risk of traffic safety conflicts.

In previous studies, stability analysis was either performed for a small number of vehicles with a fixed sequence of CAVs and HDVs in a platoon [Sun et al., 2018, Jia et al., 2019] or considered platoons of vehicles with infinite length [Talebpour and Mahmassani, 2016]. Different stability analysis methods such as transfer function method, Laplace transform based method, Lyapunov stability criterion and Leibniz-Newton formula are used to derive stability conditions. However, because the analytical-based stability analysis approach considers many assumptions such as small disturbance, fixed sequence of vehicles, small platoon

size, etc., it restricts the applicability of the stability analysis results in realistic scenarios in terms of large-scale road networks with real traffic flow, mixed traffic and unreliable communication due to the complicated traffic composition i.e., random mix of CAVs and HDVs, and uncertainties of HDVs and communication failures leading to varying IFTs in mixed traffic and unreliable communication environments. Generalizing the analytical stability analysis approach to realistic scenarios in terms of traffic patterns has not been addressed in the literature and would be challenging. In contrast, an easy way of testing traffic flow stability is through a simulation-based approach in which CAVs are simulated in a driving environment and the impact of introducing different types of disturbances is observed. In such a simulation-based stability analysis approach, stability is checked how the disturbances in terms of inter-vehicle distance and speed errors evolve over time across the downstream traffic. However, these studies are only suitable for small numbers of vehicles in a platoon. Consequently, instead of performing an analytical stability analysis, this work investigates the impact of CAVs on the overall traffic flow by using large-scale realistic simulations.

5.4 Summary

Firstly, this chapter presented an existing PF IFT-based car-following controller *PLOEG*, and how it was extended for CAVs operation in mixed traffic and unreliable communication environments. Secondly, the main contribution of this thesis work i.e., the design of MPF IFT-based car-following controller, including design approach and controller parameters tuning for CAVs operation in mixed traffic and unreliable communication scenarios was presented. Finally, this chapter presented a novel distance-based approach for assigning information weighting to different leading vehicles according to how far they are from the ego vehicle, in contrast to assigning the same control gains to all leading vehicles as in previous research [Xie et al., 2023, Avedisov et al., 2022, Zhou et al., 2023].

6 Implementation

This chapter explains in detail the implementation work required to answer the research questions addressed by this thesis. First, Section 6.1 describes the selection criteria for the simulator. Then, Section 6.2 presents the overall architecture of the simulator along with the modules, used in this work. Finally, Section 6.3 explains the implementation of the car-following control algorithms proposed in Chapter 5 on the chosen simulator.

6.1 Simulator Choice

Simulating CAVs in mixed traffic and unreliable communication environments along with realistic traffic scenarios is challenging, especially because of the unreliability of communication links and complexity of large-scale traffic networks [Jia et al., 2021]. For this reason, performing mixed traffic simulations with both realistic traffic and communication model requires using the integration of a microscopic vehicular traffic simulator and a communication network simulator.

Before describing in detail the various simulator available, we list the requirements for the platform chosen.

- **Open-Source:** the simulator must be open-access and the source code for the software must be freely available and open to modifications and extensions.
- **Software license:** all the features of the simulator must be available at no charge for academic and research purpose.
- **Active development:** the project must be well maintained and under active development.

- **Suitability:** the simulator must be capable of performing CAV simulations in realistic scenarios in terms of mixed traffic, unreliable communication, human large reaction time, vehicle modeling. If it is not capable of fulfilling all of the simulation requirements on its own, it must be able to integrate with other simulators that can do so, and must be able to perform its respective simulation component in parallel with the other components of the simulation.
- **Extension:** the simulator must allow the user to create new traffic scenarios, implement V2X communication protocols, and implement new car-following control algorithms.

This section now discusses in turn traffic simulators (Section 6.1.1), network simulators (Section 6.1.2) and vehicular network simulators (Section 6.1.3), before discussing the rationale for the choice of the platform for this work (Section 6.1.4).

6.1.1 Traffic Simulators

Various traffic simulators, widely being used for traffic simulation studies are as follows.

- **SUMO** is an open-source microscopic traffic simulator¹, which is available free-of-charge and actively maintained under the guidance of the Eclipse Foundation. This simulator facilitates the modeling and simulations of large-scale traffic networks, consisting of different types of vehicles (HDVs, AVs, CAVs, etc.) and transport modes (car, truck, train, bike, etc.). It comes with built-in tools which allow network creation, route creation, and traffic demand modeling. Furthermore, it is possible to extend the usability of SUMO with the help of APIs. Some of the car following models supported by SUMO are ACC, CACC, Krauss, Intelligent Driving Model (IDM), Enhanced Intelligent Driving Model (EIDM), W99, Wiedermann, etc.
- **AIMSUN** is a commercial traffic modelling solution, developed by AIMSUN SLU². It is closed-source, and is available free-of-charge with limited features for academic purposes upon request. This simulator supports the modeling and simulations of urban streets, motorways, interchanges, and roundabouts. It also supports 3-D animation.

¹SUMO homepage: <https://sumo.dlr.de/docs/index.html>

²AIMSUN homepage: <https://www.aimsun.com/>

- **VISSIM** is also a commercial traffic simulator developed by PTV AG³. It is a closed source and is available free-of-charge for academic purposes, just like AIMSUN.

6.1.2 Network Simulators

Various communication network simulators available are as follows.

- **OMNET++** is an open-source discrete-event network simulator⁴. It is under active development, available free of charge, and has been used to create a wide array of wireless network modeling and simulations. It supports integration with other simulation frameworks such as INET, VEINS, COSSIM, VENTOS, etc.
- **NS-2/NS-3** is another open-source discrete-event network simulation tool⁵. It is also under active development and available free of charge. A number of extensions for various networking protocols (e.g., LoraWAN, 5G-LENA) are available in this simulator.

6.1.3 Vehicular Network Simulators

Various vehicular network (i.e., VANET) simulators available are as follows.

- **VEINS** is an open-source simulation framework for running vehicular network simulations, and builds on top of SUMO and OMNeT++ [Santini et al., 2017]. It is available free-of-charge, and is actively maintained⁶.
- **PLEXE** is an extension to VEINS that enables simulating vehicle platoons and cooperative driving [Segata et al., 2014]. It is open-source, available free of charge, and is actively maintained⁷. A great deal of the related work described in Section 3.1 and 3.3 leverages PLEXE for simulation work.
- **TRANS** is another open-source integrated simulation framework (integrating the SUMO traffic simulator with the NS2/NS3 network simulator). It is available free-of-charge, but it is not being actively maintained [Piórkowski et al., 2008].

³VISSIM homepage: <https://www.ptvgroup.com/en/solutions/products/ptv-vissim/>

⁴OMNeT++ homepage: <https://omnetpp.org/>

⁵NS-3 homepage: <https://www.nsnam.org/>

⁶VEINS homepage: <http://veins.car2x.org/>

⁷PLEXE homepage: <http://plex.car2x.org/>

6.1.4 Analysis

Traffic simulators such as SUMO and VISSIM allow large-scale network simulations using realistic car-following models, and network simulators such as OMNeT++ and NS3 offer realistic modeling of physical and medium access layers to emulate an unreliable wireless communication network [Sharma et al., 2021b]. Veins is a popular open source framework which integrates the SUMO traffic simulator with the OMNeT++ network simulator. Veins is a Vehicular Ad Hoc Network (VANET) simulator, open source and free to download, that allows users to embed new algorithms, and test and validate CAV car-following control algorithms in realistic scenarios. Another option is TraNS an open-source integrated simulation framework (integrating the SUMO traffic simulator with the NS2/NS3 network simulator), but it is not actively maintained anymore. This study uses the Plexe simulator, which is an extension of VEINS for cooperative driving applications such as CACC and platooning in mixed traffic scenario [Segata et al., 2014], similarly to a number of related work [Di Vaio et al., 2019, Segata et al., 2014, Jia et al., 2018, Segata et al., 2022, Chen et al., 2021a].

6.2 Simulation Set-up

This section presents the simulation setup and its various components, used in this work during the experiments design.

In PLEXE, each simulation involves the simultaneous execution of two simulators: OMNeT++ for network simulation and SUMO for road traffic simulation. These simulators run in parallel and are connected through a TCP socket, as illustrated in Figure 6.1. The communication protocol utilized for this interaction is standardized as the Traffic Control Interface (TraCI). TraCI enables a bidirectionally-coupled simulation of road traffic and communication network traffic through the TraCIScenarioManager module in Veins. This module allows Veins to gather information about the movements of vehicles in the simulated road traffic scenario and updates their mobility information within OMNeT++. Additionally, in this work, the module's functionality is extended to transmit surrounding vehicle information collected via V2V communication to SUMO. Consequently, the movement of

vehicles in the SUMO road traffic simulator is reflected as the movement of nodes in the OMNeT++ simulation [Liu and Jaekel, 2019].

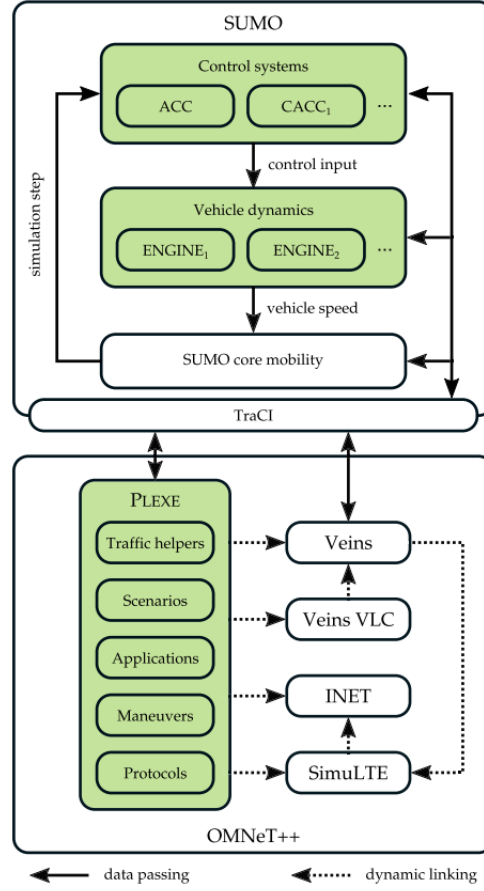


Figure 6.1: Plexe simulation framework [Segata et al., 2022].

Moreover, the number of passing vehicles, their speeds, and vehicle categories are continuously fed into the running simulation through SUMO’s TraCI. TraCI provides access to the run-time road traffic simulation, allowing retrieval of values from simulated objects and manipulation of their behavior during simulation run-time. At each SUMO simulation time step, corresponding to when vehicles are moved, Veins mirrors the movement in the corresponding OMNeT++ nodes by updating the mobility model. Through TraCI, Veins can inquire about the current simulation status from SUMO, such as the number of vehicles, positions, speeds, etc., or modify traffic dynamics, for example, by re-routing vehicles.

PLEXE further extends TraCI interactions to fetch vehicle data from SUMO, which can be transmitted to other cars or exploited by CAV car-following control protocols and applications. When a vehicle (essentially an OMNeT++ node) receives such data, it can be sent to the CACC algorithms in SUMO. Communication protocols for car-following

and application layer logics are implemented in OMNeT++, while controllers and low-level control dynamics are executed in SUMO.

The versions of the various simulators used are as follows:

- SUMO version 1.6.0
- OMNeT++ 5.5.1
- VEINS master branch commit a367f827 (August 12, 2020)
- PLEXE master branch commit 6d5f1ede (Jul 6, 2020)
- GCC 10.1.0 under Linux (Ubuntu 16.04)

These particular versions were selected following through various compatibility tests, and based on the recommendations from the authors of PLEXE [Segata et al., 2014] and a related work in [Johnston, 2020]. Moreover, the most recent version of VEINS was employed, incorporating a new feature that allows users to control the packet drop rate(commit 12170fe5).

6.3 Control Algorithms Implementation

Plexe supports a variety of car-following control algorithms such as PLOEG, PATH, FLATBED, and CONSENSUS for cooperative longitudinal control of CAVs, and also has the flexibility to implement a new car-following control algorithm for CAVs [Segata et al., 2022]. The implementation of a car-following control algorithm mainly involves two aspects as follows: firstly, incorporating car-following capabilities and basic maneuvers for vehicles, through modifications and extensions in SUMO; secondly, integrating communication protocols to support applications and the application logic in OMNeT++/Veins, along with some minor adjustments to improve bidirectional coupling. Thus, the implementation requires changes to both Plexe and SUMO simulators, as described in detail on the Plexe website⁸.

⁸Implementation Steps: <http://plexe.car2x.org/tutorial/example2/>

6.3.1 Car-following Control in SUMO

Various car-following models such as IDM, Krauss are available in SUMO to simulate human-driven vehicles. Another car-following model developed in PLEXE by Segata et al. [Segata et al., 2014] is called CC (Cruise Controllers), as shown in Figure 6.2. The idea behind this was to have all CC, ACC, and CACC controllers within a single file, and that the user can modify it to implement new car-following controllers. In addition, it is possible to set the desired speed, time headway, and desired inter-vehicle distance in this CC model.

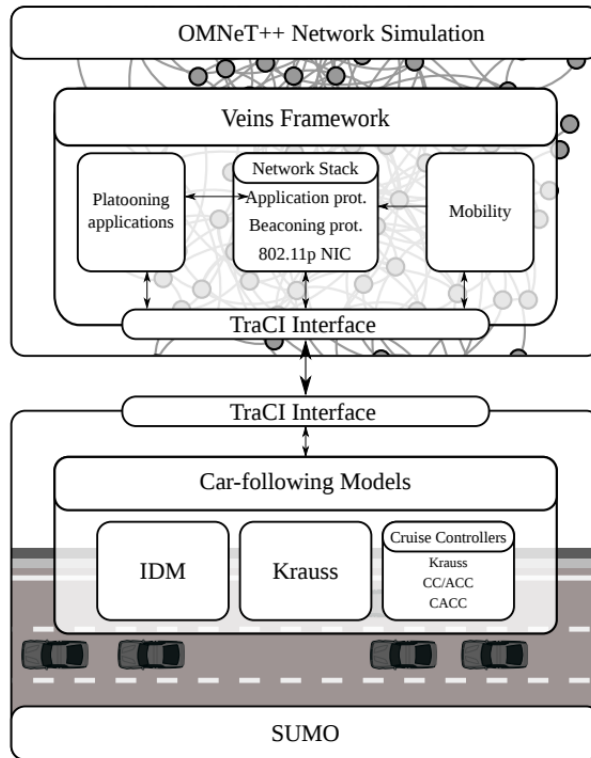


Figure 6.2: Plexe Car-following Models [Segata et al., 2014].

We use the functionalities provided by the CC car-following model in SUMO through the TraCI interface to develop a new car-following control algorithm. Through the TraCI interface, it is possible to access the model, modify its behavior and retrieve different information. Parameters such as desired speed, time headway, and other coefficients for each control algorithm are editable through the OMNeT++ configuration .ini file or by default in the .NED. interface. Note that here we describe only the functionalities used in this thesis, but for the complete list of functionalities accessible via TraCI, please refer to the PLEXE simulator documentation available at⁹.

⁹For a detailed description of the functionalities: <http://plexe.car2x.org/documentation/>

All existing car-following controllers implemented in Plexe assume the existence of a platoon, in which each node represents the vehicles belonging to a platoon with either a designated leader vehicle or follower vehicles and CAVs cooperate with each other to form or maintain this platoon. In addition, the cooperative car-following strategy relies on a fixed IFT among vehicles that, in many cases, considers information from the immediate leading vehicle only [Ploeg et al., 2011]. For instance, the PLOEG controller designed in [Ploeg et al., 2011] considers data from the immediate leading vehicle only, while the PATH controller in [Rajamani, 2006] exploits data from the platoon leader as well. These control approaches assume a static communication topology, which means that the design of the controller is based on a fixed IFT and cannot handle communication failures and delays. When an IFT changes due to, e.g., the presence of HDVs or communication failures, the controller might not be able to perform safely and efficiently anymore. Therefore, we design the PF IFT and MPF IFT-based car-following control strategies for CAVs operation on a large-scale road network (where it is not possible to assign a leader vehicle and follower vehicles), by modifying the source code of the existing car-following controllers i.e., PLOEG controller [Ploeg et al., 2011] and consensus-based controller [Santini et al., 2017], respectively, on the SUMO side. Concerning the V2V communication, on the OMNET++ side, CAVs can already receive packets from any other CAV, within their communication range.

MSCFModel

The MSCFModel is an interface for several state-of-the-art car-following models supported by SUMO. It provides the below components which are used during the experiment design for this work:

- `CC_Const.h`: we change this file in SUMO as well as in PLEXE to add constants of the new controller. For example, according to the PF IFT-based control law as shown in Equation (5.7), the controller has two parameters k_p and k_d , so we create two constants for setting the value of those parameters via the TraCI interface. The controller gain values are selected $k_p=0.2$ and $k_d=0.7$, as advised by the authors of the PLOEG controller [Ploeg et al., 2012].
- `CC_VehicleVariables.h`: this class maintains the state and the variables of a CAV

using the car-following controller, so we add two variables for storing the values of k_p and k_d for the PF IFT-based controller, and α and β for the MPF IFT-based controller.

- `MSCFModel_CC.h`: this class is the core of the Plexe extension to SUMO to introduce a new car-following controller. Concerning changes to the header file, we make changes to define the prototype of the function for our controller, e.g., the prototype for the PF IFT-based controller is defined as,

```
double _mycc(const MSVehicle *veh, double egoSpeed, double predSpeed, double gap2pred)
const;
```

where `veh` is a pointer to the ego vehicle using the controller, `egoSpeed` is its current speed, `predSpeed` is the speed of its preceding vehicle, and `gap2pred` is its distance to the preceding vehicle.

- `MSCFModel_CC.cpp`: the actual controller implementation goes into this file. Here, we edit the `_v()` function, where the model computes the vehicle speed at the next simulation step depending on the current vehicle state and the chosen controller. The model first checks whether it has received a beacon from one (for the PF IFT-based controller) or more preceding vehicles (for the MPF IFT-based controller). If that is the case, the model computes the acceleration using our car-following control algorithm. If no front beacon has been received so far, the model degrades to ACC.

Regarding modifications to Plexe, it is necessary to update the simulation environment to use the new controller available in SUMO. To do this, we first replicate the changes made to `CC_Const.h` in SUMO. Then we perform the changes in the `BaseScenario.ned` to add the two parameters of our controller to be able to set them within the `omnetpp.ini` file.

6.3.2 V2V Communication Protocols and Applications in Veins

As described in the previous section, the majority of the changes in implementing a new car-following control algorithm are made on the SUMO side. Concerning Veins, besides the required changes to the TraCI interface, Plexe provides a basic network (extensible) stack where each vehicle is provided with an IEEE 802.11p network interface card, a basic

protocol for message dissemination, and an application layer running directly on top of the message distribution. The implementation of V2V communication for CAVs is shown in Figure 6.3. The typical communication function is described by a NED file that models a car (`cpsCar`). This consists of an 802.11p-based Network Interface Card (NIC) to be able to communicate with other vehicles, an application layer directly connecting to this NIC, a scenario module describing the traffic scenario, and the mobility module responsible for updating the position of the car [Jia et al., 2021].

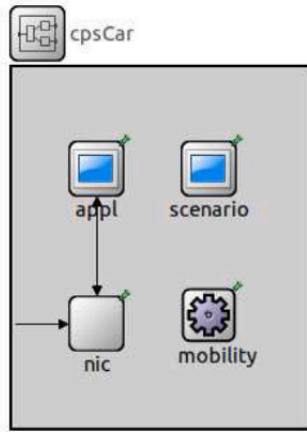


Figure 6.3: V2V communication [Jia et al., 2021].

Furthermore, using the protocol layer, a communication strategy is implemented for sharing information among vehicles. The base class, named `BaseProtocol`, provides functionalities to inheriting classes like logging of statistics, primitives for sending and receiving packets, and loading of simulation parameters. This way subclasses can focus just on the implementation of the beaconing strategy itself. The same principle applies to the application layer, where `BaseApp` takes care of loading simulation parameters, or passing data to the car-following control algorithm via TraCI, logging of statistics. In this way, inherited classes can focus just on the implementation of the desired behaviour [Segata, 2016].

Note that each vehicle updates its position and speed at the end of each synchronized interval (SI). To share the information with other vehicles, we implemented a baseline broadcast protocol, where each vehicle periodically broadcasts its current kinematic state information (collected in the last SI) within each SI. A naive CACC application was created in PLEXE to support the experiments, extending the PLEXE `BaseApp` class. This application allows CAVs to perform the following actions:

- Upon insertion, set the desired cruise control speed equal to the speed limit of the simulated road network (100 km/h), and activate the ACC controller.
- Send beacons about the vehicle position, speed and angle continuously at every beaconing interval.
- Continuously monitor the beacons sent by other CAVs.
- Discard beacons received from a vehicle moving in an opposite direction.
- Discard beacons received from a vehicle travelling in a different lane.
- Discard beacons received from a vehicle behind the ego vehicle.
- Discard beacons received from a vehicle beyond the transmission range of the ego vehicle.
- If the beacon was not discarded due to any of the aforementioned conditions, and the beacon is received from one or more leading vehicles, activate the CACC controller.
- At each time interval, check if the current leading vehicle is still within the transmission range of the ego vehicle. If not, disengage CACC and engage ACC.

6.4 Summary

In this section, we described PLEXE, a simulation framework for implementing proposed CAV car-following control strategies, and simulating CAVs in realistic scenarios. PLEXE provides several car-following controllers, including standard CC/ACC, as well as modern CACCs. The key features of this framework are the easiness of implementing and customizing new car-following controllers, the ability to model mixed traffic scenarios, and the realistic simulation of both wireless networking and vehicle dynamics. Furthermore, PLEXE is free to download from the official website. All these features make PLEXE a suitable simulation tool before the real-world deployment of CAVs on roads in the near future.

7 Evaluation

In this chapter, we present the evaluation of the proposed CAV car-following control approaches via simulation studies, to answer each of the research questions addressed by this thesis. Section 7.1 presents the objectives of the evaluation, while Section 7.2 describes the evaluation set up. We then describe in detail the evaluation of PF IFT-based control and MPF IFT-based control in Sections 7.3 and 7.4, respectively. Finally, Section 7.5 presents the process of extracting and processing the results of the simulations detailed above, and challenges encountered in performing the simulations.

7.1 Evaluation Objectives

A comprehensive evaluation of the impact of CAVs on traffic safety and efficiency is imperative before their large-scale deployment on roads in the future. This can be undertaken through a large-scale simulation study. However, accurately simulating CAVs in realistic scenarios requires appropriate simulation software i.e., simulator, realistic car-following models and communication network models, and various simulation parameters (e.g., CAV penetration rate and packet drop rate). Existing simulation studies have oversimplified the key components of large-scale traffic dynamics, vehicle modeling, and real traffic demand modeling, which make them unrealistic [Jia et al., 2021]. Previous traffic simulations-based research usually simplifies the driving behavior of CAVs in the longitudinal direction by adopting car-following models assuming second order vehicle dynamics and perfect V2V communication, therefore omitting the traffic performance evaluation in realistic scenarios with the integration of both large-scale traffic scenarios and imperfect V2V communication. To fill the above mentioned gaps and answer the research questions (RQ1- RQ3) formulated in Section 1.4, this work aims to investigate the impact of CAV performance on mixed

traffic safety and efficiency in realistic scenarios in terms of real-traffic data, imperfect communication, human drivers uncertain behaviour and employing realistic driving models for both CAVs and HDVs, and then doing a large-scale simulation study with a lot of varying parameters such as CAV penetration rate, packet drop rate, time headway, and control gains via the PLEXE simulator. Compared to other related work, the PLEXE platform can provide a more realistic simulation environment and more reliable evaluation, so that the CAV performance obtained from the simulation is closer to the reality.

