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The Hierarchical Control Method for Coordinating a Group of Connected Vehicles on Urban Roads

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THE HIERARCHICAL CONTROL METHOD FOR COORDINATING A GROUP OF
CONNECTED VEHICLES ON URBAN ROADS

A Dissertation
Presented to
the Graduate School of
Clemson University

In Partial Fulfillment
of the Requirements for the Degree
Doctor of Philosophy
Automotive Engineering

by
Zhiyuan Du
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ABSTRACT

Safety, mobility and environmental impact are the three major challenges in today's transportation system. As the advances in wireless communication and vehicle automation technologies, they have rapidly led to the emergence and development of connected and automated vehicles (CAVs). We can expect fully CAVs by 2030. The CAV technologies offer another solution for the issues we are dealing with in the current transportation system.

In the meanwhile, urban roads are one of the most important part in the transportation network. Urban roads are characterized by multiple interconnected intersections. They are more complicated than highway traffic, because the vehicles on the urban roads are moving in multiple directions with higher relative velocity. Most of the traffic accidents happened at intersections and the intersections are the major contribution to the traffic congestions. Our urban road infrastructures are also becoming more intelligent. Sensor-embedded roadways are continuously gathering traffic data from passing vehicles.

Our smart vehicles are meeting intelligent roads. However, we have not taken the fully advantages of the data rich traffic environment provided by the connected vehicle technologies and intelligent road infrastructures.

The objective of this research is to develop a coordination control strategy for a group of connected vehicles under intelligent traffic environment, which can guide the vehicles passing through the intersections and make smart lane change decisions with the

objective of improving overall fuel economy and traffic mobility. The coordination control strategy should also be robust to imperfect connectivity conditions with various connected vehicle penetration rate.

This dissertation proposes a hierarchical control method to coordinate a group of connected vehicles travelling on urban roads with intersections. The dissertation includes four parts of the application of our proposed method: First, we focus on the coordination of the connected vehicles on the multiple interconnected unsignalized intersection roads, where the traffic signals are removed and the collision avoidance at the intersection area relies on the communication and cooperation of the connected vehicles and intersection controllers. Second, a fuel efficient hierarchical control method is proposed to control the connected vehicles travel on the signalized intersection roads. With the signal phase and timing (SPAT) information, our proposed approach is able to help the connected vehicles minimize red light idling and improve the fuel economy at the same time. Third, the research is extended from single lane to multiple lane, where the connected vehicle discretionary and cooperative mandatory lane change have been explored. Finally, we have analysed the real-world implementation potential of our proposed algorithm including the communication delay and real-time implementation analysis.

DEDICATION

I dedicate this achievement to my family.

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TABLE OF CONTENTS

	Page
TITLE PAGE	i
ABSTRACT	ii
DEDICATION	iv
ACKNOWLEDGMENTS	v
LIST OF TABLES	ix
LIST OF FIGURES	x
CHAPTER 1 INTRODUCTION	1
1.1 Connected and Automated Vehicles	1
1.2 Urban Roads	3
1.3 Research Questions and Research Objective	3
1.4 General Introduction of Hierarchical Control Architecture	4
1.5 Novelty and Contribution	6
CHAPTER 2 LONGITUDINAL MOTION COORDINATION	19
2.1 Unsignalized Traffic Intersection	19
2.1.1 Introduction	19
2.1.2 Literature Review	20
2.1.3 Research Gap	23
2.1.4 Approach	25

Table of Contents (continued)	Page
2.1.5 Simulation Results	36
2.1.6 Conclusion	50
2.1.7 Related Publication	51
2.2 Signalized Traffic Intersection	53
2.2.1 Introduction.....	53
2.2.2 Literature Review.....	54
2.2.3 Approach.....	56
2.2.4 Simulation Results	63
2.2.5 Conclusion	73
2.2.6 Related Publication	73
2.3 Connected Vehicle Penetration Rate Study	74
2.3.1 Introduction.....	74
2.3.2 Modified Gipps Car Following Model	75
2.3.3 Simulation Results	77
2.3.4 Conclusion	85
2.3.5 Related Publication	85
CHAPTER 3 LANE CHANGE DECISION	87
3.1 Introduction on Lane Change Decision (LCD)	87
3.2 Literature Reviews	88
3.3 Discretionary Lane Change Decision.....	89
3.3.1 Problem Formulation	89
3.3.2 Approach.....	94

Table of Contents (continued)	Page
3.3.3