The ability of CAVs to improve traffic safety and efficiency in mixed traffic largely depends on their penetration rate. For example, at a CAV penetrate rate of 0% , all vehicles are HDVs, and to control their longitudinal motion they can only obtain information from their immediate leading vehicle via human drivers perception. Conversely, at a CAV penetration rate of 100%, a CAV can exploit information from multiple leading vehicles via V2V communication links within its communication range to control its longitudinal motion, thereby improving its situation awareness. Moreover, CAVs can perceive surrounding vehicles information more accurately and faster than HDVs, which possess large-reaction time and perception errors. Therefore, the deployment of CAVs is expected to improve traffic safety and efficiency, though it is unclear to what extent this has been evaluated in realistic scenarios in terms of imperfect communication, large human reaction time, vehicle modeling and large-scale traffic scenarios with real traffic data. The main objective of this evaluation is two-fold. Firstly, to answer RQ1, we evaluate the impact of CAVs on mixed traffic safety and efficiency using the PF IFT-based CAV car-following control algorithm, at different CAV penetration rates in realistic scenarios. Secondly, to answer RQ2 and RQ3, we evaluate the effects of our MPF IFT-based CAV car-following control algorithm exploiting information from multiple leading vehicles.

7.2 Evaluation Setup

In this section, we present the evaluation setup required to investigate the effects of the proposed PF and MPF IFT-based CAV car-following control algorithms on traffic safety and efficiency performance by considering mixed traffic consisting of different combinations of human-driven vehicles (HDVs) and connected autonomous vehicles (CAVs), in both perfect

and imperfect communication conditions, through an extensive simulation study. We use the car-following models defined in Chapter 4 to characterize human driving behaviour in these simulations and use the PF or MPF IFT-based car-following control algorithm developed in Sections 5.2 and 5.3 as well for CAVs. We develop a baseline having a traffic flow of human-driven vehicles only, and then investigate the effects of adding different ratios of connected autonomous vehicles.

This section now discusses in turn traffic scenario (the M50 motorway network with real traffic data) that we are using to measure the impact of CAVs (Section 7.2.1), simulation parameters of the wireless communication network protocols to simulate packet drops during information exchange (Section 7.2.2), performance metrics to measure the impact of CAVs on traffic safety and efficiency (Section 7.2.3), and evaluation scenarios (Section 7.2.4).

7.2.1 Traffic Scenarios

To measure the impact of CAVs on traffic safety and efficiency in realistic scenarios, this work simulates a segment of a large-scale road network (the M50 motorway, in Ireland) with real traffic data made publicly available by Gueriau and Dusparic [Gu  riaux and Dusparic, 2020]. This road network consists of a large number of vehicles (up to 25,316 vehicles during the busiest time period, 07:00-08:00) on a 7-km 4-lane stretch of the M50 motorway road. The road network includes two major interchanges with junctions to national roads (N7 and N9), and seven on/off-ramps near each junction, as shown in Figure 7.1.

On this motorway network, three different traffic levels i.e., free-flow, saturated, and congested are defined based on traffic flow data recorded as 5-minute aggregated traffic flows per lane in Ireland for several years (2012 to 2019), data available by Transport Infrastructure Ireland¹. While congested traffic level was observed during the morning peak hours (07:00-08:00) with the total number of vehicles up to 25,316, free-flow and saturated traffic levels were observed during the afternoon hours (13:00-14:00 for free-flow, and 15:00-16:00 for saturated) with total numbers of vehicles up to 20,822 and 23,508, respectively [Gu  riaux and Dusparic, 2020], with demand patterns and traffic volumes being generated from real traffic data. These road networks and traffic data are made publicly

¹Traffic Data: <https://www.nratrafficdata.ie/>



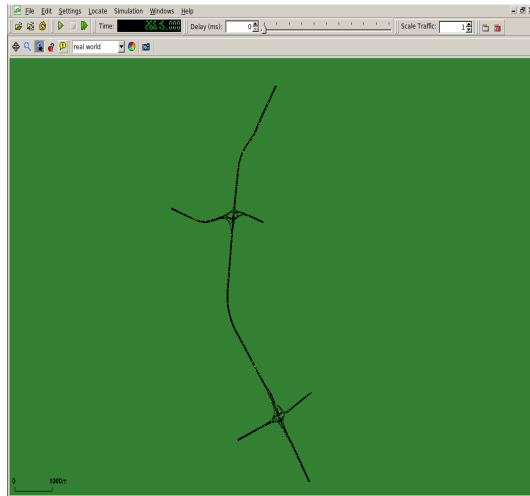
Figure 7.1: Rendering of the M50 motorway road network

available² by the original authors [Guériau and Dusparic, 2020], and are shown in Figure 7.2.

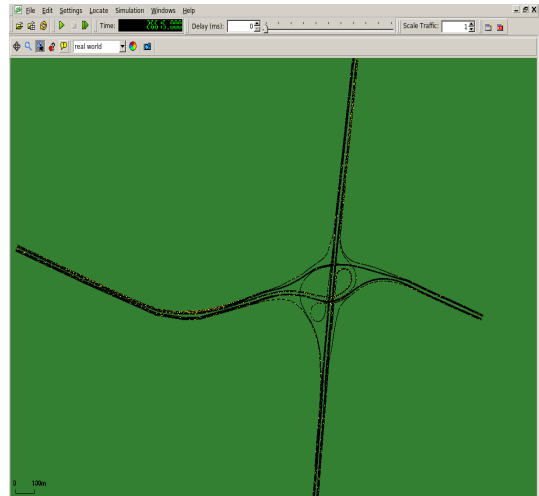
The primary focus of this thesis is to investigate the impact of CAVs at different penetration rates on traffic safety and efficiency in congested traffic scenarios on a motorway. The reasons behind focusing on congested traffic scenarios are twofold. First of all, previous research [Guériau and Dusparic, 2020, Liu and Jaekel, 2019, Rahman et al., 2021] claims that stop-and-go waves produced by HDVs are most visible during peak traffic hours, and therefore the potential wave-dampening effect of CAVs is likely to be most pronounced during congested traffic conditions. Secondly, we are interested in designing CAV car-following control algorithms to handle varying IFTs resulting from mixed traffic and unreliable communication environments, and in this thesis, communication failures are mainly assumed to be due to very high communication channel load in congested traffic scenarios. Nevertheless, for completeness, we show some preliminary results to measure the effectiveness of CAVs in improving traffic safety and efficiency in other traffic conditions also i.e., free-flow and saturated.

We choose a simulation time window of 30 minutes for each traffic scenario i.e., 07:00-07:30 for congested, 13:00-13:30 for free-flow, and 15:00-15:30 for saturated traffic scenario

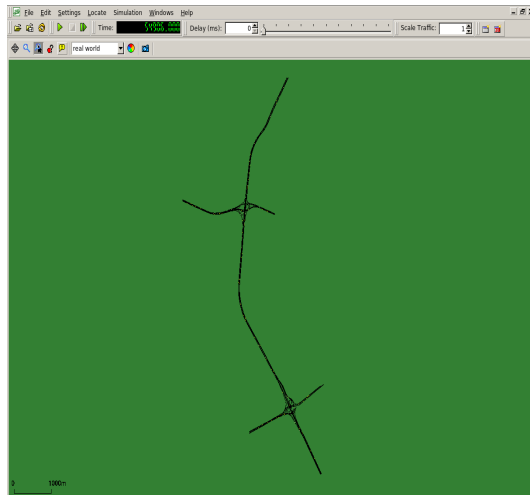
²Traffic Scenarios: https://github.com/maxime-gueriau/ITSC2020_CAV_impact



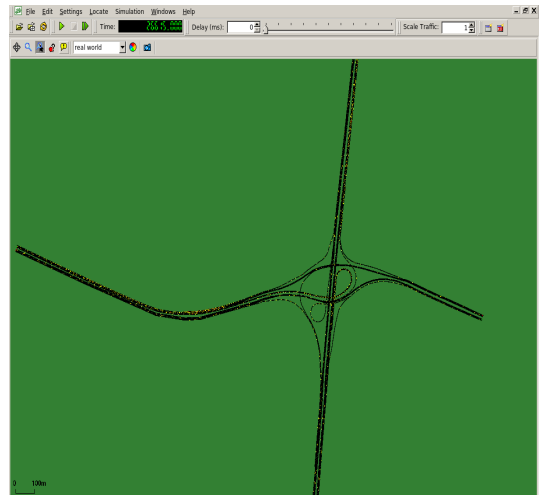
(a) Congested traffic scenario



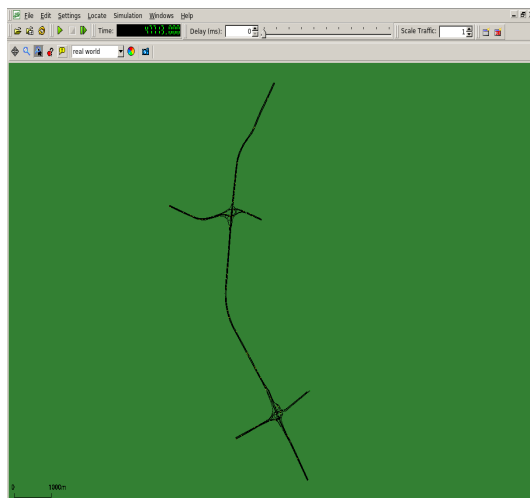
(b) Congested traffic scenario (zoomed-in)



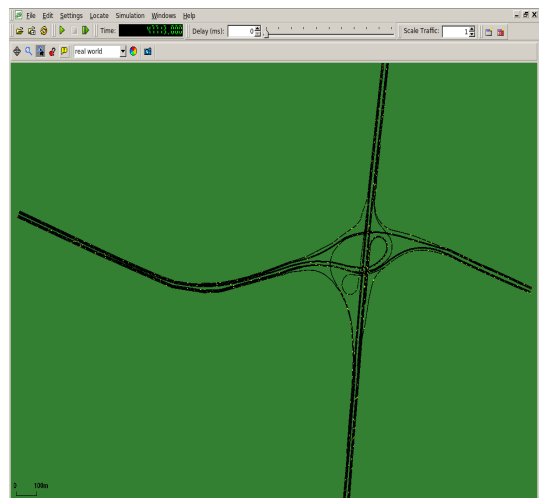
(c) Saturated traffic scenario



(d) Saturated traffic scenario (zoomed-in)



(e) Free-flow traffic scenario



(f) Free-flow traffic scenario (zoomed-in)

Figure 7.2: Screenshot of realistic traffic scenario along M50 motorway, Ireland using SUMO

to reduce simulation duration with a step-length of 0.1 s. When performing a simulation to analyze the impact in a particular time period, a simulation parameter manager.firstStepAt is leveraged to advance the simulation to a specified point in time without the additional overhead of network simulation, and then proceed to perform the rest of the network simulation logic with a fully loaded traffic network. Hence, we choose the firstStepAt parameter value of 06:45, 12:45 and 14:45 for congested, free-flow and saturated scenarios, respectively so that veins will start synchronising with SUMO 15 minutes before, allowing both traffic and communication networks to be loaded in these 15 minutes. Since the road network is reasonably large, we found the optimal warm-up time to be around 15 min to load the network with enough vehicles and no output were recorded during this period. Moreover, due to the single-threaded nature of both the SUMO and OMNeT++, multiple simulations needed to be run in parallel. To support parallel simulation execution, simulations were performed on a high-performance computing cluster and found to be extremely resource extensive. Each simulation for the congested traffic hours at 100% penetration rate, with packet drop, took over 5 days of real time to complete.

7.2.2 Communication Network Simulation

To exchange information in real-time with other vehicles, each CAV is equipped with a network interface card according to the IEEE 802.11p communication protocol. CAVs transmit information at 10 Hz frequency using the default network parameters used in [Segata et al., 2014]. The communication network model parameters used to emulate imperfect communication are described in detail in this section.

Physical layer characteristics

CAVs exchange information on the physical layer of the IEEE 802.11P-based communication protocol stack. Physical layer parameters such as transmission power, background noise level, receiver sensitivity vary in real-life scenarios and may have a negative impact on CAVs driving performance. For the motorway traffic scenario without any obstacles, the channel model is chosen as a simple free-space path loss model with monopole antenna. To replicate a realistic physical layer, Sharma *et al.* investigated CAVs platoon performance at different

parameters values to simulate packet losses in unreliable communication environments under different traffic scenarios [Sharma et al., 2021b].

Medium access layer characteristics

An unreliable communication network can also be modeled by inducing packet drops at the medium access layer. A simple, but accurate model for inducing packet drop is through the Bernoulli loss model. In this work, to simulate imperfect communication, we use the Bernoulli loss model to create packet losses at the MAC layer. In this model, we define the probability to loss a packet by a *frameErrorRate* parameter. Two values of *frameErrorRate* i.e. 0 and 0.7 are chosen to represent no packet drops and 70% packet drops, respectively. The frame error rate of 0.7 represents a realistic value in congested traffic scenarios, according to the work in [Sepulcre et al., 2020]. Other communication network parameters are selected according to [Segata et al., 2014] and are listed in the Table 7.1.

Table 7.1: V2V communication protocol related simulation parameters

Communication parameters	
Communication protocol	IEEE 802.11p
Channel data rate	6 Mbps
Beacon frequency	10 Hz
Beacon size	200 bytes
Packet losses	Bernouli loss model
Transmission power	20 dBm
Antenna type	Monopole
Analogue Model	SimplePathLossModel with thresholding

7.2.3 Performance Metrics

This section presents the metric considered to evaluate the impact of CAVs on traffic safety first, and then on efficiency.

Traffic Safety

To evaluate the impact of CAVs on traffic safety, different surrogate safety measures (SSMs) such as time to collision (TTC), post encroachment time (PET), standard deviation of

vehicle speed (SD), deceleration rate to avoid a crash (DRAC), etc. are used in the literature. In this thesis, we measure traffic safety using the TTC metric, as this metric is best suited to analyze the number of safety conflicts on motorways, unlike PET which is better suited for evaluating safety conflicts in intersections [Papadoulis et al., 2019, Ye and Yamamoto, 2019, Sharma et al., 2021a, Rahman et al., 2021]. A safety conflict is counted when the value of a TTC indicator is below the TTC threshold value.

- **Time to collision** *TTC* is a widely used traffic safety indicator in car-following control applications. It refers to the remaining time before a rear-end collision between two adjacent vehicles if they travel in the same lane and maintain their speed.

$$TTC(t) = \frac{x_{i-1}(t) - x_i(t) - l_{i-1}}{v_i(t) - v_{i-1}(t)}, v_i(t) > v_{i-1}(t) \quad (7.1)$$

x_{i-1} and x_i are the position of the leading vehicle and the ego vehicle, respectively; v_{i-1} and v_i are the speed of the leading vehicle and the ego vehicle, respectively; and l_{i-1} is the length of the leading vehicle. The vehicle length is selected $l=5m$, as advised by the authors of SUMO [Lopez et al., 2018].

Algorithm 3 Calculation of TTC pseudocode

```

1: Initialize: TTC threshold (CAV)  $\leftarrow 0.75s$ , TTC threshold (HDV)  $\leftarrow 1.5s$ ,
2: Parse output XML tripinfo file, and retrieve vehicle id and vehicle type (CAV or HDV)
   for each vehicle
3: Parse output ssm device file and retrieve TTC value, conflict type, ego and following
   vehicle id for the required simulation interval time
4: if conflictType==2 and TTC value<1.5 then
5:   if ego vehicle is a HDV then
6:     if leading vehicle is a HDV then
7:       HDV-to-HDV conflict
8:   else
9:     HDV-to-CAV conflict
10:  if ego vehicle is a CAV then
11:    if TTC value<0.75 then
12:      if leading vehicle is a HDV then
13:        CAV-to-HDV conflict
14:    else
15:      CAV-to-CAV conflict
16: Compute total number of conflicts by summing up above four types of conflicts

```

The algorithm 3 shows the pseudocode for the calculation of the number of safety con-

licts based on the TTC value. A low TTC value represents a risky traffic situation and hence a suitable TTC threshold value must be selected to distinguish between risky and safe traffic situations. Furthermore, most studies have considered the same TTC threshold value for both CAVs and HDVs. This is inadequate because CAVs can follow their leading vehicles with shorter time headways due to their faster reaction times, compared to HDVs. This thesis not only considers different TTC threshold values for CAVs and HDVs, but also computes the number of safety conflicts for the different combinations of CAVs and HDVs. Different threshold values varying between 1 to 3 s are selected in existing studies. Two different threshold values of 0.75 s and 1.5 s are chosen in this work for CAVs and HDVs, respectively, as per related work [Guériau and Dusparic, 2020]. We measure the total number of safety conflicts for different possible combinations of vehicles (i.e. HDV-HDV, HDV-CAV, CAV-CAV, CAV-HDV), similarly to the work [Guériau and Dusparic, 2020]. Since the SSM output in SUMO does not provide any information about the vehicle type, we add a tripinfo device to each vehicle to obtain the type of the vehicle.

Traffic Efficiency

Different metrics such as travel time, throughput, average speed, total travel delay, congestion index, etc. have been used in previous studies to evaluate the impact of CAVs on traffic efficiency [Guériau and Dusparic, 2020, Rahman et al., 2021, Shladover et al., 2012, Liu and Fan, 2020, Talebpour and Mahmassani, 2016, Fries et al., 2017]. In this work, we measure traffic efficiency using the travel time metric as this metric is best suited for a large-scale road network. Moreover, evaluating the impact of the different penetration rates of CAVs on traffic efficiency is not straightforward in realistic traffic scenarios since traffic disturbances can happen locally and overall traffic behavior results from the interaction of several factors. Therefore, we evaluate the impact of CAVs at an edge level instead of measuring the number of vehicles passing through a specific location, allowing us to better capture traffic flow and its spreading over the network.

- **Travel time**

The *Travel time* (TT) gives information about the time vehicles take to travel a certain edge of the road network. To calculate the travel time, we collected the travel time

for each edge of the road network using edge-based network state devices, and these were divided by the length of each edge to get the *travel time rate*.

$$\text{TTR (min/km)} = \sum_i \frac{TT_i}{q_i} * 16.6667 \quad (7.2)$$

where TT_i and q_i are the travel time (in seconds) and length of the i th edge (in meters), respectively.

Algorithm 4 Calculation of travel time rate pseudocode

- 1: Parse input XML network file and store edge_id, lane_id, lane_index, speed, length and allowed_vehicle_classes
 - 2: Parse edge device xml file and retrieve edge level data for required simulation interval time
 - 3: **for** every edge i calculate **do**:
 - 4: travel time rate $\leftarrow$ travel time / edge length
 - 5: **end for**
 - 6: Export edge level XML data file with new calculated fields
-

Our evaluation relies on the computation of traffic efficiency, aggregated for each edge. To evaluate traffic efficiency for the full network, we collected travel time for each edge (segment) of a road network. This was further divided by the length of that segment to get the travel time rate. This required the use of edge-based network state devices. The algorithm 4 shows the pseudocode for the calculation of the travel time metric. To represent the significance of the change in travel time rate, heatmaps are generated using these modified edge-based data files. These heatmaps are generated using the `plot_net_dumps.py` visualization tool³ provided by SUMO.

7.2.4 Evaluation Scenarios

In this thesis, a number of simulation experiments were conducted to evaluate traffic performance using both the PF IFT-based car-following control algorithm and MPF IFT-based car-following control algorithm at CAV different penetration rates (i.e., 0%, 20%, 40%, 70%, 100%) with and without packet drops (i.e., 0 and 0.7 packet error rate). Motivated by previous studies showing traffic performance improvements at different penetration rates of CAVs, we also evaluate for 0%, 20%, 40%, 70% and 100% MPR to investigate the impact

³SUMO Visualization Tools: <https://sumo.dlr.de/docs/Tools/Visualization.html>

of CAVs including low, medium, and high penetration rates. Two different values of packet drops, 0% and 70% are selected to represent no packet drops and packet drops, respectively. The packet error rate (PER) of 0.7 is chosen to model realistic communication in congested traffic scenarios, as described in Section 7.2.2. This resulted in one baseline scenario with no CAVs, four scenarios with CAVs and no packet losses and four scenarios with CAVs and packet error rate of 0.7, as shown in Table 7.2. Each of these 17 scenarios is evaluated in terms of traffic safety and efficiency in each experiment. We run each experiment five times, following the simulation run requirement analysis presented in [Rahman et al., 2021, Ali et al., 2020, Yao et al., 2020, Liu et al., 2018]. Moreover, our simulation results demonstrate that five simulation runs are sufficient for traffic safety and efficiency analysis on a motorway road network due to the low variability among different groups of results (travel time and number of safety conflicts), as shown through the confidence interval based box plots in subsequent sections. Finally, we also show one-way ANOVA test analysis to investigate the statistical significance of the results at different penetration rates and packet drops.

Table 7.2: Evaluation scenarios summary

CAV car-following controller	MPR (%)	PER (%)
N/A	0	N/A
	0	N/A
PF IFT	20	0
	20	70
PF IFT	40	0
	40	70
PF IFT	70	0
	70	70
PF IFT	100	0
	100	70
MPF IFT	20	0
	20	70
MPF IFT	40	0
	40	70
MPF IFT	70	0
	70	70
MPF IFT	100	0
	100	70

7.3 Evaluation of PF IFT-based Control

In this section, we present evaluating the impact of CAVs using the PF IFT-based car-following controller, where a CAV can exploit information from its immediate leading vehicle only and degrades to ACC in the presence of communication failures or leading vehicle being a HDV. This section first presents the simulation results of CAV different penetration rates focusing on analyzing the detrimental effects of unreliable communication only (Section 7.3.1), in congested traffic scenarios. It then presents the detrimental effects of large reaction time and perception errors, in addition to unreliable V2V communication (Section 7.3.2). Section 7.3.3 presents the results of the proposed cautious car-following approach. Section 7.3.4 presents the results of CAV different penetration rates in free-flow and saturated traffic conditions. Finally, the evaluation summary of PF IFT-based control is presented in Section 7.3.5.

7.3.1 Effect of Unreliable V2V Communication Links

In this section, we evaluate the detrimental effects of unreliable V2V communication on traffic safety and efficiency at different CAV penetration rates. Figure 7.3 shows the simulation results of the number of safety conflicts based on time-to-collision value for the case of only human-driven vehicles (0% penetration rate of CAV). It indicates that the number of safety conflicts is high in vast parts of the road network, as expected. This is due to the stop-and-go waves i.e., high-speed variations produced by HDVs.

Table 7.3 shows the number of safety conflicts based on time-to-collision value at different penetration rates (20%, 40%, 70%, 100%), with and without packet drops, for one run only. It shows that with the increase in CAVs' penetration rate, the number of safety conflicts decreases and this is more significant at high penetration rates. Finally, at 100% penetration of CAVs, the number of safety conflicts becomes zero. In the presence of packet drops, however, a substantial increase in the number of safety conflicts is observed at all penetration rates except the 100% penetration rate, compared to results without packet drops. The number of safety conflicts is zero at 100% penetration rate with packet drops. Furthermore, it is observed that most safety conflicts are located close to interchanges,

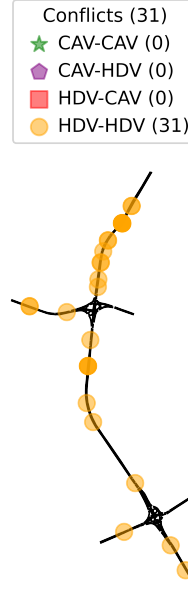


Figure 7.3: Number and location of safety conflicts using the MPF IFT-based CAV control at 0% penetration rate

i.e., where high-speed fluctuations are expected, usually caused by traffic flow oscillations propagating backward from on/off-ramps to the main road. Moreover, the unreliability of wireless communication links further increases the number of safety conflicts near the interchanges. Another interesting observation is that most safety conflicts are between human-driven vehicles (i.e., HDV-HDV conflicts) both in perfect and imperfect communication environments (even at high penetration rate of CAVs), and only a small proportion of conflicts resulting from HDV-CAV interactions. This shows that while CAVs were able to safely degrade their driving mode to ACC in the presence of unreliable communication links or when the preceding vehicle is a HDV, they produced traffic disturbance oscillations in the downstream flow, which increased the number of HDV-HDV conflicts. Overall, CAVs provide a significant reduction in the number of safety conflicts as their penetration rate increases and the maximum reduction is found in pure CAVs traffic i.e. 100% penetration rate. These results are consistent with the fact that most road accidents occur due to the uncertainty in human's driving behavior [Papadoulis et al., 2019, Yao et al., 2020].

Figure 7.4 shows the travel time rate at different penetration rates (0%, 20%, 40%, 70%, 100%), with and without packet drops, for one run only. It is observed that, as in other studies [Liu et al., 2018, Talebpour and Mahmassani, 2016, Rahman et al., 2021], traffic efficiency improves significantly as the penetration rate of CAVs increases. The improvement

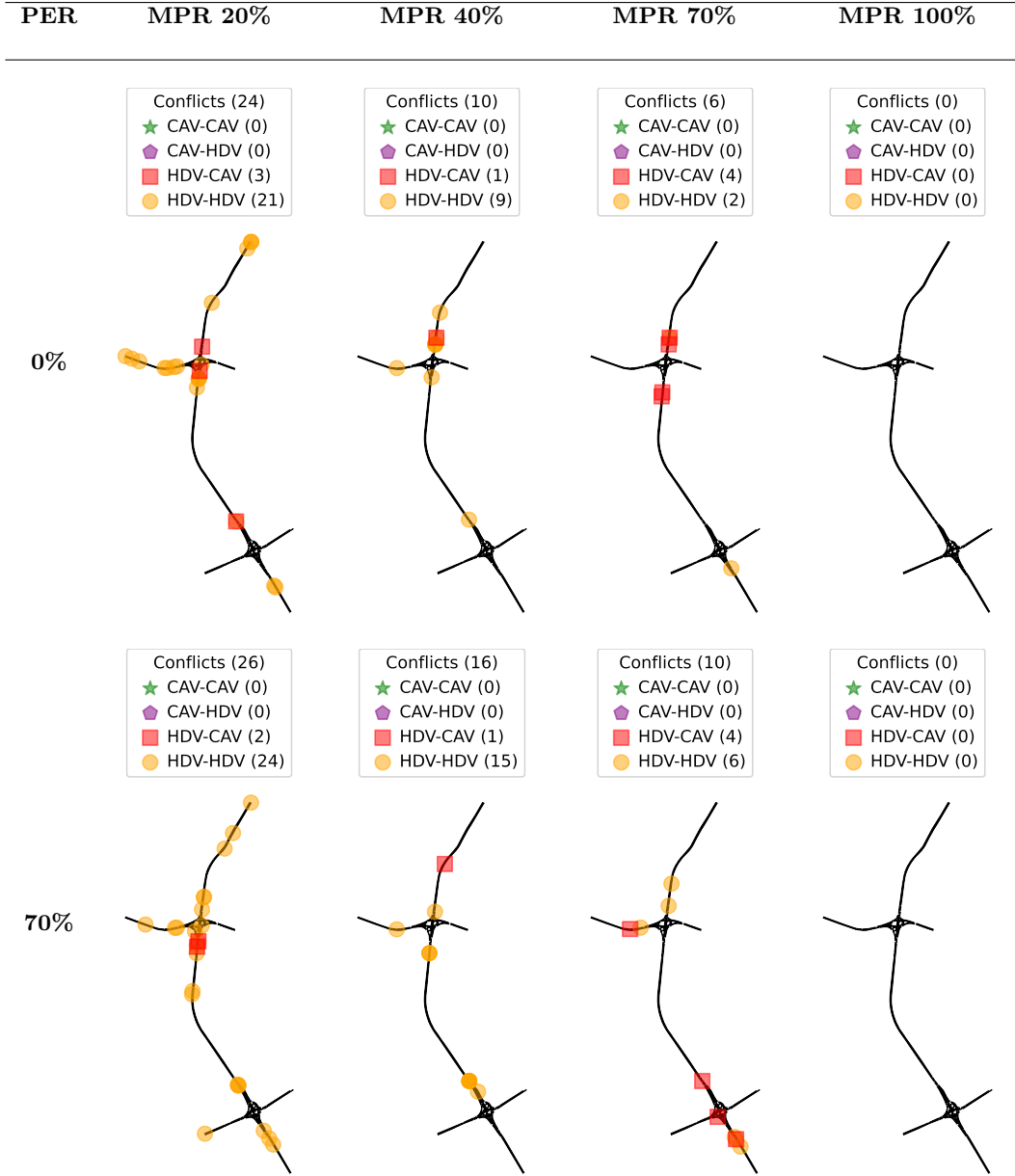


Table 7.3: Number and location of safety conflicts using the PF IFT-based CAV control at different penetration rates, with and without packet drops

in traffic efficiency is, however, not significant in the presence of imperfect communication compared to the baseline scenario i.e. only HDVs. The results also indicate that a high penetration rate of CAVs corresponds to a higher improvement in traffic efficiency, as expected. These results show a significant improvement in both traffic safety and efficiency by introducing CAVs in the traffic flow, especially at high penetration rates. This is due to the ability of the designed CAV car-following control algorithm, driving the longitudinal

motion of the connected autonomous vehicles, in dampening downstream traffic waves, by reducing the speed variations between adjacent vehicles, resulting in improved traffic safety and efficiency.

As Figures with road layout are not depicting much relevant information, we plot those graphs in one scenario and for one run only, to show the number of the different types of safety conflicts and to see how the traffic efficiency performance is improved locally by introducing CAVs on the road network. It is also worthwhile observing the effect of simulations randomness on travel safety and efficiency results by analyzing multiple simulation runs. Figure 7.5a presents the statistical analysis of simulation results for five simulation runs, to observe the randomness effect of simulation experiments on safety results. It is observed that the number of safety conflicts varies slightly due to the randomness in traffic generation on the road network. Furthermore, results show that five simulation runs are sufficient for traffic safety analysis on a highway road network due to the low variability among different group of results, as shown through the distribution in confidence interval-based plots in Figure 7.5a. In addition, Figure 7.5b depicts the statistical analysis of the travel time results for five simulation runs. It shows that the overall travel time does not differ significantly in different simulation experiments. These results also show that motorway traffic efficiency could be confidently estimated using five simulation runs. Subsequently, we present simulation results based on the average over five simulation runs to ensure robustness and consistency in our results.

7.3.2 Effect of Large Reaction Times and Perception Errors

After evaluating the detrimental effects of unreliable V2V communication on traffic safety and efficiency at different CAV penetration rates, we now consider incorporating human's large reaction time in HDV car-following behavior, in addition to considering packet losses in exploiting information for CAV car-following control algorithm. HDV drivers will inevitably make errors in perceiving the speed and position of their leading vehicles, and will also possess large reaction times. Therefore, this section evaluates the effects of large reaction time and perception errors in the relative speed and position of adjacent vehicles in the original IDM model, by modeling them using a driver state device, as discussed in Section 4.1.

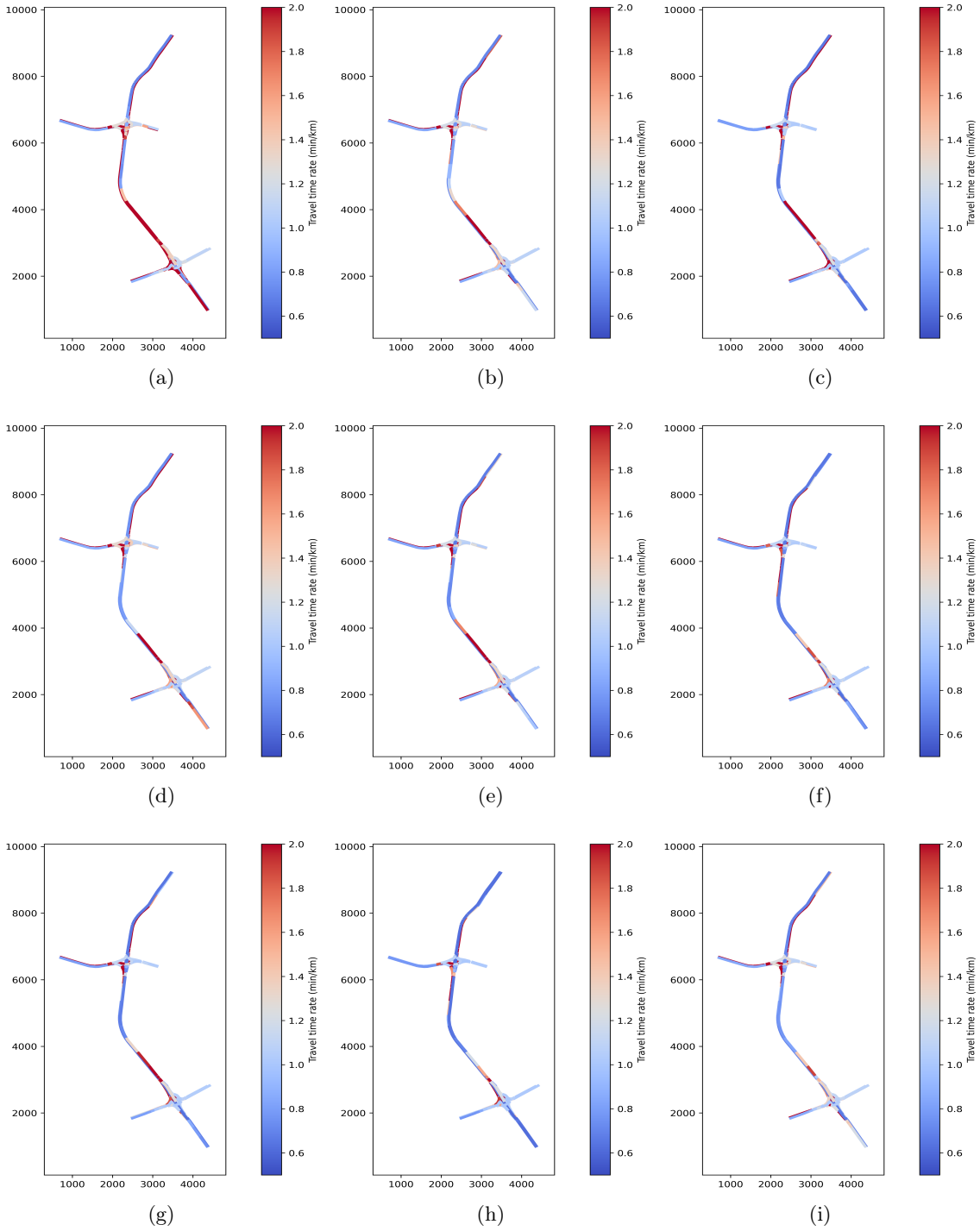


Figure 7.4: Travel time rate (min/km) using the PF IFT-based CAV control at different penetration rates, with and without packet drops, (a) MPR 0%, (b) MPR 20% and PER 0%, (c) MPR 20% and PER 70%, (d) MPR 40% and PER 0%, (e) MPR 40% and PER 70%, (f) MPR 70% and PER 0%, (g) MPR 70% and PER 70%, (h) MPR 100% and PER 0%, (i) MPR 100% and PER 70%

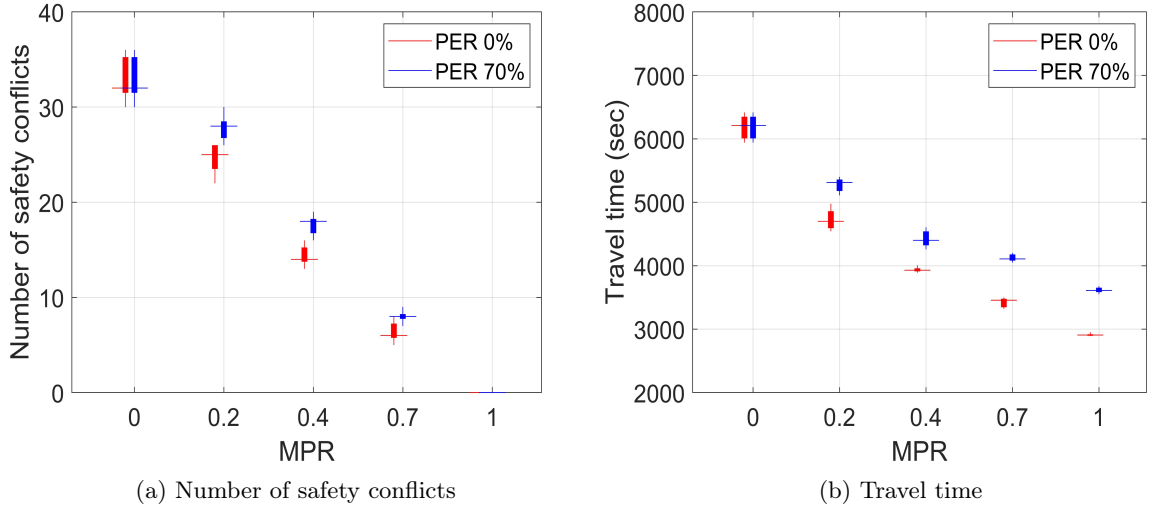


Figure 7.5: Traffic safety and efficiency performance using the PF IFT-based CAV control at different penetration rates, with and without packet drops.

Figure 7.6a shows the quantitative effect of human's large reaction time on the number of safety conflicts at different penetration rates (0%, 20%, 40%, 70%, 100%), with and without packet drops. The horizontal axis indicates the CAVs' market penetration rates and the vertical axis represents the total number of safety conflicts. For instance, the red and blue lines indicate the number of safety conflicts at a small reaction time of 0.1s, with and without packet drops, respectively while the black and green lines indicate the number of safety conflicts at a large reaction time of 0.5s, with and without packet drops, respectively. From the figure, it can be seen that the number of safety conflicts is higher for the large reaction time scenarios as compared to the small reaction time and CAVs driving is 100% safe only at full penetration rate i.e. 100% as most accidents are due to the uncertainties in human's driving behavior. On the other hand, Figure 7.6b shows the effect of large reaction time on travel time results at different penetration rates of CAVs, with and without packet drops. From the figure, it can be seen that the travel time is higher for all penetration rates at a large reaction time. In addition, the percentage increase in the number of safety conflicts and travel time are calculated and summarized in Table 7.4. This table shows that both safety conflicts and overall travel time increase at all penetration rates, with and without packet drops when considering a large human reaction time (i.e., 0.5s) as compared to the number of safety conflicts and travel time calculated when considering a small human reaction time of 0.1s. These findings illustrate the importance of incorporating human large reaction time

and perception errors to accurately simulate HDVs in our simulations, contributing to more realistic simulation models. Considering these findings, in the subsequent section, we will include human large reaction time and perception errors, in addition to the unreliable V2V communication links.

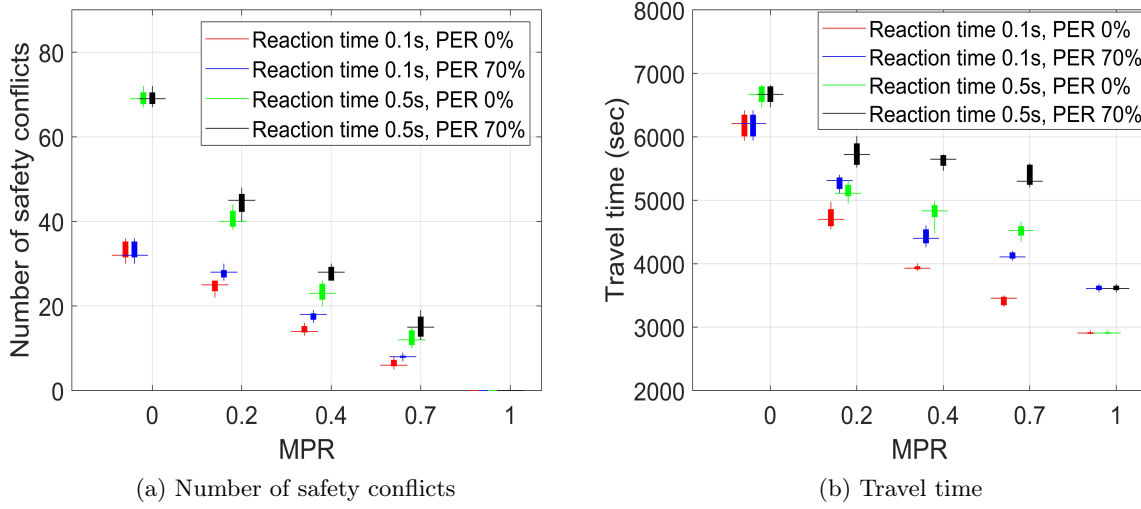


Figure 7.6: Traffic safety and efficiency performance using the PF IFT-based CAV control at different penetration rates, packet error rates, and human driver reaction times.

Table 7.4: Summary of the effect of human driver's large reaction time on traffic safety and efficiency results, compared to smaller human reaction times

MPR (%)	PER	Safety conflicts increase (%)	Travel time increase (%)
0	NA	115.62	7.74
20	0	64.00	8.69
20	0.7	60.71	8.76
40	0	64.28	21.99
40	0.7	55.55	27.05
70	0	100.00	32.01
70	0.7	87.50	30.44

7.3.3 Cautious Car-following Approach

This section evaluates the impact of using the cautious car-following approach i.e., adopting more conservative time headway for both CAVs and HDVs in reducing the detrimental effects of the unreliability of V2V communication links and the uncertainties of HDVs, with the PF IFT-based controller. The adjustment of desired time headways for CAVs and HDVs is

one of the most straightforward approach to improve traffic safety, by allowing vehicles to maintain a large inter-vehicle distance between each other [Ye and Yamamoto, 2019, Bian et al., 2019, Abolfazli et al., 2022]. Increasing the time headway leads to increased safety, but it can have a negative impact on traffic efficiency. Thus, a balance between traffic safety and efficiency needs to be considered while choosing the time headway parameter. To quantify this, scenarios with a higher headway (1 s instead of 0.6 s for CAVs and 2 s instead of 1.5 s for HDVs) were used.

Figure 7.7a shows the quantitative effect of the increased time headway on the number of safety conflicts at different penetration rates (0%, 20%, 40%, 70%, 100%), with and without packet drops. The horizontal axis indicates the CAV market penetration rates and the vertical axis represents the total number of safety conflicts. The red and blue lines indicate the number of safety conflicts using a small time headway of 0.6s (for CAVs) and 1.5s (for HDVs), with and without packet drops, respectively, while the black and green lines indicate the number of safety conflicts using a large time headway of 1s (for CAVs) and 2s (for HDVs), with and without packet drops, respectively. From Figure 7.7a, it can be seen that the number of safety conflicts reduces drastically at an increased time headway. This reduction is, however, at the expense of increased travel time as depicted through Figure 7.7b. Our results show that a more cautious car-following strategy adopted for CAVs may provide resilience against communication failures in terms of safety (decreasing both HDV-HDV and HDV-CAV conflicts), but at the expense of a slight reduction in traffic efficiency. Similarly, a more cautious car-following strategy adopted for HDVs may provide resilience against large reaction times in terms of safety (decreasing both HDV-HDV and HDV-CAV conflicts), but at the expense of a slight reduction in traffic efficiency. Table 7.5 summarizes the percentage decrease in the number of safety conflicts and the percentage increase in the travel time at different penetration rates and packet error rates (PERs). This table shows that, despite using larger human reaction times, the number of safety conflicts decreases significantly at all penetration rates of CAVs (with and without packet drops), when both CAVs and HDVs adopt more cautious car-following strategies (i.e., larger time headways). This reduction in the number of safety conflicts is however at the cost of a slight increase in travel time.

Finally, to demonstrate the statistical significance of simulation results in different scen-

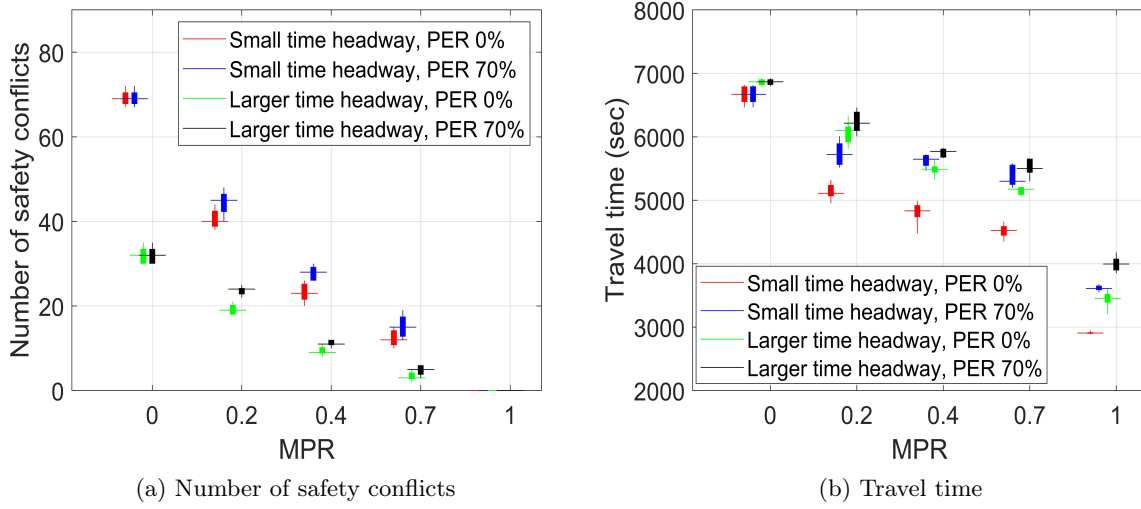


Figure 7.7: Traffic safety and efficiency performance using the PF IFT-based CAV control at different penetration rates, packet error rates, and time headways (smaller CAV 0.6s, HDV 1.5s), (larger CAV 1s, HDV 2s) for a reaction time of 0.5s.

Table 7.5: Summary of traffic safety and efficiency results with larger time headways, compared to shorter time headways

MPR (%)	PER	Safety conflicts decrease (%)	Travel time increase (%)
0	NA	53.62	2.98
20	0	53.17	18.59
20	0.7	45.45	8.71
40	0	60.86	14.15
40	0.7	60.71	2.24
70	0	75.00	14.08
70	0.7	66.67	2.60

arios, Table 7.6 and 7.7 show the results of traffic safety and efficiency, respectively, based on one-way ANOVA test at different penetration rates, packet drop rates, human driver reaction times, and time headways. It is observed that the number of safety conflicts and overall travel time are significantly different at different penetration rates of CAVs, with 95% confidence interval. From the ANOVA test results, if the p-value is less than or equal to the significance level 0.05, it is concluded that the differences between some of the means are statistically significant with 95% confidence.

Table 7.6: Comparison of safety conflicts at different penetration rates of CAVs

One-way ANOVA						
Scenarios	Source of variation	Sum of squares	df	Mean squares	F-value	P-value
Without packet drops	Between groups	3565.84	4	891.46	390.99	1.12001e-18
	Within groups	45.6	20	2.28		
	Total	3611.44	24			
With packet drops	Between groups	3713.04	4	928.26	464.13	2.06031e-19
	Within groups	40	20	2		
	Total	3753.04	24			
With packet drops & large reaction time	Between groups	14295.8	4	3573.96	732.37	2.24677e-21
	Within groups	97.6	20	4.88		
	Total	14393.4	24			
Using more cautious car-following strategy	Between groups	3520.64	4	880.16	536.68	4.89758e-20
	Within groups	32.8	20	1.64		
	Total	3553.44	24			

Table 7.7: Comparison of overall travel time at different penetration rates of CAVs

One-way ANOVA						
Scenarios	Source of variation	Sum of squares	df	Mean squares	F-value	P-value
Without packet drops	Between groups	32749073.8	4	8187268.5	526.78	5.8888e-20
	Within groups	310841.2	20	15542.1		
	Total	33059915	24			
With packet drops	Between groups	20561782.6	4	5140445.7	327.75	6.36744e-18
	Within groups	313682.8	20	15684.1		
	Total	20875465.4	24			
With packet drops & large reaction time	Between groups	24712439.4	4	6178109.9	287.64	2.29565e-17
	Within groups	429567.2	20	21478.4		
	Total	25142006.6	24			
Using more cautious car-following strategy	Between groups	22871119.4	4	5717779.9	360.27	2.50899e-18
	Within groups	317415.2	20	15870.8		
	Total	23188534.6	24			

7.3.4 Evaluation of PF IFT-based CAV Control in Free-flow and Saturated Traffic Conditions

This section shows some preliminary results to measure the effectiveness of CAVs in improving traffic safety and efficiency in free-flow and saturated traffic conditions, as shown in Figures 7.8 and 7.9, respectively.

Figures 7.8a and 7.8b show that both traffic safety and efficiency improve only slightly when introducing CAVs in free-flow traffic conditions. In addition, Figures 7.9a and 7.9b show that, in saturated traffic conditions, traffic safety improves significantly as CAV penetration rate increases, with a very minor improvement in traffic efficiency.

Note that the experiments above measured CAV performance in free-flow and saturated traffic conditions in perfect communication environments only. In free-flow and saturated

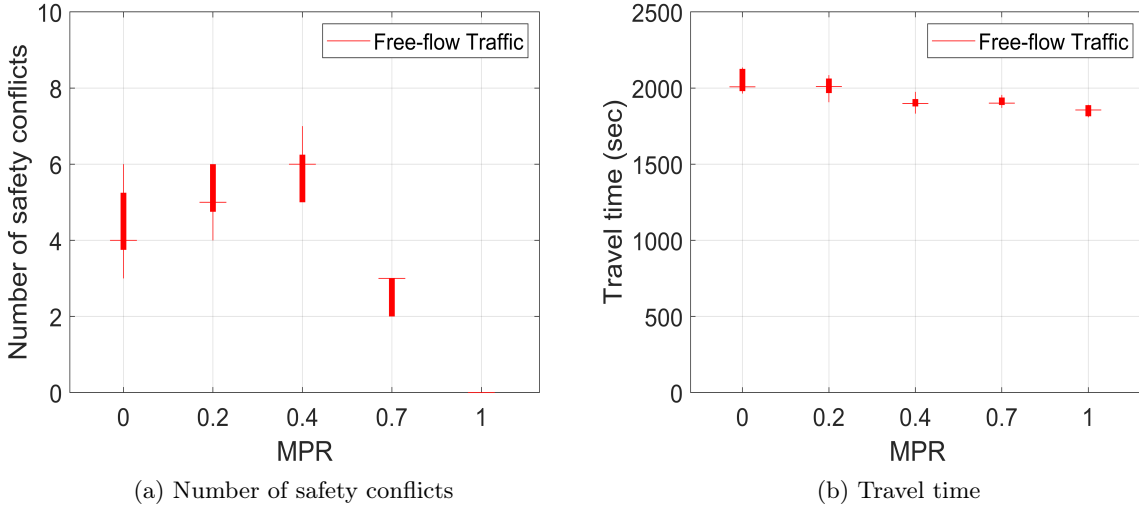


Figure 7.8: Traffic safety and efficiency performance using the PF IFT-based CAV control in free-flow traffic condition at different penetration rates, with and without packet drops.

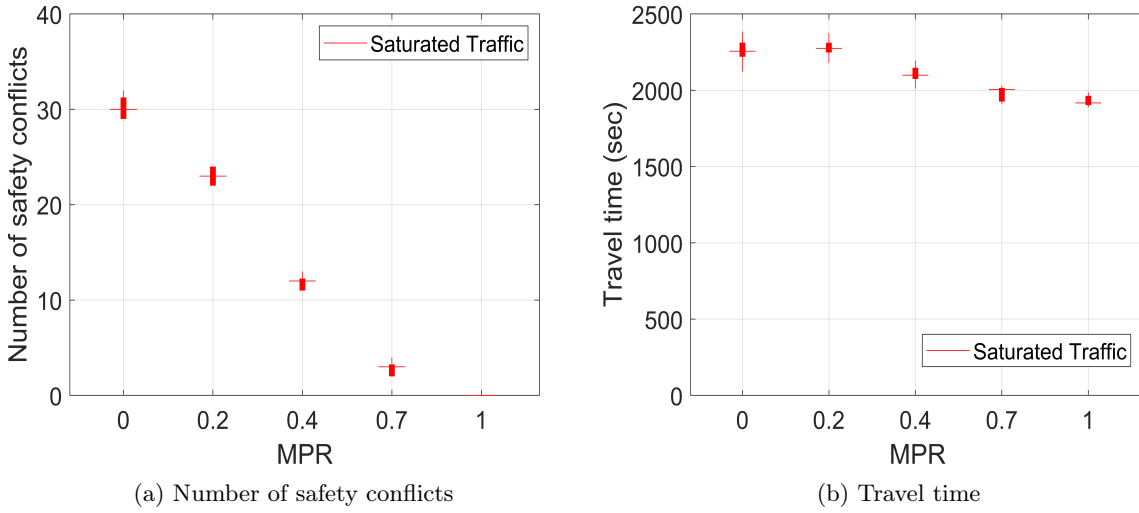


Figure 7.9: Traffic safety and efficiency performance using the PF IFT-based CAV control in saturated traffic conditions at different penetration rates, with and without packet drops.

traffic conditions the communication channel load is lower than in congested scenarios as the vehicle density is lower. For this reason, while communication is unlikely to be perfect in these conditions, the PER value of 0.7 chosen for congested traffic conditions is likely to be unrealistic. Therefore, this work focuses on evaluating CAV performance in congested traffic scenarios. The evaluation of the performance of the proposed algorithms in realistic scenarios in free-flow and saturated traffic conditions is left to future work.

7.3.5 Evaluation Summary of PF IFT-based Control

In this section, firstly, we evaluated the effects of unreliable V2V communication links on PF IFT-based CAV control performance at different CAV penetration rates on traffic safety and efficiency in congested traffic scenarios. Secondly, we evaluated the effects of human driver's large reaction time and perception errors in HDV car-following behaviour, in addition to unreliable V2V communication links. Then the benefits of the proposed cautious car-following approach in the PF IFT CAV controller are measured on traffic safety and efficiency to assess to what extent using information from the immediate leading vehicle only is beneficial in such realistic scenarios (imperfect communication, humans' large reaction time and perception errors, and large scale traffic scenario with real traffic demand). Finally, the impact of CAVs on traffic safety and efficiency in free-flow and saturated traffic conditions is evaluated.

Results from the evaluation of PF IFT-based control answers the research question RQ1 "*Can CAVs improve both mixed traffic safety and efficiency in mixed traffic and unreliable communication environments on large-scale road networks?*", addressed by this thesis. Results have reported two primary findings. Firstly, they show that imperfections in V2V communication links and driver's large reaction time have adverse effects on both safety and efficiency, though both traffic safety and efficiency still improve significantly as the CAV penetration rate increases. For example, a 70% penetration rate of CAVs can improve safety by 81.25% and traffic efficiency by 44.7% if perfect communication is assumed. With a packet error rate of 70% (likely in congested traffic), the improvements become 75% for safety and 33.32% for efficiency. Secondly, they illustrate that traffic safety can be improved significantly by increasing the time headways, however, this is at the expense of reduced traffic efficiency. Specifically, when realistic human reaction times are considered and perfect communication is assumed, increasing the time headway improves traffic safety by up to 75% at 70% penetration rate, but at a cost of an increase in travel time of 14.08%. Assuming a packet error rate of 70%, increasing the time headway still improves traffic safety by 66.67% at a 70% CAVs penetration rate, and the corresponding increase in travel time is only 2.60%. Overall, it is reported that the uncertainties of HDVs and communication links failures in mixed traffic and unreliable communication environments degrade the po-

tential benefits of CAVs. However, the proposed design of the PF IFT-based CAV controller with the cautious car-following approach ensures that a good trade-off between traffic safety and efficiency is maintained by carrying out more smoother transitions in CAV longitudinal mode degradation from CACC to ACC controller.

7.4 Evaluation of MPF IFT-based Control

The previous section presented the evaluation of the impact of CAVs using the simple PF IFT-based car-following controller, where a CAV can exploit information from its immediate leading vehicle only. This section outlines the traffic performance using the MPF IFT-based car-following controller, where each CAV can exploit information from multiple leading vehicles, at different CAV penetration rates, and assesses whether using information from several vehicles is more efficient. Furthermore, this section presents the traffic performance comparison between the proposed approaches and the baseline approach.

This section presents the simulation results of CAV different penetration rates focusing first on analyzing the detrimental effects of unreliable communication only (Section 7.4.1), in congested traffic scenarios. The evaluation of controller parameters tuning to improve the resilience of CAV controller against the uncertainties of HDVs and communication failures for CAVs operation in mixed traffic and unreliable communication environments is presented (Section 7.4.2). It then presents the effects of large human reaction time and perception errors, in addition to unreliable V2V communication (Section 7.4.3). Section 7.4.4 presents the results of the proposed adaptive weights assignment approach. Section 7.4.6 presents the results of CAV different penetration rates in free-flow and saturated traffic conditions. Finally, the evaluation summary of MPF IFT-based control is presented in Section 7.4.7.

7.4.1 Effect of Unreliable V2V Communication Links

In this section, we evaluate the detrimental effects of unreliable V2V communication on traffic safety and efficiency at different CAV penetration rates using the proposed MPF IFT-based CAV car-following control algorithm. Similarly to the PF IFT-based controller evaluation, Figure 7.10 shows the simulation results of the number of safety conflicts based

on time-to-collision value for the case of only human-driven vehicles (0% penetration rate of CAV). It indicates that the number of safety conflicts is high in vast parts of the road network, as expected.

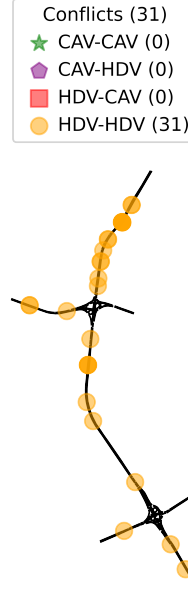


Figure 7.10: Number and location of safety conflicts using the MPF IFT-based CAV control at 0% penetration rate

Table 7.8 shows the number of safety conflicts based on time-to-collision value at different penetration rates (20%, 40%, 70%, 100%), with and without packet drops, for one run only. It shows that with the increase in CAVs' penetration rate, the number of safety conflicts decreases and this is more significant at high penetration rates. This is due to the high probability of information availability from multiple leading vehicles in the CAV controller design, at high penetration rates of CAVs. Finally, at 100% penetration of CAVs, the number of safety conflicts becomes zero. In the presence of packet drops, however, a substantial increase in the number of safety conflicts is observed at all penetration rates except the 100% penetration rate, compared to results without packet drops. The number of safety conflicts is zero at 100% penetration rate with packet drops. Furthermore, it is observed that most safety conflicts are located close to interchanges, i.e., where high speed fluctuations are expected, usually caused by traffic flow oscillations propagating backward from on/off-ramps to the main road. Moreover, the unreliability of wireless communication links further increases the number of safety conflicts near the interchanges. Similarly to the PF IFT-based controller evaluation, most safety conflicts are between human-driven vehicles

(i.e., HDV-HDV conflicts) both in perfect and imperfect communication environments (even at high penetration rate of CAVs), and only a small proportion of conflicts resulting from HDV-CAV interactions. This shows that though CAVs were able to avoid CACC to ACC mode degradation in the presence of unreliable communication links or when the immediate leading vehicle is a HDV using the MPF IFT-based controller, the information flow topology (IFT) varies dynamically due to communication failures or the presence of human-driven vehicles, leading to traffic disturbance oscillations in the downstream flow, which increased the number of HDV-HDV conflicts. At 20% MPR with perfect communication, a small number of safety conflicts are observed from CAV-HDV interactions. This might usually occur when CAVs obtain information from farther vehicles ahead, but not from the nearer leading vehicles. Overall, CAVs provide a significant reduction in the number of safety conflicts as penetration rate increases and maximum reduction is found in pure CAVs traffic i.e., 100% penetration rate. These results are consistent with the fact that most road accidents occur due to the uncertainty in human's driving behavior [Papadoulis et al., 2019, Yao et al., 2020] and CAVs can provide a significant reduction in the number of safety conflicts when exploiting information from multiple leading vehicles in their controller design, especially at high penetration rates.

Figure 7.11 shows the travel time rate at different penetration rates (0%, 20%, 40%, 70%, 100%), with and without packet drops, for one run only. It is observed that, as in other studies [Shi et al., 2021, Ding et al., 2022, Rahman et al., 2021], traffic efficiency improves significantly as the penetration rate of CAVs increases. The improvement in traffic efficiency is, however, more significant at CAV high penetration rates. The results also indicate that at high penetration rate of CAVs, they can exploit information from multiple leading vehicles, resulting in higher improvement in traffic efficiency, as expected.

Similarly to the PF IFT-based CAV controller evaluation, figures with road layout are not depicting much relevant information, we show those graphs in one scenario and for one run only, to show the number of the different types of safety conflicts and to see how traffic efficiency performance is improved locally by introducing CAVs on the road network. It is also worthwhile observing the effect of simulations randomness on travel safety and efficiency results and to show results in a statistical way by performing multiple simulation runs. Figure 7.12a shows the number of safety conflicts based on time-to-collision (TTC)

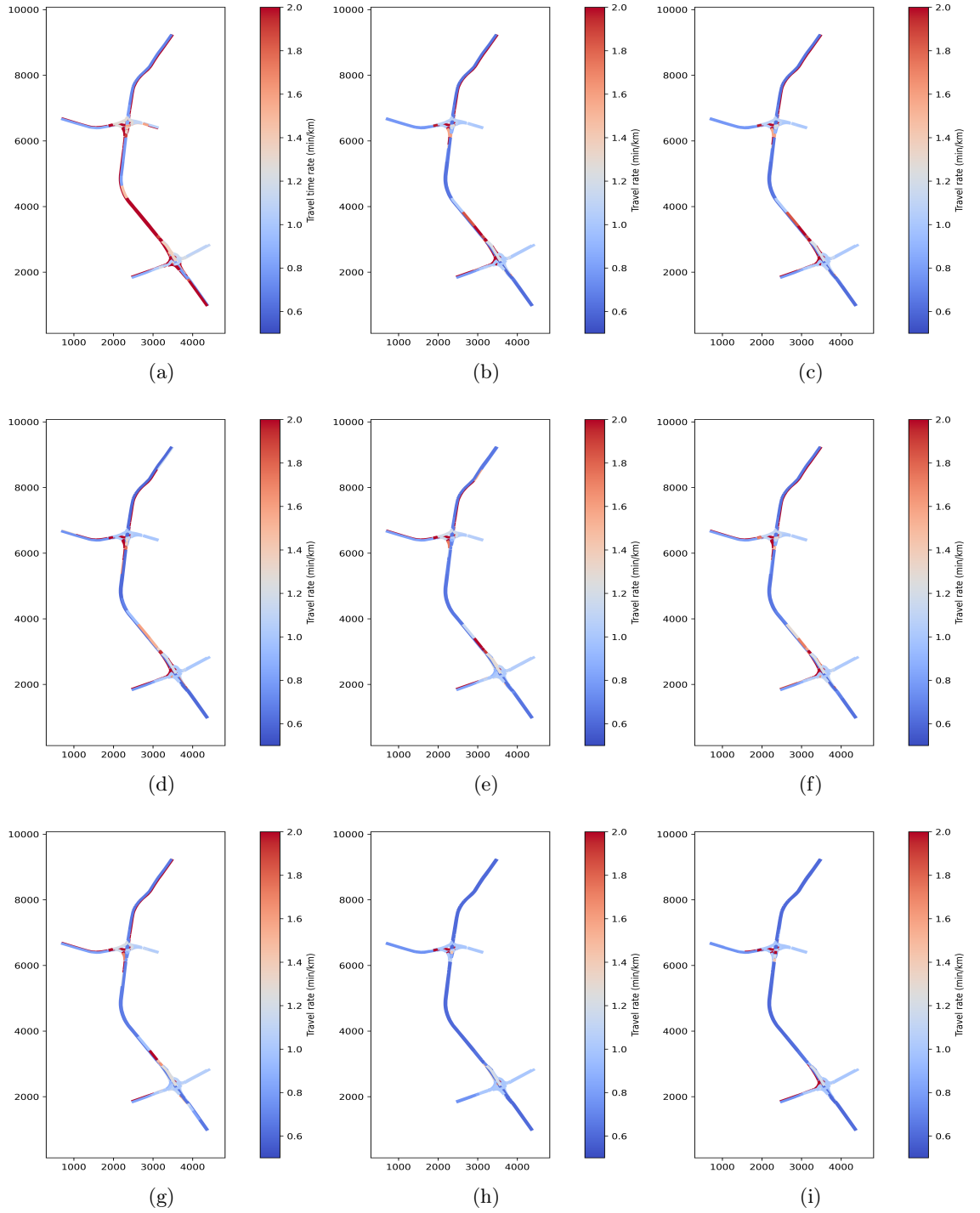


Figure 7.11: Travel time rate (min/km) using the MPF IFT-based CAV control at different penetration rates, with and without packet drops, (a) MPR 0%, (b) MPR 20% and PER 0%, (c) MPR 20% and PER 70%, (d) MPR 40% and PER 0%, (e) MPR 40% and PER 70%, (f) MPR 70% and PER 0%, (g) MPR 70% and PER 70%, (h) MPR 100% and PER 0%, (i) MPR 100% and PER 70%

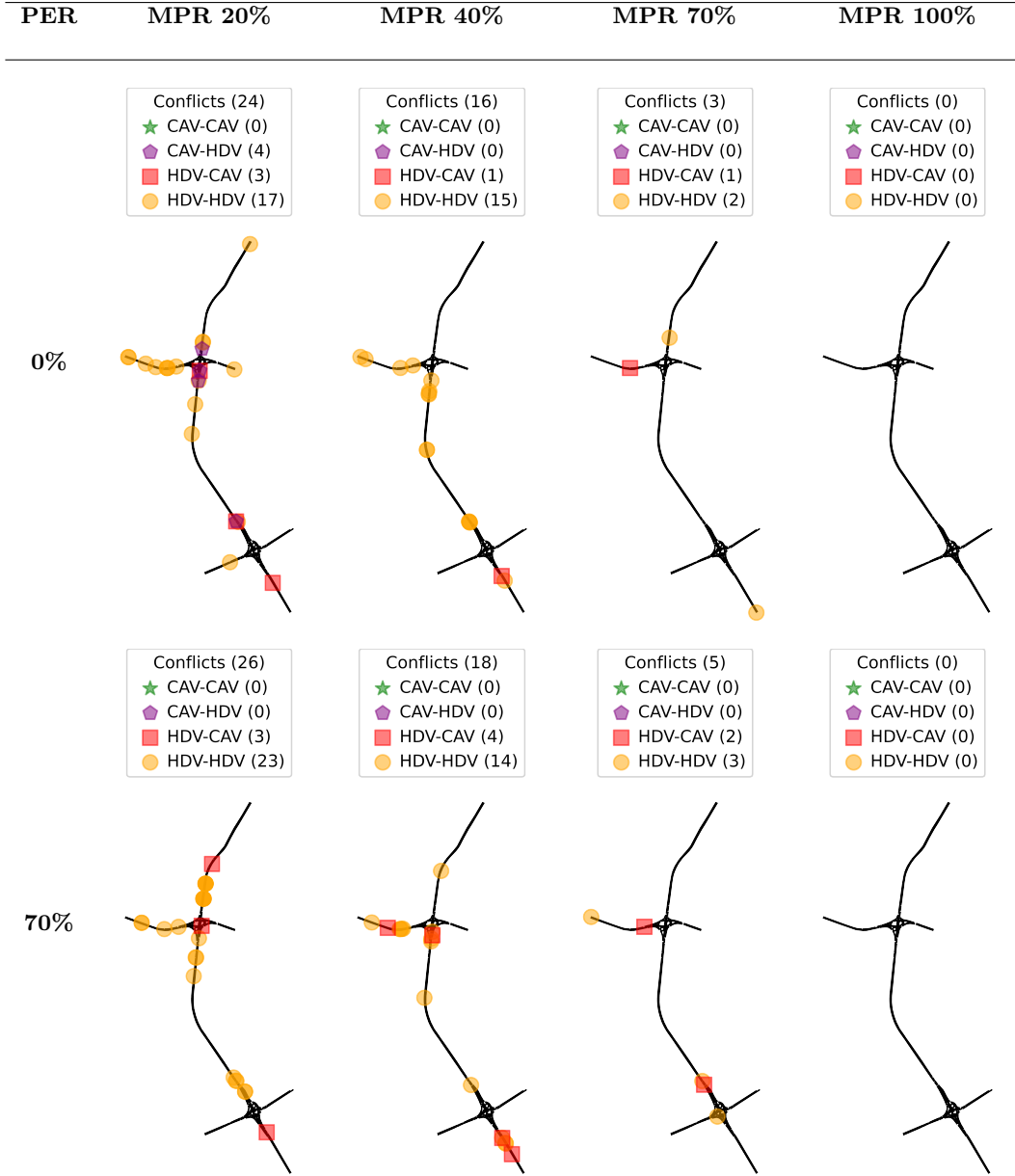


Table 7.8: Number and location of safety conflicts using the MPF IFT-based CAV control at different penetration rates, with and without packet drops

value at different penetration rates (0%, 20%, 40%, 70%, 100%), with and without packet drops, using both the PF IFT and MPF IFT-based controllers, for five simulation runs. It shows that when CAV controller uses information from multiple leading vehicles (MPF IFT) rather than the single leading vehicle (PF IFT), the number of safety conflicts decreases and this is more significant at high penetration rates. In the presence of packet drops, however, a substantial increase in the number of safety conflicts is observed at all penetration rates

except the 100% penetration rate for both single vehicle and multiple vehicles information-based control, compared to results without packet drops. For both controllers, the number of safety conflicts is zero at 100% penetration rate with packet drops, thanks to suitable tuning of control gains and time headways (presented in Section 5.3.2). Overall, CAVs provide a significant reduction in the number of safety conflicts when exploiting information from multiple leading vehicles in their controller design and the maximum reduction is found at high penetration rates. These results are consistent with the fact that by increasing the number of predecessors, CAVs can provide better traffic efficiency without compromising safety [Bian et al., 2019, Abolfazli et al., 2022]. These studies were, however, limited to pure CAVs traffic with perfect communication, where information is always available from multiple leading vehicles. Our results extend existing results by investigating the impact of unreliable V2V communication links on the MPF IFT-based CAV controller performance. Note that, in subsequent sections, we present simulation results based on total five simulation runs to ensure robustness and consistency in our results.

Furthermore, Figure 7.12b shows the travel time at different penetration rates (0%, 20%, 40%, 70%, 100%), with and without packet drops. It is observed that, as in other studies [Bian et al., 2019, Abolfazli et al., 2022, Rahman et al., 2021], in a perfect communication environment (PER 0%), traffic efficiency improves significantly when CAVs use information from multiple leading vehicles (MPF IFT) rather than a single leading vehicle (PF IFT) in their controller design, especially at high penetration rates. In the presence of packet drops (PER 70%), however, a small decrease in traffic efficiency is observed at all penetration rates except the 100% penetration rate, compared to results without packet drops. This is due to the fact that in imperfect communication environments, the improvement in traffic efficiency is not only dependent on increasing the number of leading vehicles, but also on proper tuning of time headways and control gains. Note that, in this section, we present results based on controller parameters tuning performed at 100% CAV penetration rate only, but the effects of controller parameters on traffic safety and efficiency at different penetration rates will be further investigated in the next section.

In addition, the percentage decrease in the number of safety conflicts and travel time are calculated and summarized in Table 7.9. This table shows that both safety conflicts and overall travel time decrease at most penetration rates, with and without packet drops when

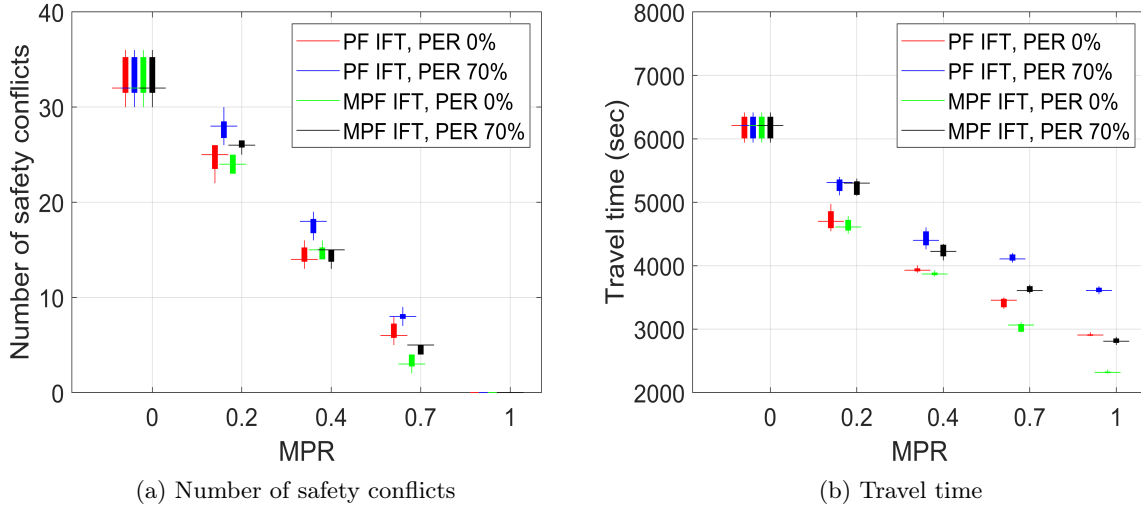


Figure 7.12: Traffic safety and efficiency at CAV different penetration rates, packet error rates, and controllers.

considering information from multiple leading vehicles in CAV car-following control design as compared to the number of safety conflicts and travel time calculated when considering immediate leading vehicle information only.

Table 7.9: Summary of the effects of multiple leading vehicle information on traffic safety and efficiency results, compared to single leader vehicle information

MPR (%)	PER	Safety conflicts decrease (%)	Travel time decrease (%)
20	0	4.00	2.03
20	0.7	7.14	0.59
40	0	0	1.65
40	0.7	16.67	4.41
70	0	50.00	11.37
70	0.7	37.50	12.05
100	0	0	20.20
100	0.7	0	22.12

7.4.2 Control Parameter Tuning Evaluation

This section evaluates the effect of tuning the control parameters for the specific MPR on traffic safety and efficiency by comparing the proposed MPR-tuned MPF IFT controller to the baseline MPF IFT-based controller, which considers controller parameters tuning at 100% CAV penetration rate only. Figures 7.13a and 7.13b depict the effect of controller

parameters tuning for specific MPRs on the number of safety conflicts and travel time, respectively, at different penetration rates (0%, 20%, 40%, 70%, 100%), with and without packet drops. It is observed that using values for desired time headway and control gains tuned for a specific penetration rate improves traffic safety and efficiency in both perfect and imperfect communication conditions at all penetration rates except at 70% and 100% CAV penetration. At 70% and 100% penetration rates, controller parameters tuning does not show any improvement in traffic safety and efficiency because we found the same controller parameters settings derived in Section 5.3.2 optimal for high CAV penetration rates. Overall, choosing different time headways and control gains at different CAV penetration rates leads to improvements in traffic safety of up to 26.67% (at 40% penetration rate) and efficiency of up to 8.02% (at 20% penetration rate) when exploiting information from multiple leading vehicles.

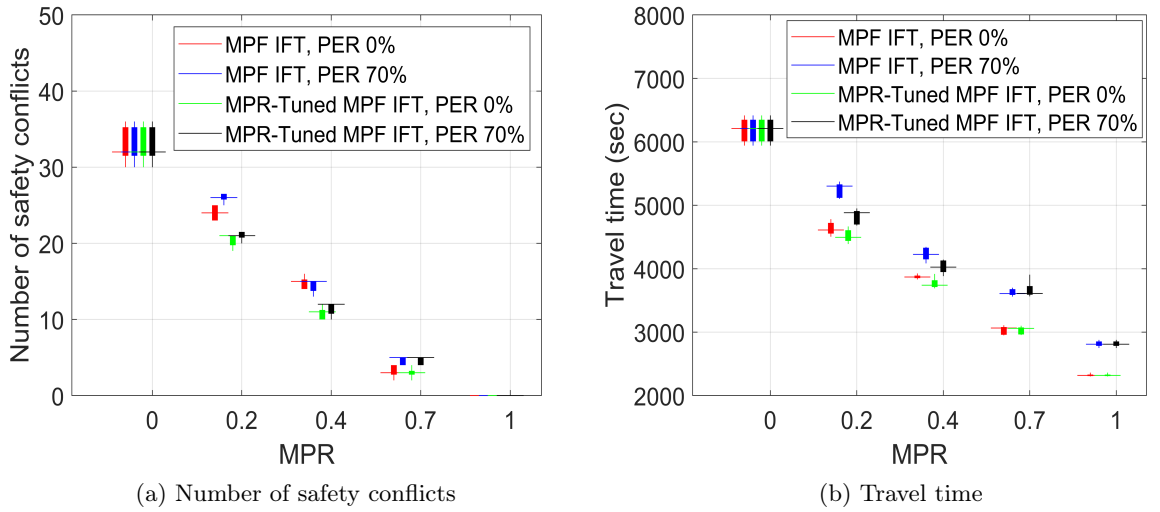


Figure 7.13: Effect on controller parameters tuning for specific MPR on the number of safety conflicts and travel time at different penetration rates and packet error rates.

In addition, the percentage decrease in the number of safety conflicts and travel time are calculated and summarized in Table 7.10. This table shows that both safety conflicts and overall travel time decrease at low-to-medium penetration rates, with and without packet drops when controller parameters (control gains and time headways) tuning is performed for each MPR exclusively, as compared to the number of safety conflicts and travel time calculated when controller parameters tuning is performed at 100% CAV penetration only.

Table 7.10: Summary of the effect of controller parameters tuning for specific MPR on traffic safety and efficiency results

MPR (%)	PER	Safety conflicts decrease (%)	Travel time decrease (%)
20	0	16.67	2.48
20	0.7	19.23	8.02
40	0	26.67	2.64
40	0.7	21.42	4.75
70	0	0	0.06
70	0.7	0	0.45
100	0	0	0
100	0.7	0	0

7.4.3 Effect of Large Reaction Times and Perception Errors

This section evaluates the effects of using information from several leading vehicles (MPF IFT) over using information from one leading vehicle only (PF IFT) by comparing the proposed MPR-tuned MPF IFT controller with our previous PF IFT controller. Figures 7.14a and 7.14b show the comparison of the number of safety conflicts and travel time respectively for different CAV penetration rates (0%, 20%, 40%, 70%, 100%), with and without packet drops, with large human reaction time, for both controllers. The simulation results, demonstrate the significant superiority of MPF IFT over PF IFT in improving both traffic safety and efficiency. It is observed that, as in other studies [Bian et al., 2019, Abolfazli et al., 2022, Rahman et al., 2021], in a perfect communication environment (PER 0%), both traffic safety and efficiency improve significantly when CAVs use information from multiple leading vehicles rather than a single leading vehicle in their controller design, especially from medium-to-high penetration rates. In the presence of packet drops (PER 70%), a small decrease in traffic safety and efficiency is observed at all penetration rates, compared to results without packet drops, but using information from several leading vehicles still improves safety by up to 32.14% (at 40% penetration rate) and efficiency by up to 26.8% (at 40% penetration rate). Similarly to the PF IFT-based CAV controller evaluation discussed in Section 7.3.2, these findings illustrate the importance of incorporating human large reaction time and perception errors to accurately simulate HDVs in our simulations, contributing to more realistic simulation models. Considering these findings, in the subsequent section, we will include human large reaction time and perception errors, in addition to the unreliable

V2V communication links.

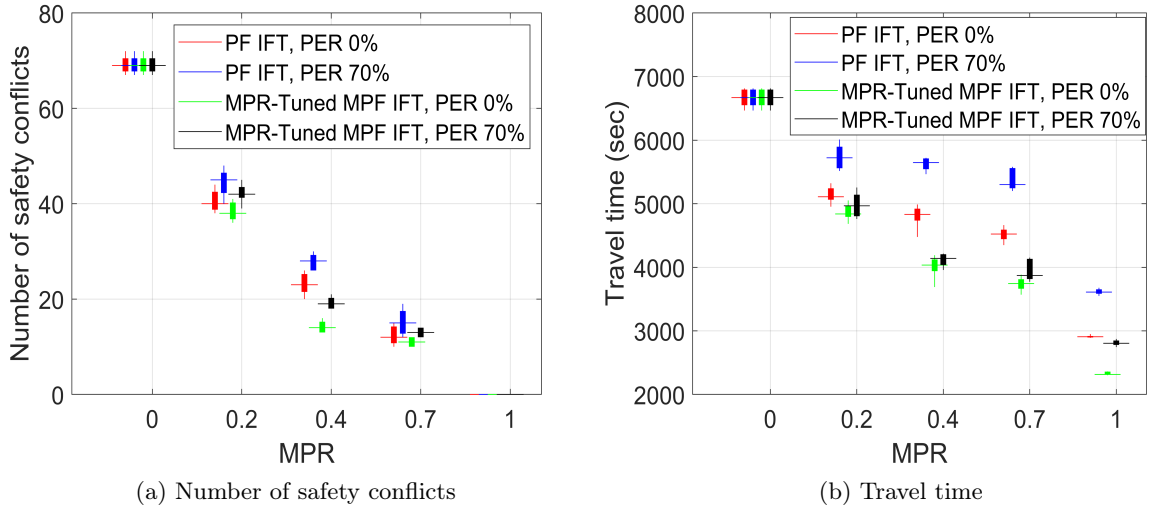


Figure 7.14: Number of safety conflicts and travel time for both PF-IFT and MPR-tuned MPF-IFT controllers, for different penetration rates and packet error rates, considering large human reaction times.

7.4.4 Adaptive Information Weights Assignment Approach

In the MPF IFT, the weight coefficients assigned to the information from each vehicle dictate the relative importance given to information from that vehicle. This section evaluates the impact of assigning different weights to the information from different leading vehicles rather than assigning the same weight to the information from all leading vehicles by comparing the proposed adaptive information weights assignment approach (presented in Section 5.3.3) with the MPR-tuned MPF IFT controller. Figures 7.15a and 7.15b show the comparison of the number of safety conflicts and travel time respectively at different CAV penetration rates (0%, 20%, 40%, 70%, 100%), with and without packet drops, with human large reaction time, for both controllers. The simulation results, utilizing adaptive information weights assignment, demonstrate the significant superiority of multiple-predecessor following IFT over the predecessor-following IFT in improving both traffic safety and efficiency. It is observed that, as in other studies [Ding et al., 2022, Rahman et al., 2021, Shi et al., 2023], in perfect communication environments (PER 0%), both traffic safety and efficiency improve significantly when CAVs use information from multiple leading vehicles with different weights assigned rather than assuming same weights to all leading vehicles information in their

controller design, especially from medium-to-high penetration rates. In the presence of packet drops (PER 70%), a slight improvement in traffic safety and efficiency is observed at all penetration rates, compared to results without packet drops, but assigning adaptive information weights from several leading vehicles still improves safety by up to 11.90% (at 20% penetration rate) and efficiency by up to 4.72% (at 70% penetration rate).

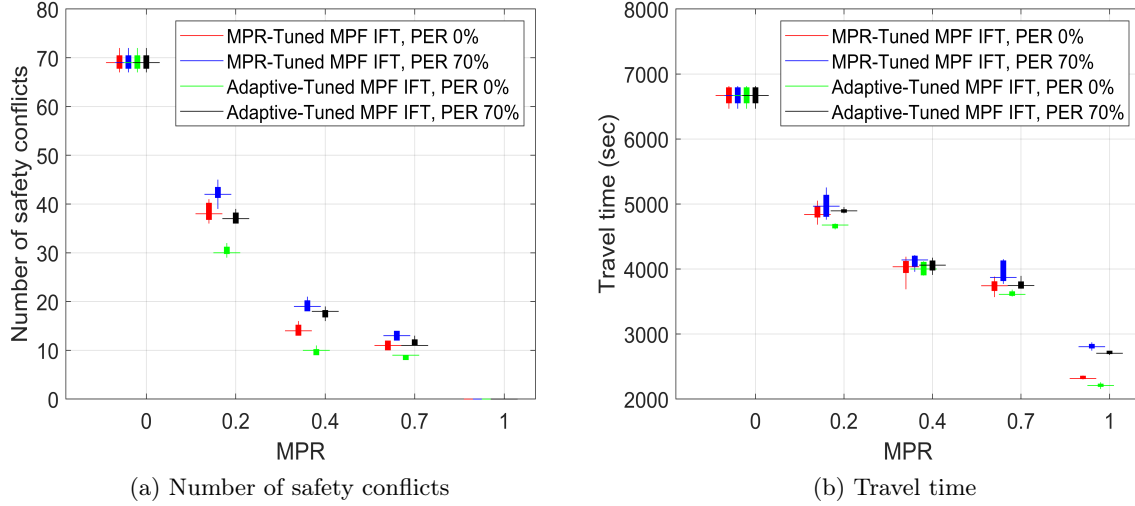


Figure 7.15: Number of safety conflicts and travel time for both MPR-tuned MPF IFT and Adaptive-tuned MPF IFT controllers, for different penetration rates and packet error rates, considering large human reaction times.

In addition, Table 7.11 summarizes the percentage decrease in the number of safety conflicts and the percentage increase in the travel time at different penetration rates and packet error rates (PERs). This table shows that, despite performing controller parameters tuning at each penetration rate and packet error rate, the number of safety conflicts and travel time decreases significantly at all penetration rates of CAVs (with and without packet drops), when CAVs assign adaptive information weighing to multiple leading vehicles rather than assigning the same weights to all leading vehicle information.

Finally, to demonstrate the statistical significance of simulation results of the MPF IFT-based CAV control algorithm in different scenarios, Table 7.12 and 7.13 show the results of traffic safety and efficiency, respectively, based on one-way ANOVA test at different penetration rates, packet drop rates, human driver reaction times, and tuned controller parameters. It is observed that the number of safety conflicts and overall travel time are significantly different at different penetration rates of CAVs, with 95% confidence interval.

Table 7.11: Summary of traffic safety and efficiency results with different weights assigned to different leading vehicles, compared to same weights assigned to leading vehicles

MPR (%)	PER	Safety conflicts % decrease	Travel time % increase
20	0	21.05	4.27
20	0.7	11.90	1.68
40	0	28.57	0.03
40	0.7	5.26	1.53
70	0	18.18	3.03
70	0.7	7.69	4.72
100	0	0	5.11
100	0.7	0	2.97

From the ANOVA test results, if the p-value is less than or equal to the significance level 0.05, it is concluded that the differences between some of the means are statistically significant with 95% confidence.

Table 7.12: Comparison of safety conflicts at different penetration rates of CAVs

One-way ANOVA						
Scenarios	Source of variation	Sum of squares	df	Mean squares	F-value	P-value
Without packet drops	Between groups	3846.4	4	961.6	572.38	2.58843e-20
	Within groups	33.6	20	1.68		
	Total	3880	24			
With packet drops	Between groups	3904.56	4	976.14	588.04	1.98125e-20
	Within groups	33.2	20	1.66		
	Total	3937.76	24			
MPR-based tuning in the presence of packet drops	Between groups	3519.76	4	879.94	530.08	5.53561e-20
	Within groups	33.2	20	1.66		
	Total	3552.96	24			
MPR-based tuning in the presence of packet drops & large reaction time	Between groups	14914.6	4	3728.66	1679.58	5.82119e-25
	Within groups	44.4	20	2.22		
	Total	14959	24			
Adaptive distance-based tuning in the presence of packet drops & large reaction time	Between groups	14696.6	4	3674.16	2449.44	1.35134e-26
	Within groups	30	20	1.5		
	Total	14726.6	24			

7.4.5 Proposed Approach and Baseline Comparison

In previous sections, we evaluated the impact of CAVs on traffic safety and efficiency using the proposed PF IFT and MPF IFT-based controllers. In this section, we present the comparison of the proposed control approaches discussed in Chapter 5 with the baseline approach discussed in Section 3.5 to show the benefits of the proposed approach in coping with the uncertainties of HDVs and communication failures for CAVs operation in realistic scenarios. To do this, we choose two MPR values (20% and 70%) and four PER values (0%,

Table 7.13: Comparison of overall travel time at different penetration rates of CAVs

One-way ANOVA						
Scenarios	Source of variation	Sum of squares	df	Mean squares	F-value	P-value
MPF IFT without packet drops	Between groups	44696965.2	4	11174241.3	960.18	1.52389e-22
	Within groups	232752.8	20	11637.6		
	Total	44929718	24			
MPF IFT with packet drops	Between groups	35144096.2	4	8786024.1	609.81	1.3819e-20
	Within groups	288157.2	20	14407.9		
	Total	35432253.4	24			
MPR-tuned MPF IFT in the presence of packet drops	Between groups	32487817	4	8121954.3	464.28	2.05388e-19
	Within groups	349875.6	20	17493.8		
	Total	32837692.6	24			
MPR-tuned MPF IFT in the presence of packet drops & large reaction time	Between groups	41072069.4	4	10268017.4	478.06	1.53796e-19
	Within groups	429567.2	20	21478.4		
	Total	41501636.6	24			
Adaptive information weights assignment approach	Between groups	43456514.2	4	10864128.56	1228.7	1.31033e-23
	Within groups	176838.8	20	8841.94		
	Total	43633353	24			

20%, 40%, and 70%) to evaluate the impact of different PERs on traffic safety and efficiency using the proposed approach and the baseline approach. In contrast to previous experiments considering more MPR values (0%, 20%, 40%, 70%, and 100%) and only two PER values (0% and 70%), only two MRR values and more PER values are chosen here to investigate the benefits of the proposed approach as compared to the baseline approach in mixed traffic and unreliable communication environments, under low and high CAV penetration rates with different levels of packet drops (ranging from low to high).

Tables 7.14 and 7.15 show the quantitative analysis of traffic safety and efficiency performance, respectively between the proposed PF/MPF IFT approach and the baseline approach. The values presented in green indicate the percentage decrease, while those in red indicate the percentage increase in the number of safety conflicts and travel time, respectively. From Table 7.14, it can be seen that the number of safety conflicts was reduced significantly under both low and high CAV penetration rates at different PERs using the proposed approaches as compared to the baseline approach. Better improvement in traffic safety is achieved using the PF IFT approach due to the use of a cautious car-following strategy i.e., more conservative time headways used for both CAVs and HDVs. This improvement in traffic safety is, however, at the cost of a reduction in traffic efficiency using the proposed PF IFT approach, as shown in Table 7.15. First of all, travel time was decreased slightly using the proposed PF IFT-based approach as compared to the baseline approach. Secondly, travel time is even higher for the proposed PF IFT approach at low MPR and

small PERs, highlighting that the baseline approach is to some extent tolerable for small PERs.

To improve traffic safety without compromising efficiency, both time headway and control gains are tuned in the proposed MPF IFT control approach, as discussed in Section 5.3.2. Tables 7.14 and 7.15 show that both traffic safety and efficiency are significantly improved using the proposed MPF IFT-based approach as compared to the baseline approach. It is worth highlighting that using the proposed MPF IFT approach, the detrimental effects of unreliable communication are diminished at all PER values as compared to the baseline approach. This shows the generalization ability of the proposed MPF IFT approach to cope with the negative effects of varying IFTs in mixed traffic and unreliable communication environments.

Table 7.14: Comparison of traffic safety performance between the proposed control approach and the baseline approach

MPR	PER	Number of safety conflicts				
		Baseline approach	Proposed PF IFT approach	% Change	Proposed MPF IFT approach	% Change
20%	0%	61	19	↓ 68.85	30	↓ 50.81
	20%	63	19	↓ 69.84	31	↓ 50.79
	40%	66	20	↓ 69.69	33	↓ 50.00
	70%	70	23	↓ 67.14	37	↓ 47.14
70%	0%	25	3	↓ 88.00	9	↓ 64.00
	20%	26	3	↓ 88.46	9	↓ 65.38
	40%	28	3	↓ 89.28	9	↓ 67.85
	70%	32	5	↓ 84.37	11	↓ 65.62

Table 7.15: Comparison of traffic efficiency performance between the proposed control approach and the baseline approach

MPR	PER	Travel time (sec)				
		Baseline approach	Proposed PF IFT approach	% Change	Proposed MPF IFT approach	% Change
20%	0%	5780	6101	↑ 5.55	4677	↓ 19.08
	20%	5988	6109	↑ 2.02	4705	↓ 21.42
	40%	6145	6210	↑ 1.05	4768	↓ 22.40
	70%	6577	6215	↓ 5.50	4895	↓ 25.57
70%	0%	5406	5174	↓ 4.29	3611	↓ 33.20
	20%	5618	5202	↓ 7.40	3634	↓ 35.31
	40%	5876	5312	↓ 9.59	3685	↓ 37.28
	70%	6235	5500	↓ 11.78	3745	↓ 39.93

7.4.6 Evaluation of MPF IFT-based Control in Free-Flow and Saturated Traffic Conditions

Similarly to the PF IFT-based CAV controller evaluation in free-flow and saturated traffic conditions, we evaluate the performance of MPF IFT-based CAV controller in free-flow and saturated conditions, considering perfect communication environments only. Figures 7.16a and 7.16b show that traffic safety and efficiency improve slightly by introducing CAVs in free-flow traffic conditions.



Figure 7.16: Traffic safety and efficiency performance using the MPF IFT-based CAV control in free-flow traffic condition at different penetration rates, with and without packet drops.

Furthermore, Figures 7.17a and 7.17b show that in saturated traffic condition, traffic safety improves significantly as CAV penetration rate increases with minor improvement in traffic efficiency.

Furthermore, it is again important to make it clear that we measure CAV performance in free-flow and saturated traffic conditions in perfect communication environments only. This is due to the fact that, in this thesis, we considered the PER value of 0.7 to simulate packet drops in congested traffic conditions and performed controller parameters (time headway and control gains) tuning for congested traffic condition only with PER value of 0.7, which does not seem realistic as communication channel load would be significantly lower in free-flow and saturated traffic conditions, as compared to the congested traffic condition. If we had considered the different PERs in free-flow and saturated traffic conditions, we would

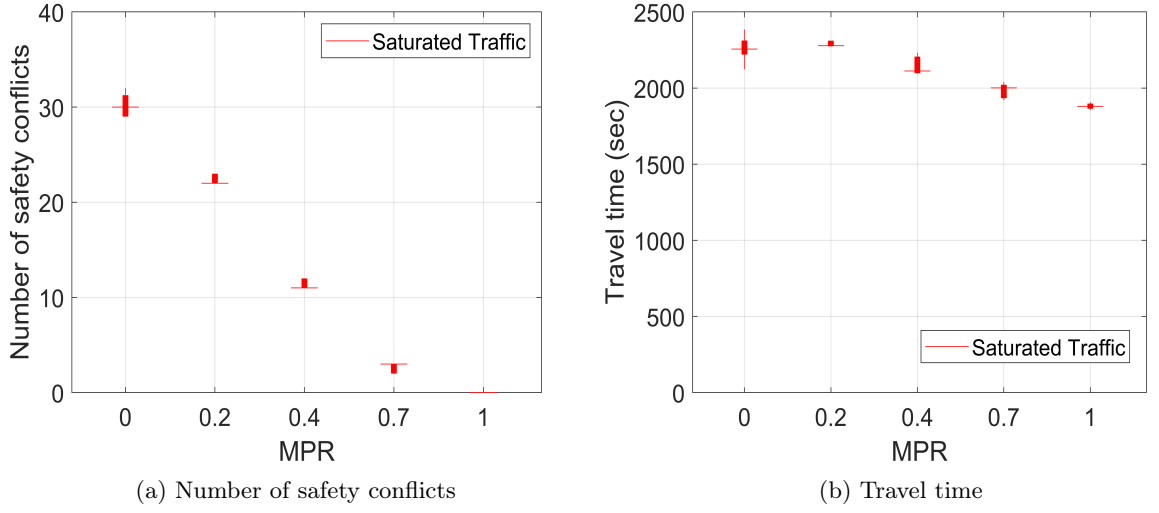


Figure 7.17: Traffic safety and efficiency performance using the MPF IFT-based CAV control in saturated traffic condition at different penetration rates, with and without packet drops.

have to perform the controller parameters tuning separately as controller parameters are dependent on both the MPR and PER. Therefore, this work is limited to evaluating CAV performance in congested traffic scenarios, but the effects of controller parameters on traffic safety and efficiency in other traffic conditions considering different packet error rates need to be further investigated in future work to evaluate the effects of the CAV car-following control algorithms in other traffic conditions.

7.4.7 Evaluation Summary of MPF IFT-based Control

Firstly, in this section, we evaluated the effects of unreliable V2V communication links on MPF IFT-based CAV control performance at different CAV penetration rates on traffic safety and efficiency. Then, the effects of tuning the desired time headway and control gains of the MPF IFT controller for specific penetration rates were evaluated in congested traffic scenarios. Then the performance of the tuned MPF IFT controller was compared to the performance of a Predecessor-Following (PF) IFT controller to assess to what extent using information from multiple leading vehicles is beneficial in such realistic scenarios (imperfect communication, humans' large reaction time and perception errors, and real traffic demand). Furthermore, we evaluated the impact of the proposed adaptive information weights assignment approach on mixed traffic safety and efficiency at different CAV penetration rates in realistic scenarios. In addition, a comprehensive comparison between

the proposed approach and the baseline approach was performed to highlight the benefits of the proposed approach in improving traffic performance in realistic scenarios. Finally, the impact of MPF IFT-based CAV control on traffic safety and efficiency in free-flow and saturated traffic conditions was evaluated.

Results from this section answer the research questions RQ2 (*Does exploiting information from multiple leading vehicles within their communication range give an advantage to CAVs in terms of traffic safety and efficiency?*), and RQ3 (*Can a CAV car-following controller designed based on multiple leading vehicles information further improves traffic safety and efficiency in the presence of the uncertainties of HDVs and communication failures?*), addressed by this thesis. Results show that exploiting information from multiple, rather than a single, leading vehicles in CAV controller design further improves both traffic safety and efficiency, especially at high penetration rates. In addition to proper tuning of CAV controller parameters (control gains and time headways), the scale of the improvement depends on both market penetration rate (MPR) and communication reliability. With a PER of 70%, the use of MPF IFT-based CAV controller leads to an increase in traffic safety by 37.50% (at 70% MPR) and efficiency by 12.05% (at 70% MPR), compared to the simple single leading vehicle information based controller. Furthermore, we demonstrated the effectiveness of tuning the CAV controller parameters (time headway and control gains) to cope with the uncertainties of HDVs and the unreliability of V2V communication links, with the aim of improving both traffic safety and efficiency at different CAV penetration rates and packet error rates. The simulation results show that controller parameters tuning can further improve both mixed traffic safety (by up to 26.67%) and efficiency (by up to 8.02%) when using information from multiple leading vehicles. Overall, the controller with tuned algorithm improves safety and efficiency compared to single-vehicle information-based control by up to 32.14% and 26.8% respectively, in realistic scenarios. Additionally, the MPF IFT-based CAV controller designed based on multiple leading vehicles information further improves safety and efficiency using an adaptive information weights assignment approach. Specifically, with the proposed adaptive weights assignment approach, in perfect communication, traffic safety and efficiency are improved by up to 28.57% at 40% penetration rate and by up to 4.27% at 20% penetration rate, respectively. Assuming a packet error rate of 70%, using the adaptive weights assignment approach still improves traffic safety

and efficiency by 11.90% at a 20% CAVs penetration rate and 4.72% at a 70% penetration rate, respectively, as compared to results using the MPR-Tuned MPF IFT-based controller, which assumes the same weights to information from several leading vehicles.

7.5 Evaluation Challenges

Considering the uncertainties of human-driven vehicles in mixed traffic, the unreliability of wireless communication networks, and high traffic demands in realistic traffic scenarios, the evaluation work in this thesis encountered the following main challenges:

- Although performing realistic simulation of V2V communication may allow greater fidelity and more accurate results in terms of CAV performance evaluation, it also increases the overhead and complexity to an already computationally expensive traffic simulation operation. These simulations required days of real computer time to run, and produced gigabytes of vehicle trajectory data. As detailed in the previous sections, a total of seventeen experiments were run in parallel, producing over 300GB of data in the OMNeT++ vector format (*.vec). Although SUMO can be configured to provide useful output for each edge of the simulated road network, it was not found possible to override the path of this output while running multiple simulations in parallel. Therefore, the data needed to be emitted in a different format, and reconstructed afterwards. Initially, the scavetool program supplied with OMNeT++ was used to export the data to CSV format [Segata et al., 2014]. This proved to be untenable, due to both the size of the resulting files and the time taken to perform the conversion. To work around this, we used Python scripts created by the author in [Johnston, 2020] to convert a vector file sequentially into a SQLite database and then reconstruct the edge-based vehicle data that SUMO is capable of analysing using available visualization tools.
- Performing road traffic simulations in realistic scenarios is found to be extremely resource extensive. Simulation for the congested traffic hours at 70% penetration rate took over 72 hours of real-time to complete. Additionally, an enormous volume of data i.e., over 39.5 million rows of data is produced by simulations of such large-scale

networks, hence, the data analysis was a daunting task. Finally, due to the single-threaded nature of both the SUMO and OMNeT++, multiple simulations needed to be run in parallel. To support parallel simulation execution, simulations were performed at both a personal desktop computer and a high performance computing cluster. Each cluster node has a Linux OS with 12, 2.67GHz Intel Xeon X5650 processors, and 24GB of RAM per node⁴.

- Based on the evaluation of the proposed car-following control algorithms, we can see that the capacity bottleneck of the platform is the heavy communication load among traffic and communication network simulators (i.e., SUMO and OMNET++) which is implemented via the TraCI API. In addition, it is noted that in the current version, the microscopic traffic simulator, SUMO can only run on a single core. To fully utilize the powerful multi-core capacity of computer resources, multi-node parallelization of SUMO is being developed but the work is still ongoing, according to the latest release from the SUMO official website⁵.
- This work synchronizes information among two simulators (i.e., SUMO and VEINS) via the TraCI API, which, however, brings heavy communication loads especially in congested traffic scenarios. An alternative option is Libsumo [Lopez et al., 2018] to have a more efficient coupling without the need for socket communication with TraCI. But, currently, it has several limitations in terms of working with sumo-gui, exception handling, and multi-clients support⁶. In the future, however, the usage of the Libsumo functionality could be implemented by overcoming these limitations.

7.6 Summary

This chapter presented the evaluation of the algorithms proposed in Chapter 5 to answer each research question formulated in Section 1.4 via a large-scale simulation study of CAVs at different penetration rates and packet error rates. Firstly, this chapter presented the evaluation of the PF IFT-based CAV car-following controller and its impact on mixed traffic

⁴Kelvin Details - <https://www.tchpc.tcd.ie/hpc-clusters>, accessed on 27-10-2021

⁵SUMO Parallelization issue: <https://github.com/eclipse/sumo/issues/4767>, accessed on 12-09-2020

⁶Libsumo Functionalities and Limitations: <https://sumo.dlr.de/docs/Libsumo.html>, accessed on 15-12-2023

safety and efficiency in realistic scenarios in terms of unreliable communication, large reaction time and large-scale traffic scenarios with real-traffic demand. Using the above simulations, we were able to quantify the benefits of CAVs on traffic safety and efficiency at different penetration rates. The results show a significant improvement in both traffic safety and efficiency by introducing CAVs in the traffic flow, especially at CAV high penetration rate with perfect communication. This is due to the ability of the designed CAV car-following control algorithm, driving the longitudinal motion of the connected autonomous vehicles, in dampening downstream traffic waves, by reducing the speed variations between adjacent vehicles. By exploiting information from one or more surrounding vehicles, a CAV determines its acceleration to reduce speed fluctuations from its leading vehicles. This results in improved traffic safety and efficiency. In addition, we were able to highlight the detrimental effects of both the unreliable V2V communication links and the uncertainties of HDVs, on traffic safety and efficiency, and then focused on mitigating their effects using the cautious car-following approach. In particular, we evaluated the impact of different time headways using the proposed PF IFT-based control approach to show the trade-off between traffic safety and efficiency, as shown in Figure 7.7. Results indicate that traffic safety is improved significantly by using a large time headway, however, this is an expense of reduction in traffic efficiency. Secondly, the main contribution of this thesis work i.e., the design of the MPF IFT-based car-following controller, to improve traffic safety without compromising efficiency, including design approach and controller parameters tuning for CAVs operation in mixed traffic and unreliable communication scenarios was evaluated. Furthermore, we discussed the merits of our proposed MPF IFT-based controller design and showed that exploiting information from multiple leading vehicles would yield significant benefits in improving both traffic safety and efficiency when control gain parameters are tuned in addition to CAV time headway. As discussed, this thesis focuses on examining the merits of CAVs in motorways in congested traffic conditions only, and car-following control algorithms that are generalized towards different traffic conditions need to be developed in the future. Finally, this chapter presented the main challenges encountered when performing the evaluation studies.

8 Conclusions and Future Scope

This thesis focused on the design of CAV car-following control algorithms that enable CAVs to cope with varying IFTs resulting due to the presence of HDVs and communication failures, and then investigated the impact of CAVs on mixed traffic safety and efficiency in realistic scenarios, including imperfect communication, large-reaction time, vehicle modelling, and large-scale traffic scenario with real traffic data on the busiest motorway in Ireland. This chapter summarises the most significant contributions of the work described in this thesis, discusses some limitations of this work, and presents possible future research directions for this work. Section 8.1 presents the contributions of the thesis to the state of the art. Section 8.2 discusses the limitations of the thesis work and Section 8.3 presents the potential directions for the future research.

8.1 Thesis Contributions

The main goal of this thesis has been to investigate whether a CAV car-following control strategy can improve traffic safety and efficiency for CAVs operation in realistic scenarios, i.e., mixed traffic, unreliable communication, large-scale traffic, etc. Specifically, this thesis addressed three research questions in turn to realize this goal. RQ1 focuses on evaluating to what extent CAVs can improve mixed traffic safety and efficiency in mixed traffic and unreliable communication environments on large-scale road networks using the simple PF IFT-based CAV car-following control algorithm, where CAVs can exploit information from their immediate leading vehicle only for car-following control. RQ2 explores the advantages of exploiting information from multiple leading vehicles rather than a single leading vehicle, by designing the MPF IFT-based CAV car-following controller. In the MPF IFT-based controller, the weight coefficients of connections between vehicles are crucial in determining

the relative importance of information from a vehicle among multiple leading vehicles. RQ3 focuses on assigning adaptive weight coefficients according to the distance from the leading vehicle, as compared to assigning the same weighting to all leading vehicles information in RQ2. Each research question is answered via an extensive simulation study, to assess the impact of CAVs at different penetration rates on traffic safety and efficiency in realistic scenarios via the PLEXE simulator. The results in this work thus represent a significant step towards the deployment of CAVs on motorways in the near future.

The contributions and the answers brought through each research question to the state of the art are discussed in brief in the following.

We considered first the simple PF IFT-based controller for CAVs operation in mixed traffic and unreliable communication environments, by degrading to ACC controller and adopting a cautious car-following approach in the presence of communication failures or when the preceding vehicle is a HDV. We performed simulation studies at different penetration rates of CAVs in realistic scenarios in terms of imperfect communication, humans' large reaction time and perception errors, and traffic scenarios, to measure the impact of CAVs on traffic safety and efficiency. We particularly focused on evaluating the impact of CAV penetration on both traffic safety and efficiency in realistic scenarios, and investigating the trade-off between them. Results have reported two primary findings. Firstly, they showed that imperfections in V2V communication links and driver's large reaction time have adverse effects on both safety and efficiency, though both traffic safety and efficiency still improve significantly as the CAV penetration rate increases. For example, a 70% penetration rate of CAVs can improve safety by 81.25% and traffic efficiency by 44.7% if perfect communication is assumed. With a packet error rate of 70% (likely in congested traffic), the improvements become 75% for safety and 33.32% for efficiency. Secondly, they illustrated that traffic safety can be improved significantly by increasing the time headways, however, this is at the expense of reduced traffic efficiency. Specifically, when realistic human reaction times are considered and perfect communication is assumed, increasing the time headway improves traffic safety by up to 75% at 70% penetration rate, but at a cost of an increase in travel time of 14.08%, compared to results using small time headways. Assuming a packet error rate of 70%, increasing the time headway still improves traffic safety by 66.67% at a 70% CAVs penetration rate, and the corresponding increase in travel time is only 2.60%. In

summary, this contribution showed that CAVs can provide significant improvement in mixed traffic safety in the presence of unreliable communication links and humans' large reaction time by adopting a more cautious car-following strategy, however, this improvement is at the cost of a slight reduction in traffic efficiency.

We then extended the scope of information exchange from multiple leading vehicles (i.e., MPF IFT-based control), rather than the single leading vehicle in the PF IFT-based CAV controller. To investigate the effects of exploiting information from multiple leading vehicles, this work proposed the first MPF IFT-based controller for mixed traffic with unreliable communication. Furthermore, we showed via a simulation-based study how tuning its parameters (control gains and time headways) carefully can mitigate the detrimental effects of the uncertainties of HDVs and communication failures leading to varying IFTs. Similarly to the evaluation of the PF IFT-based CAV control, we investigated the impact of CAV penetration rates on both traffic safety and efficiency when they can exploit information received from multiple, rather than a single, leading vehicles in realistic scenarios. Results have reported two primary findings. Firstly, they show that selecting different controller parameters (time headway and control gains) can provide significant improvements in both safety and efficiency as the CAV penetration rate increases. Secondly, they illustrate that multiple-predecessor IFT-based control is better than the predecessor-following IFT-based control in improving both mixed traffic safety and efficiency, even with packet drops. In addition to proper tuning of CAV controller parameters (control gains and time headways), the scale of the improvement depends on both market penetration rate (MPR) and communication reliability. With a PER of 70%, the use of MPF IFT-based controller leads to an increase in traffic efficiency by 37.50% (at 70% MPR) and efficiency by 12.05% (at 70% MPR), compared to the simple single leading vehicle information based controller.

We finally extended the MPF IFT-based controller by proposing a specially-designed adaptive weights assignment approach for the MPF IFT-based controller design that can maximize CAVs' ability to cope with the varying IFTs due to the uncertainties of HDVs and communication failures associated with CAVs operation in mixed traffic and unreliable communication environment. Results showed that in perfect communication conditions, CAVs can improve traffic safety and efficiency more effectively at all penetration rates, when they assign adaptive weights to information from vehicles based on their distance rather than

using the same weight for all leading vehicles. Furthermore, they show that imperfections in V2V communication links have adverse effects on both safety and efficiency. By using the proposed adaptive weights assignment approach, however, both traffic safety and efficiency are improved. Specifically, with the proposed adaptive weights assignment approach, in perfect communication, traffic safety and efficiency are improved by up to 28.57% at 40% penetration rate and by up to 4.27% at 20% penetration rate, respectively. Assuming a packet error rate of 70%, using the adaptive weights assignment approach still improves traffic safety and efficiency by 11.90% at a 20% CAVs penetration rate and 4.72% at a 70% penetration rate, respectively.

8.2 Limitations

This thesis is the first rigorous study of the impact of CAVs on both traffic safety and efficiency in realistic scenarios, and analyses the trade-off between them. Time headway, control gain parameters, max acceleration and deceleration, sensor and actuator delays, wireless network condition, penetration rate, traffic demand and road network type, can all affect traffic safety and efficiency. Though this thesis considered a lot of parameters into account e.g., different MPRs, different PERs, different time headways, and different control gain parameters, due to the large number, and complexity, of these factors, the generality of the conclusion in the thesis can still be challenged by a different set of parameters e.g., only motorway road type is considered, sensor and actuator delays are neglected, or very high traffic demand in congested traffic conditions is emphasized. This section highlights some limitations and direct extensions of this work.

1. In this thesis, we considered the PER value of 0.7 to simulate packet drops in congested traffic conditions and performed controller parameters (time headway and control gains) tuning with PER value of 0.7, which does not seem realistic as communication channel load would be significantly lower in free-flow and saturated traffic conditions, as compared to the congested traffic condition. Therefore, this work is limited to evaluating CAV performance in congested traffic scenarios, but the effects of controller parameters on traffic safety and efficiency in other traffic conditions considering

different packet error rates need to be investigated further. Therefore the most immediate extension of our research is the design of generalized CAV car-following control algorithms to different traffic conditions (free-flow, saturated and congested).

2. Another limitation lies in that the proposed car-following control algorithms have focused on motorway road network only, and they might not be suitable for different road types beyond motorways e.g., a national road network with a lot of on-ramps/off-ramps and roundabouts, or an urban network with signalized/un-signalized intersections. In addition, safety is considered with respect to rear-end collisions only, as the actual focus of the work is in practice restricted to car-following. However, it would be worth investigating the effects of unreliable communication and the uncertainties of HDVs on traffic safety and efficiency on other road networks.
3. Due to the simulation scale and the computational complexity, the proposed CAV car-following control algorithm is designed based on 2nd order vehicle model and therefore does not take into consideration the acceleration of the leading vehicles. This work could be extended to designing car-following control algorithms considering 3rd order models using more powerful hardware system configurations. In addition, system uncertainties and hardware limitations (e.g., actuator lags and sensor delays), could be modeled in the vehicle longitudinal dynamics using the 3rd order models.
4. This study assumes a fixed human reaction time for all HDVs, which seems quite unrealistic due to the highly stochastic driving behavior of HDVs. Though the effects of large reaction time and perception errors on traffic performance have been well investigated in previous research, (e.g., in [Sun et al., 2018, Jie et al., 2020]), these studies also assume fixed and same reaction time for all HDVs and do not consider realistic traffic scenarios consisting of a large number of vehicles.
5. For the sake of simplicity, this work assumed only a single vehicle class i.e., passenger car. In practice, however, there will be other vehicles also e.g., bus, truck, etc. on the road. Therefore, this study needs to be extended to other vehicle types (e.g., heavy vehicles) to make the simulations more realistic. In addition, because car-following model parameters that are suitable for one vehicle type might not be effective in modelling another vehicle type, it would be worth investigating different model parameters

for different vehicle types, specifically, passenger car and heavy duty vehicles.

8.3 Future Research Directions

Although this thesis work concludes that the proposed CAV car-following control strategy can improve traffic safety and efficiency for CAVs operation in realistic scenarios i.e., mixed traffic, unreliable communication and large-scale traffic, a number of points remain to be addressed in future as follows.

- **V2X communication-based control** This thesis focuses on the V2V communication-based longitudinal control of CAVs, and does not address the existing efforts on control methods based on V2I communication. In the future, this work could be extended by enhancing connectivity with V2X (Vehicle-to-Vehicle and Vehicle-to-Infrastructure) communication, to ensure safe and quick response to traffic perturbation events much further downstream in a timely manner, and thus, generating smoother responses.
- **Integration of car-following with lane-changing control** It is important to point out that the scope of this thesis is limited to the longitudinal control of CAVs, and does not include many existing efforts on various lateral control strategies. Though the impact of lane-changing manoeuvres was not investigated in this work, these manoeuvres might have significant effects on traffic safety and efficiency, especially around intersections, on/off-ramps merging, etc. [Wang et al., 2023a, Ying and Feng, 2024]. Furthermore, as packet loss is likely to have a detrimental effect on such lane-changing manoeuvres, incorporating such research into this work would provide greater insights into the robustness of such algorithms in the face of communication degradation.
- **Real world experiments** While simulation platforms are very useful to evaluate and refine CAVs control models, they need to be tested and validated in experimental studies. Though many car-following control strategies for CAVs have been proposed to mitigate the effect of unreliable communication links and the uncertainties of HDVs, most have not been validated in the real-world. A number of experimental studies have been performed for cooperative driving applications such as CACC and platooning, but those address very limited scenarios e.g., a small number of vehicles, perfect

communication and simple road networks. More real vehicle experiments and empirical data are needed to support the improvement and optimization of car-following control algorithms. Validating the proposed CAV car-following controller first using hardware-in-loop experiments and then real-world tests could be performed in the future.

- **Reinforcement learning-based control algorithms** With the emergence of reinforcement learning as a technique for control of CAVs with promising initial simulation results in [Shi et al., 2021, Shi et al., 2023, Kreidieh et al., 2018], a promising future direction would be to explore the potential role of Deep Reinforcement Learning (DRL)-based algorithms for CAV car-following control algorithms design in mixed traffic and unreliable communication environments. Firstly, DRL algorithms have been proven most suitable for capturing complex and stochastic system characteristics, for instance, the HDV stochastic nature. Secondly, the computational burden of a DRL algorithm mainly lies in its offline training process, while the learned driving policy can be implemented for real-time CAV control [Shi et al., 2021].
- **Leveraging HDVs information** A potential research direction would be to estimate HDVs information further up the stream than the front vehicle, and then incorporate it in the CAV car-following controller design to make CAVs more aware of the surrounding vehicles in mixed traffic conditions. Though a large number of existing studies has already addressed this kind of problem by equipping HDVs with communication devices, it might increase communication overhead further. In addition, the cost of retrofitting HDVs with communication capability is likely to be prohibitive for at least a proportion of their owners.
- **Other performance metrics** In addition to evaluating the impact of CAVs on traffic safety and efficiency, one can extend the control algorithms developed in this thesis to look at other key performance metrics including fuel consumption and driver comfort. When considering such performance metrics, it would be important to distinguish and consider both the benefits reaped by the individual CAVs as well as the benefits for the entire road network. This way we can assess the customers' motivation behind adopting CAVs as well as the overall traffic benefits once a critical penetration of CAVs has been reached.

Bibliography

- [Abolfazli et al., 2022] Abolfazli, E., Besselink, B., and Charalambous, T. (2022). On time headway selection in platoons under the mpf topology in the presence of communication delays. *IEEE Transactions on Intelligent Transportation Systems*, 23(7):8881–8894.
- [Acciani et al., 2018] Acciani, F., Frasca, P., Stoorvogel, A., Semsar-Kazerooni, E., and Heijenk, G. (2018). Cooperative adaptive cruise control over unreliable networks: an observer-based approach to increase robustness to packet loss. In *European Control Conference (ECC)*, pages 1399–1404.
- [Ahangar et al., 2021] Ahangar, M. N., Ahmed, Q. Z., Khan, F. A., and Hafeez, M. (2021). A survey of autonomous vehicles: Enabling communication technologies and challenges. *Sensors*, 21(3).
- [Ali et al., 2020] Ali, Y., Sharma, A., Haque, M. M., Zheng, Z., and Saifuzzaman, M. (2020). The impact of the connected environment on driving behavior and safety: A driving simulator study. *Accident Analysis & Prevention*, 144:105643.
- [Andreotti et al., 2020] Andreotti, E., Boyraz, P., and Selpi (2020). Safety-centred analysis of transition stages to traffic with fully autonomous vehicles. In *IEEE International Conference on Intelligent Transportation Systems (ITSC)*.
- [Arnaout and Arnaout, 2014] Arnaout, G. M. and Arnaout, J.-P. (2014). Exploring the effects of cooperative adaptive cruise control on highway traffic flow using microscopic traffic simulation. *Transportation Planning and Technology*, 37(2):186–199.
- [Avedisov et al., 2022] Avedisov, S. S., Bansal, G., and Orosz, G. (2022). Impacts of connected automated vehicles on freeway traffic patterns at different penetration levels. *IEEE Transactions on Intelligent Transportation Systems*, 23(5):4305–4318.
- [Badnava et al., 2021] Badnava, S., Meskin, N., Gastli, A., Al-Hitmi, M. A., Ghommam, J., Mesbah, M., and Mnif, F. (2021). Platoon transitional maneuver control system: A review. *IEEE Access*, 9:88327–88347.
- [Bagloee et al., 2016] Bagloee, S. A., Tavana, M., Asadi, M., and Oliver, T. (2016). Autonomous vehicles: challenges, opportunities, and future implications for transportation policies. *Journal of Modern Transportation*, 24:284–303.
- [Balador et al., 2022] Balador, A., Bazzi, A., Hernandez-Jayo, U., de la Iglesia, I., and Ahmadvand, H. (2022). A survey on vehicular communication for cooperative truck platooning application. *Vehicular Communications*, 35:100460.
- [Bansal and Kockelman, 2017] Bansal, P. and Kockelman, K. M. (2017). Forecasting americans’ long-term adoption of connected and autonomous vehicle technologies. *Transportation Research Part A: Policy and Practice*, 95:49–63.

- [Beregi et al., 2021] Beregi, S., Avedisov, S. S., He, C. R., Takacs, D., and Orosz, G. (2021). Connectivity-based delay-tolerant control of automated vehicles: theory and experiments. *IEEE Transactions on Intelligent Vehicles*.
- [Bevly et al., 2016] Bevly, D., Cao, X., Gordon, M., Ozbilgin, G., Kari, D., Nelson, B., Woodruff, J., Barth, M., Murray, C., Kurt, A., Redmill, K., and Ozguner, U. (2016). Lane change and merge maneuvers for connected and automated vehicles: A survey. *IEEE Transactions on Intelligent Vehicles*, 1(1):105–120.
- [Bian et al., 2019] Bian, Y., Zheng, Y., Ren, W., Li, S. E., Wang, J., and Li, K. (2019). Reducing time headway for platooning of connected vehicles via v2v communication. *Transportation Research Part C: Emerging Technologies*, 102:87–105.
- [Biron et al., 2017] Biron, Z. A., Dey, S., and Pisu, P. (2017). Resilient control strategy under denial of service in connected vehicles. In *American Control Conference (ACC)*, pages 4971–4976.
- [Bischoff et al., 2020] Bischoff, D., Schiegg, F., Meuser, T., and Steinmetz, R. (2020). Impact of imperfect communication on cooperative vehicular maneuvering at intersections. In *IEEE Vehicular Technology Conference (VTC2020-Spring)*.
- [Calvert et al., 2017] Calvert, S., Schakel, W., and Lint, J. (2017). Will automated vehicles negatively impact traffic flow? *Journal of Advanced Transportation*, 2017.
- [Chekkouri et al., 2015] Chekkouri, A., Ezzouhairi, A., and Pierre, S. (2015). Connected vehicles in an intelligent transport system. In *Vehicular Communications and Networks*, pages 193–221. Woodhead Publishing Series in Electronic and Optical Materials.
- [Chen et al., 2021a] Chen, J., Liang, H., Li, J., and Lv, Z. (2021a). Connected automated vehicle platoon control with input saturation and variable time headway strategy. *IEEE Transactions on Intelligent Transportation Systems*, 22(8):4929–4940.
- [Chen et al., 2021b] Chen, J., Liang, H., Li, J., and Xu, Z. (2021b). A novel distributed cooperative approach for mixed platoon consisting of connected and automated vehicles and human-driven vehicles. *Physica A: Statistical Mechanics and its Applications*, 573:125939.
- [Chu et al., 2018] Chu, Z., Sun, Y., Wu, C., and Sepehri, N. (2018). Active disturbance rejection control applied to automated steering for lane keeping in autonomous vehicles. *Control Engineering Practice*, 74:13–21.
- [Committee, 2021] Committee, S. O.-R. A. D. O. (2021). *Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles- SAE International*.
- [Cui et al., 2021] Cui, S., Cao, F., Yu, B., and Yao, B. (2021). Modeling heterogeneous traffic mixing regular, connected, and connected-autonomous vehicles under connected environment. *IEEE Transactions on Intelligent Transportation Systems (Early-Access)*.
- [Deng, 2016] Deng, Q. (2016). A general simulation framework for modeling and analysis of heavy-duty vehicle platooning. *IEEE Transactions on Intelligent Transportation Systems*, 17(11):3252–3262.
- [Di Vaio et al., 2019] Di Vaio, M., Fiengo, G., Petrillo, A., Salvi, A., Santini, S., and Tufo, M. (2019). Cooperative shock waves mitigation in mixed traffic flow environment. *IEEE Transactions on Intelligent Transportation Systems*, 20(12):4339–4353.

- [Ding et al., 2022] Ding, H., Pan, H., Bai, H., Zheng, X., Chen, J., and Zhang, W. (2022). Driving strategy of connected and autonomous vehicles based on multiple preceding vehicles state estimation in mixed vehicular traffic. *Physica A: Statistical Mechanics and its Applications*, 596:127154.
- [Do et al., 2019] Do, W., M. Rouhani, O., and Miranda-Moreno, L. (2019). Simulation-based connected and automated vehicle models on highway sections: A literature review. *Journal of Advanced Transportation*, 2019:1–14.
- [El Ganaoui-Mourlan et al., 2021] El Ganaoui-Mourlan, O., Camp, S., Hannagan, T., Arora, V., De Neuville, M., and Kousournas, V. A. (2021). Path planning for autonomous platoon formation. *Sustainability*, 13(9).
- [Erdmann, 2015] Erdmann, J. (2015). SUMO’s Lane-changing model. In Behrisch, M. and Weber, M., editors, *LECTURE NOTES IN CONTROL AND INFORMATION SCIENCES*, volume 13, pages 105–123, Berlin. Springer Verlag.
- [Ersal et al., 2020] Ersal, T., Kolmanovsky, I., Masoud, N., Ozay, N., Scruggs, J., Vasudevan, R., and Orosz, G. (2020). Connected and automated road vehicles: state of the art and future challenges. *Vehicle System Dynamics*, 58.
- [Feng et al., 2019] Feng, S., Zhang, Y., Li, S. E., Cao, Z., Liu, H. X., and Li, L. (2019). String stability for vehicular platoon control: Definitions and analysis methods. *Annual Reviews in Control*, 47:81–97.
- [FENICHE and MAZRI, 2019] FENICHE, M. and MAZRI, T. (2019). Lane detection and tracking for intelligent vehicles: A survey. In *International Conference of Computer Science and Renewable Energies (ICCSRE)*.
- [Fries et al., 2017] Fries, R., Qi, Y., and Leight, S. (2017). How many times should i run the model? performance measure specific findings from vissim models in missouri. In *Transportation Research Board 96th Annual Meeting*.
- [Galvani, 2019] Galvani, M. (2019). History and future of driver assistance. *IEEE Instrumentation & Measurement Magazine*, 22:11–16.
- [Garg and Bouroche, 2023a] Garg, M. and Bouroche, M. (2023a). Can connected autonomous vehicles improve mixed traffic safety without compromising efficiency in realistic scenarios? *IEEE Transactions on Intelligent Transportation Systems*, pages 1–16.
- [Garg and Bouroche, 2023b] Garg, M. and Bouroche, M. (2023b). Can listening to more neighbours help cavs be faster and safer? In *2023 IEEE Intelligent Vehicles Symposium (IV)*.
- [Garg et al., 2021] Garg, M., Johnston, C., and Bouroche, M. (2021). Can connected autonomous vehicles really improve mixed traffic efficiency in realistic scenarios? In *IEEE International Conference on Intelligent Transportation Systems (ITSC)*.
- [Ge and Orosz, 2016] Ge, J. I. and Orosz, G. (2016). Estimation of feedback gains and delays in connected vehicle systems. In *2016 American Control Conference (ACC)*, pages 6000–6005.
- [Ge and Orosz, 2017] Ge, J. I. and Orosz, G. (2017). Optimal control of connected vehicle systems with communication delay and driver reaction time. *IEEE Transactions on Intelligent Transportation Systems*, 18(8):2056–2070.

- [Ghiasi et al., 2017] Ghiasi, A., Hussain, O., Qian, Z. S., and Li, X. (2017). A mixed traffic capacity analysis and lane management model for connected automated vehicles: A markov chain method. *Transportation Research Part B: Methodological*, 106:266–292.
- [Gong et al., 2019] Gong, S., Zhou, A., and Peeta, S. (2019). Cooperative adaptive cruise control for a platoon of connected and autonomous vehicles considering dynamic information flow topology. *Transportation Research Record*, 2673(10):185–198.
- [Guanetti et al., 2018] Guanetti, J., Kim, Y., and Borrelli, F. (2018). Control of connected and automated vehicles: State of the art and future challenges. *Annual Reviews in Control*, 45:18–40.
- [Guériau and Dusparic, 2020] Guériau, M. and Dusparic, I. (2020). Quantifying the impact of connected and autonomous vehicles on traffic efficiency and safety in mixed traffic. In *IEEE International Conference on Intelligent Transportation Systems (ITSC)*.
- [Gómez et al., 2014] Gómez, A. E., dos Santos, T. C., Filho, C. M., Gomes, D., Perafan, J. C., and Wolf, D. F. (2014). Simulation platform for cooperative vehicle systems. In *IEEE International Conference on Intelligent Transportation Systems (ITSC)*, pages 1347–1352.
- [Hall and Chin, 2005] Hall, R. and Chin, C. (2005). Vehicle sorting for platoon formation: Impacts on highway entry and throughput. *Transportation Research Part C: Emerging Technologies*, 13(5):405–420.
- [Hancock et al., 2019] Hancock, P., Nourbakhsh, I., and Stewart, J. (2019). On the future of transportation in an era of automated and autonomous vehicles. *Proceedings of the National Academy of Sciences of the United States of America*, 116:7684–7691.
- [Hao and Barooah, 2013] Hao, H. and Barooah, P. (2013). Stability and robustness of large platoons of vehicles with double-integrator models and nearest neighbor interaction. *International Journal of Robust and Nonlinear Control*, 23(18):2097–2122.
- [Harfouch et al., 2018] Harfouch, Y. A., Yuan, S., and Baldi, S. (2018). An adaptive switched control approach to heterogeneous platooning with intervehicle communication losses. *IEEE Transactions on Control of Network Systems*, 5(3):1434–1444.
- [Hegde and Bouroche, 2022] Hegde, B. and Bouroche, M. (2022). Design of ai-based lane changing modules in connected and autonomous vehicles: a survey. In *ATT’22: Workshop Agents in Traffic and Transportation*.
- [Horcas et al., 2017] Horcas, J.-M., Monteil, J., Bouroche, M., Pinto, M., Fuentes, L., and Clarke, S. (2017). Context-dependent reconfiguration of autonomous vehicles in mixed traffic. *Journal of Software: Evolution and Process*, 30.
- [Hu et al., 2019] Hu, C., Qin, Y., Cao, H., Song, X., Jiang, K., Rath, J. J., and Wei, C. (2019). Lane keeping of autonomous vehicles based on differential steering with adaptive multivariable super-twisting control. *Mechanical Systems and Signal Processing*, 125:330–346.
- [Hussain et al., 2016] Hussain, O., Ghiasi, A., Li, X., and Qian, Z. (2016). Freeway lane management approach in mixed traffic environment with connected autonomous vehicles. *ArXiv*, abs/1609.02946.

- [Hussain and Zeadally, 2019] Hussain, R. and Zeadally, S. (2019). Autonomous cars: Research results, issues, and future challenges. *IEEE Communications Surveys Tutorials*, 21(2):1275–1313.
- [Ivanchev et al., 2019] Ivanchev, J., Eckhoff, D., and Knoll, A. (2019). System-level optimization of longitudinal acceleration of autonomous vehicles in mixed traffic. In *IEEE International Conference on Intelligent Transportation Systems (ITSC)*, pages 1968–1974.
- [Jefferson and McDonald, 2019] Jefferson, J. and McDonald, A. D. (2019). The autonomous vehicle social network: Analyzing tweets after a recent tesla autopilot crash. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, 63(1):2071–2075.
- [Jia and Ngoduy, 2016a] Jia, D. and Ngoduy, D. (2016a). Enhanced cooperative car-following traffic model with the combination of V2V and V2I communication. *Transportation Research Part B: Methodological*, 90:172–191.
- [Jia and Ngoduy, 2016b] Jia, D. and Ngoduy, D. (2016b). Platoon based cooperative driving model with consideration of realistic inter-vehicle communication. *Transportation Research Part C: Emerging Technologies*, 68:245–264.
- [Jia et al., 2018] Jia, D., Ngoduy, D., and Vu, H. (2018). A multi-class microscopic model for heterogeneous platoon with vehicle-to-vehicle communication. *Transportmetrica B*, 7.
- [Jia et al., 2019] Jia, D., Ngoduy, D., and Vu, H. L. (2019). A multiclass microscopic model for heterogeneous platoon with vehicle-to-vehicle communication. *Transportmetrica B: Transport Dynamics*, 7(1):311–335.
- [Jia et al., 2021] Jia, D., Sun, J., Sharma, A., Zheng, Z., and Liu, B. (2021). Integrated simulation platform for conventional, connected and automated driving: A design from cyber-physical systems perspective. *Transportation Research Part C: Emerging Technologies*, 124:102984.
- [Jie et al., 2020] Jie, S., Zuduo, Z., and Jian, S. (2020). The relationship between car following string instability and traffic oscillations in finite-sized platoons and its use in easing congestion via connected and automated vehicles with IDM based controller. *Transportation Research Part B: Methodological*, 142:58–83.
- [Johnston, 2020] Johnston, C. (2020). Realistic simulation of cooperative adaptive cruise control (cacc) degradation under random packet loss. Available at <https://publications.scss.tcd.ie/theses/diss/2020/TCD-SCSS-DISSERTATION-2020-087.pdf>.
- [Kesting and Treiber, 2006] Kesting, A. and Treiber, M. (2006). Influence of reaction times and anticipation on the stability of vehicular traffic flow. *IFAC Proceedings Volumes*, 39(10):205–210. 6th IFAC Workshop on Time Delay Systems.
- [Kesting et al., 2007] Kesting, A., Treiber, M., and Helbing, D. (2007). General lane-changing model MOBIL for car-following models. *Transportation Research Record*, 1999(1):86–94.
- [Kreidieh et al., 2018] Kreidieh, A. R., Wu, C., and Bayen, A. M. (2018). Dissipating stop-and-go waves in closed and open networks via deep reinforcement learning. In *2018 21st International Conference on Intelligent Transportation Systems (ITSC)*, pages 1475–1480.

- [Lai et al., 2020] Lai, J., Hu, J., Cui, L., Chen, Z., and Yang, X. (2020). A generic simulation platform for cooperative adaptive cruise control under partially connected and automated environment. *Transportation Research Part C: Emerging Technologies*, 121:102874.
- [Lefèvre et al., 2016] Lefèvre, S., Carvalho, A., and Borrelli, F. (2016). A learning-based framework for velocity control in autonomous driving. *IEEE Transactions on Automation Science and Engineering*, 13(1):32–42.
- [Li et al., 2022] Li, K., Wang, J., and Zheng, Y. (2022). Cooperative formation of autonomous vehicles in mixed traffic flow: Beyond platooning. *IEEE Transactions on Intelligent Transportation Systems*, 23(9):15951–15966.
- [Li et al., 2023] Li, S., Zhou, B., and Xu, M. (2023). Longitudinal car-following control strategy integrating predictive collision risk. *Applied Mathematical Modelling*, 121:1–20.
- [Li et al., 2017] Li, S. E., Zheng, Y., Li, K., Wang, L.-Y., and Zhang, H. (2017). Platoon control of connected vehicles from a networked control perspective: Literature review, component modeling, and controller synthesis. *IEEE Transactions on Vehicular Technology*.
- [Li et al., 2021] Li, Y., Chen, B., Zhao, H., Peeta, S., Hu, S., Wang, Y., and Zheng, Z. (2021). A car-following model for connected and automated vehicles with heterogeneous time delays under fixed and switching communication topologies. *IEEE Transactions on Intelligent Transportation Systems*, pages 1–13.
- [Li et al., 2020] Li, Y., Chen, W., Peeta, S., and Wang, Y. (2020). Platoon control of connected multi-vehicle systems under v2x communications: Design and experiments. *IEEE Transactions on Intelligent Transportation Systems*, 21(5):1891–1902.
- [Liangye et al., 2019] Liangye, L., Defeng, H., Shiming, Y., and Shijian, D. (2019). Distributed predictive control for string stability of heterogonous vehicle platoons with multiple communication topologies. In *Chinese Control Conference (CCC)*, pages 2930–2935.
- [Liu et al., 2018] Liu, H., Kan, X. D., Shladover, S. E., Lu, X.-Y., and Ferlis, R. E. (2018). Modeling impacts of cooperative adaptive cruise control on mixed traffic flow in multi-lane freeway facilities. *Transportation Research Part C: Emerging Technologies*, 95:261–279.
- [Liu and Fan, 2020] Liu, P. and Fan, W. D. (2020). Exploring the impact of connected and autonomous vehicles on freeway capacity using a revised intelligent driver model. *Transportation Planning and Technology*, 43(3):279–292.
- [Liu and Jaekel, 2019] Liu, X. and Jaekel, A. (2019). Congestion control in v2v safety communication: Problem, analysis, approaches. *Electronics*, 8(5).
- [Lopez et al., 2018] Lopez, P. A., Behrisch, M., Bieker-Walz, L., Erdmann, J., Flotterod, Y.-P., Hilbrich, R., Lucken, L., Rummel, J., Wagner, P., and Wiessner, E. (2018). Microscopic traffic simulation using sumo. In *The 21st IEEE International Conference on Intelligent Transportation Systems*. IEEE.
- [Mahmud et al., 2019] Mahmud, S. S., Ferreira, L., Hoque, M. S., and Tavassoli, A. (2019). Micro-simulation modelling for traffic safety: A review and potential application to heterogeneous traffic environment. *IATSS Research*, 43(1):27–36.

- [Marino et al., 2011] Marino, R., Scalzi, S., and Netto, M. (2011). Nested PID steering control for lane keeping in autonomous vehicles. *Control Engineering Practice*, 19(12):1459–1467.
- [Mena-Oreja and Gozalvez, 2018] Mena-Oreja, J. and Gozalvez, J. (2018). On the impact of platooning maneuvers on traffic. In *2018 IEEE International Conference on Vehicular Electronics and Safety (ICVES)*, pages 1–6.
- [Milanés and Shladover, 2014] Milanés, V. and Shladover, S. E. (2014). Modeling cooperative and autonomous adaptive cruise control dynamic responses using experimental data. *Transportation Research Part C: Emerging Technologies*, 48:285–300.
- [Mitsakis et al., 2019] Mitsakis, E., Erdmann, J., Flötteröd, Y.-P., Alms, R., Rondinone, M., Carlier, K., Blokpoel, R., and Boerma, S. (2019). Transaid deliverable 3.1 - modelling, simulation and assessment of vehicle automations and automated vehicles’ driver behaviour in mixed traffic - iteration 2. Technical report, CERTH - HIT (CRT).
- [Montanaro et al., 2019] Montanaro, U., Dixit, S., Fallah, S., Dianati, M., Stevens, A., Oxtoby, D., and Mouzakitis, A. (2019). Towards connected autonomous driving: review of use-cases. *Vehicle System Dynamics*, 57(6):779–814.
- [Monteil et al., 2014] Monteil, J., Billot, R., Sau, J., and El Faouzi, N.-E. (2014). Linear and weakly nonlinear stability analyses of cooperative car-following models. *IEEE Transactions on Intelligent Transportation Systems*, 15(5):2001–2013.
- [Monteil et al., 2019] Monteil, J., Bouroche, M., and Leith, D. J. (2019). $\mathcal{L}_2$ and $\mathcal{L}_\infty$ stability analysis of heterogeneous traffic with application to parameter optimization for the control of automated vehicles. *IEEE Transactions on Control Systems Technology*, 27(3):934–949.
- [Monteil et al., 2016] Monteil, J., Sau, J., and Bouroche, M. (2016). Adaptive PID feedback control for the longitudinal dynamics of driver-assisted vehicles in mixed traffic. In *IEEE International Conference on Intelligent Transportation Systems (ITSC)*, pages 1634–1641.
- [Moridpour et al., 2010] Moridpour, S., Rose, G., and Sarvi, M. (2010). Effect of surrounding traffic characteristics on lane changing behavior. *Journal of Transportation Engineering*, 136(11):973–985.
- [Navas and Milanés, 2019] Navas, F. and Milanés, V. (2019). Mixing V2V and non-V2V-equipped vehicles in car following. *Transportation Research Part C: Emerging Technologies*, 108:167–181.
- [Nowakowski et al., 2015] Nowakowski, C., Shladover, S. E., Lu, X.-Y., Thompson, D., and Kailas, A. (2015). Cooperative adaptive cruise control (CACC) for truck platooning: Operational concept alternatives. Technical report, Institute of Transportation Studies, UC Berkeley.
- [O’Hara et al., 2015] O’Hara, N., Slot, M., Monteil, J., Cahill, V., and Bouroche, M. (2015). Towards evaluating the benefits of inter-vehicle coordination. In *IEEE International Conference on Intelligent Transportation Systems (ITSC)*, pages 2444–2450.
- [Oliveira et al., 2021] Oliveira, R., Montez, C., Boukerche, A., and Wingham, M. S. (2021). Co-design of consensus-based approach and reliable communication protocol for vehicular platoon control. *IEEE Transactions on Vehicular Technology*, 70(9):9510–9524.

- [Paden et al., 2016] Paden, B., Čáp, M., Yong, S. Z., Yershov, D., and Frazzoli, E. (2016). A survey of motion planning and control techniques for self-driving urban vehicles. *IEEE Transactions on Intelligent Vehicles*, 1(1):33–55.
- [Papadoulis et al., 2019] Papadoulis, A., Quddus, M., and Imprialou, M. (2019). Evaluating the safety impact of connected and autonomous vehicles on motorways. *Accident Analysis & Prevention*, 124:12–22.
- [Peters et al., 2014] Peters, A. A., Middleton, R. H., and Mason, O. (2014). Leader tracking in homogeneous vehicle platoons with broadcast delays. *Automatica*, 50(1):64–74.
- [Piórkowski et al., 2008] Piórkowski, M., Raya, M., Lugo, A. L., Papadimitratos, P., Grossglauser, M., and Hubaux, J.-P. (2008). Trans: Realistic joint traffic and network simulator for vanets. *SIGMOBILE Mob. Comput. Commun. Rev.*, 12(1):31–33.
- [Ploeg et al., 2011] Ploeg, J., Scheepers, B. T. M., van Nunen, E., van de Wouw, N., and Nijmeijer, H. (2011). Design and experimental evaluation of cooperative adaptive cruise control. In *IEEE International Conference on Intelligent Transportation Systems (ITSC)*, pages 260–265.
- [Ploeg et al., 2015] Ploeg, J., Semsar-Kazerooni, E., Lijster, G., van de Wouw, N., and Nijmeijer, H. (2015). Graceful degradation of cooperative adaptive cruise control. *IEEE Transactions on Intelligent Transportation Systems*, 16(1):488–497.
- [Ploeg et al., 2012] Ploeg, J., Shladover, S., Nijmeijer, H., and van de Wouw, N. (2012). Introduction to the special issue on the 2011 grand cooperative driving challenge. *IEEE Transactions on Intelligent Transportation Systems*, 13(3):989–993.
- [Qin et al., 2019] Qin, Y.-Y., He, Z.-Y., and Ran, B. (2019). Rear-end crash risk of cacc-manual driven mixed flow considering the degeneration of cacc systems. *IEEE Access*, 7:140421–140429.
- [Rahman et al., 2021] Rahman, M. H., Abdel-Aty, M., and Wu, Y. (2021). A multi-vehicle communication system to assess the safety and mobility of connected and automated vehicles. *Transportation Research Part C: Emerging Technologies*, 124:102887.
- [Rajamani, 2006] Rajamani, R. (2006). *Vehicle Dynamics and Control*. Springer book, 2nd ed. edition.
- [Rajamani et al., 2000] Rajamani, R., Tan, H.-S., Law, B. K., and Zhang, W.-B. (2000). Demonstration of integrated longitudinal and lateral control for the operation of automated vehicles in platoons. *IEEE Transactions on Control Systems Technology*, 8(4):695–708.
- [Razmi Rad et al., 2020] Razmi Rad, S., Farah, H., Taale, H., van Arem, B., and Hoogenboom, S. P. (2020). Design and operation of dedicated lanes for connected and automated vehicles on motorways: A conceptual framework and research agenda. *Transportation Research Part C: Emerging Technologies*, 117:102664.
- [Ruan et al., 2022] Ruan, T., Wang, H., Zhou, L., Zhang, Y., Dong, C., and Zuo, Z. (2022). Impacts of information flow topology on traffic dynamics of cav-mv heterogeneous flow. *IEEE Transactions on Intelligent Transportation Systems*, pages 1–16.

- [Santini et al., 2017] Santini, S., Salvi, A., Valente, A. S., Pescapé, A., Segata, M., and Lo Cigno, R. (2017). A consensus-based approach for platooning with intervehicular communications and its validation in realistic scenarios. *IEEE Transactions on Vehicular Technology*, 66(3):1985–1999.
- [Sarakis et al., 2016] Sarakis, L., Orphanoudakis, T., Leligou, H. C., Voliotis, S., and Voulkidis, A. (2016). Providing entertainment applications in vanet environments. *IEEE Wireless Communications*, 23(1):30–37.
- [Sarker et al., 2020] Sarker, A., Shen, H., Rahman, M., Chowdhury, M., Dey, K., Li, F., Wang, Y., and Narman, H. S. (2020). A review of sensing and communication, human factors, and controller aspects for information-aware connected and automated vehicles. *IEEE Transactions on Intelligent Transportation Systems*, 21(1):7–29.
- [Sawant et al., 2020] Sawant, J., Chaskar, U., and Ginoya, D. (2020). Robust control of cooperative adaptive cruise control in the absence of information about preceding vehicle acceleration. *IEEE Transactions on Intelligent Transportation Systems*.
- [Schrack et al., 2019] Schrank, D., Eisele, B., and Lomax, T. (2019). Urban mobility report. Technical report, The Texas A&M Transportation Institute with cooperation from INRIX.
- [Segata, 2016] Segata, M. (2016). *Safe and Efficient Communication Protocols for Platooning Control*. Phd thesis, University of Innsbruck.
- [Segata et al., 2014] Segata, M., Joerer, S., Bloessl, B., Sommer, C., Dressler, F., and L., C. R. (2014). Plexe: A platooning extension for veins. In *IEEE Vehicular Networking Conference (VNC)*, pages 53–60.
- [Segata et al., 2022] Segata, M., Lo Cigno, R., Hardes, T., Heinovski, J., Schettler, M., Bloessl, B., Sommer, C., and Dressler, F. (2022). Multi-technology cooperative driving: An analysis based on plexe. *IEEE Transactions on Mobile Computing*.
- [Sepulcre et al., 2020] Sepulcre, M., Mira, J., Thandavarayan, G., and Gozalvez, J. (2020). Is packet dropping a suitable congestion control mechanism for vehicular networks? In *2020 IEEE 91st Vehicular Technology Conference (VTC2020-Spring)*.
- [Sharma et al., 2019] Sharma, A., Zheng, Z., Bhaskar, A., and Haque, M. M. (2019). Modelling car-following behaviour of connected vehicles with a focus on driver compliance. *Transportation Research Part B: Methodological*, 126:256–279.
- [Sharma et al., 2021a] Sharma, A., Zheng, Z., Kim, J., Bhaskar, A., and Mazharul Haque, M. (2021a). Assessing traffic disturbance, efficiency, and safety of the mixed traffic flow of connected vehicles and traditional vehicles by considering human factors. *Transportation Research Part C: Emerging Technologies*, 124:102934.
- [Sharma et al., 2021b] Sharma, S., Al-Khannaq, E., Riebl, R., Schakel, W., Knoppers, P., Verbraeck, A., and van Lint, H. (2021b). Impact of radio channel characteristics on the longitudinal behavior of truck platoons in critical car-following situations. In *Conference on Networked Systems (NetSys)*.
- [Shet and Yao, 2021] Shet, R. A. and Yao, S. (2021). Cooperative driving in mixed traffic: An infrastructure-assisted approach. *IEEE Open Journal of Intelligent Transportation Systems*, 2:429–447.

- [Shi et al., 2023] Shi, H., Chen, D., Zheng, N., Wang, X., Zhou, Y., and Ran, B. (2023). A deep reinforcement learning based distributed control strategy for connected automated vehicles in mixed traffic platoon. *Transportation Research Part C: Emerging Technologies*, 148:104019.
- [Shi et al., 2021] Shi, H., Zhou, Y., Wu, K., Wang, X., Lin, Y., and Ran, B. (2021). Connected automated vehicle cooperative control with a deep reinforcement learning approach in a mixed traffic environment. *Transportation Research Part C: Emerging Technologies*, 133:103421.
- [Shladover et al., 2012] Shladover, S. E., Su, D., and Lu, X.-Y. (2012). Impacts of cooperative adaptive cruise control on freeway traffic flow. *Transportation Research Record*, 2324(1):63–70.
- [Siegel et al., 2018] Siegel, J. E., Erb, D. C., and Sarma, S. E. (2018). A survey of the connected vehicle landscape—architectures, enabling technologies, applications, and development areas. *IEEE Transactions on Intelligent Transportation Systems*, 19(8):2391–2406.
- [Singh et al., 2019] Singh, P. K., Nandi, S. K., and Nandi, S. (2019). A tutorial survey on vehicular communication state of the art, and future research directions. *Vehicular Communications*, 18:100164.
- [Sun et al., 2018] Sun, J., Zheng, Z., and Sun, J. (2018). Stability analysis methods and their applicability to car-following models in conventional and connected environments. *Transportation Research Part B: Methodological*, 109:212–237.
- [Sybis et al., 2019] Sybis, M., Vukadinovic, V., Rodziewicz, M., Sroka, P., Langowski, A., Lenarska, K., and Wesołowski, K. (2019). Communication aspects of a modified cooperative adaptive cruise control algorithm. *IEEE Transactions on Intelligent Transportation Systems*, 20(12):4513–4523.
- [Talebpour and Mahmassani, 2016] Talebpour, A. and Mahmassani, H. S. (2016). Influence of connected and autonomous vehicles on traffic flow stability and throughput. *Transportation Research Part C: Emerging Technologies*, 71:143–163.
- [Tian et al., 2021] Tian, B., Wang, G., Xu, Z., Zhang, Y., and Zhao, X. (2021). Communication delay compensation for string stability of cacc system using lstm prediction. *Vehicular Communications*, 29:100333.
- [Tian et al., 2018] Tian, D., Wu, G., Boriboonsomsin, K., and Barth, M. J. (2018). Performance measurement evaluation framework and co-benefittradeoff analysis for connected and automated vehicles (CAV) applications: A survey. *IEEE Intelligent Transportation Systems Magazine*, 10(3):110–122.
- [Treiber et al., 2006] Treiber, M., Kesting, A., and Helbing, D. (2006). Delays, inaccuracies and anticipation in microscopic traffic models. *Physica A: Statistical Mechanics and its Applications*, 360(1):71–88.
- [Tu et al., 2019] Tu, Y., Wang, W., Li, Y., Xu, C., Xu, T., and Li, X. (2019). Longitudinal safety impacts of cooperative adaptive cruise control vehicle’s degradation. *Journal of Safety Research*, 69:177–192.

- [van Nunen et al., 2019] van Nunen, E., Reinders, J., Semsar-Kazerooni, E., and van de Wouw, N. (2019). String stable model predictive cooperative adaptive cruise control for heterogeneous platoons. *IEEE Transactions on Intelligent Vehicles*, 4(2):186–196.
- [Viittala et al., 2013] Viittala, H., Soderi, S., Saloranta, J., Hämäläinen, M., and Iinatti, J. (2013). An experimental evaluation of wifi-based vehicle-to-vehicle (V2V) communication in a tunnel. In *IEEE Vehicular Technology Conference*.
- [Wang et al., 2020a] Wang, C., Gong, S., Zhou, A., Li, T., and Peeta, S. (2020a). Cooperative adaptive cruise control for connected autonomous vehicles by factoring communication-related constraints. *Transportation Research Part C: Emerging Technologies*, 113:124–145.
- [Wang et al., 2019a] Wang, H., Qin, Y., Wang, W., and Chen, J. (2019a). Stability of CACC-manual heterogeneous vehicular flow with partial CACC performance degrading. *Transportmetrica B: Transport Dynamics*, 7(1):788–813.
- [Wang et al., 2023a] Wang, H. M., Avedisov, S. S., Altintas, O., and Orosz, G. (2023a). Multi-vehicle conflict management with status and intent sharing under time delays. *IEEE Transactions on Intelligent Vehicles*, 8(2):1624–1637.
- [Wang et al., 2019b] Wang, J., Liu, J., and Kato, N. (2019b). Networking and communications in autonomous driving: A survey. *IEEE Communications Surveys Tutorials*, 21(2):1243–1274.
- [Wang et al., 2021] Wang, J., Zheng, Y., Chen, C., Xu, Q., and Li, K. (2021). Leading cruise control in mixed traffic flow: System modeling, controllability, and string stability. *IEEE Transactions on Intelligent Transportation Systems (Early Access)*.
- [Wang et al., 2020b] Wang, Z., Bian, Y., Shladover, S. E., Wu, G., Li, S. E., and Barth, M. J. (2020b). A survey on cooperative longitudinal motion control of multiple connected and automated vehicles. *IEEE Intelligent Transportation Systems Magazine*, 12(1):4–24.
- [Wang et al., 2023b] Wang, Z., Gao, Y., Fang, C., Liu, L., Zeng, D., and Dong, M. (2023b). State-estimation-based control strategy design for connected cruise control with delays. *IEEE Systems Journal*, 17(1):99–110.
- [Wang et al., 2019c] Wang, Z., Shi, X., and Li, X. (2019c). Review of lane-changing maneuvers of connected and automated vehicles: Models, algorithms and traffic impact analyses. *Journal of the Indian Institute of Science*, 99:589–599.
- [Wang et al., 2018] Wang, Z., Wu, G., and Barth, M. J. (2018). A review on cooperative adaptive cruise control (CACC) systems: Architectures, controls, and applications. In *IEEE International Conference on Intelligent Transportation Systems (ITSC)*, pages 2884–2891.
- [World Health Organization, 2018] World Health Organization (2018). Global status report on road safety.
- [Wu et al., 2020] Wu, C., Xu, Z., Liu, Y., Fu, C., Li, K., and Hu, M. (2020). Spacing policies for adaptive cruise control: A survey. *IEEE Access*, 8:50149–50162.
- [Xiao and Gao, 2010] Xiao, L. and Gao, F. (2010). A comprehensive review of the development of adaptive cruise control systems. *Vehicle System Dynamics*, 48:1167–1192.

- [Xiao et al., 2017] Xiao, L., Wang, M., and Aram, B. (2017). Realistic car-following models for microscopic simulation of adaptive and cooperative adaptive cruise control vehicles. *Transportation Research Record Journal of the Transportation Research Board*, 2623.
- [XIAO, 2020] XIAO, W. (2020). Safety evaluation of heterogeneous traffic: Experiments using different models in sumo. M.s. thesis, Dept. OF Mechanics and Maritime Sci., Div. of Veh. Safety, Chalmers University of Technology, Gothenburg, Sweden.
- [Xie et al., 2023] Xie, S., Hu, J., Ding, Z., and Arvin, F. (2023). Cooperative adaptive cruise control for connected autonomous vehicles using spring damping energy model. *IEEE Transactions on Vehicular Technology*, 72(3):2974–2987.
- [Xing et al., 2020] Xing, H., Ploeg, J., and Nijmeijer, H. (2020). Compensation of communication delays in a cooperative ACC system. *IEEE Transactions on Vehicular Technology*, 69(2):1177–1189.
- [Xu and Peng, 2020] Xu, S. and Peng, H. (2020). Design, analysis, and experiments of preview path tracking control for autonomous vehicles. *IEEE Transactions on Intelligent Transportation Systems*, 21(1):48–58.
- [Yang et al., 2019] Yang, D., Kuijpers, A., Dane, G., and van der Sande, T. (2019). Impacts of large-scale truck platooning on dutch highways. *Transportation Research Procedia*, 37:425–432.
- [Yao et al., 2020] Yao, Z., Hu, R., Jiang, Y., and Xu, T. (2020). Stability and safety evaluation of mixed traffic flow with connected automated vehicles on expressways. *Journal of Safety Research*, 75:262–274.
- [Yao et al., 2023] Yao, Z., Wu, Y., Wang, Y., Zhao, B., and Jiang, Y. (2023). Analysis of the impact of maximum platoon size of cavs on mixed traffic flow: An analytical and simulation method. *Transportation Research Part C: Emerging Technologies*, 147:103989.
- [Ye and Yamamoto, 2019] Ye, L. and Yamamoto, T. (2019). Evaluating the impact of connected and autonomous vehicles on traffic safety. *Physica A: Statistical Mechanics and its Applications*, 526:121009.
- [Ying and Feng, 2024] Ying, J. and Feng, Y. (2024). Infrastructure-assisted cooperative driving and intersection management in mixed traffic conditions. *Transportation Research Part C: Emerging Technologies*, 158:104443.
- [Yu et al., 2023] Yu, W., Hua, X., Ngoduy, D., and Wang, W. (2023). On the assessment of the dynamic platoon and information flow topology on mixed traffic flow under connected environment. *Transportation Research Part C: Emerging Technologies*, 154:104265.
- [Zeng et al., 2019] Zeng, T., Semari, O., Saad, W., and Bennis, M. (2019). Joint communication and control for wireless autonomous vehicular platoon systems. *IEEE Transactions on Communications*, 67(11):7907–7922.
- [Zhang et al., 2021] Zhang, J., Xu, K., Li, G., Li, S., and Wang, T. (2021). Dynamics of traffic flow affected by the future motion of multiple preceding vehicles under vehicle-connected environment: Modeling and stabilization. *Physica A: Statistical Mechanics and its Applications*, 565:125538.

- [Zhang, 2018] Zhang, L. (2018). Cooperative adaptive cruise control in mixed traffic with selective use of vehicle-to-vehicle communication. *IET Intelligent Transport Systems*, 12(10):1243–1254.
- [Zhang and Orosz, 2016] Zhang, L. and Orosz, G. (2016). Motif-based design for connected vehicle systems in presence of heterogeneous connectivity structures and time delays. *IEEE Transactions on Intelligent Transportation Systems*, 17(6):1638–1651.
- [Zhang et al., 2018] Zhang, L., Sun, J., and Orosz, G. (2018). Hierarchical design of connected cruise control in the presence of information delays and uncertain vehicle dynamics. *IEEE Transactions on Control Systems Technology*, 26(1):139–150.
- [Zhang et al., 2020] Zhang, Y., Bai, Y., Hu, J., and Wang, M. (2020). Control design, stability analysis, and traffic flow implications for cooperative adaptive cruise control systems with compensation of communication delay. *Transportation Research Record*, 2674(8):638–652.
- [Zhao et al., 2021] Zhao, C., Cai, L., and Cheng, P. (2021). Stability analysis of vehicle platooning with limited communication range and random packet losses. *IEEE Internet of Things Journal*, 8(1):262–277.
- [Zheng et al., 2016] Zheng, Y., Eben Li, S., Wang, J., Cao, D., and Li, K. (2016). Stability and scalability of homogeneous vehicular platoon: Study on the influence of information flow topologies. *IEEE Transactions on Intelligent Transportation Systems*, 17(1):14–26.
- [Zheng et al., 2018] Zheng, Y., Li, S. E., Li, K., and Ren, W. (2018). Platooning of connected vehicles with undirected topologies: Robustness analysis and distributed h-infinity controller synthesis. *IEEE Transactions on Intelligent Transportation Systems*, 19(5):1353–1364.
- [Zheng, 2014] Zheng, Z. (2014). Recent developments and research needs in modeling lane changing. *Transportation Research Part B: Methodological*, 60:16–32.
- [Zhong et al., 2020] Zhong, Z., Lee, E. E., Nejad, M., and Lee, J. (2020). Influence of CAV clustering strategies on mixed traffic flow characteristics: An analysis of vehicle trajectory data. *Transportation Research Part C: Emerging Technologies*, 115:102611.
- [Zhong and Lee, 2019] Zhong, Z. and Lee, J. (2019). The effectiveness of managed lane strategies for the near-term deployment of cooperative adaptive cruise control. *Transportation Research Part A: Policy and Practice*, 129:257–270.
- [Zhou et al., 2023] Zhou, A., Peeta, S., and Wang, J. (2023). Cooperative control of a platoon of connected autonomous vehicles and unconnected human-driven vehicles. *Computer-Aided Civil and Infrastructure Engineering*.
- [Zhu et al., 2019] Zhu, Y., Zhao, D., and Zhong, Z. (2019). Adaptive optimal control of heterogeneous CACC system with uncertain dynamics. *IEEE Transactions on Control Systems Technology*, 27(4):1772–1779.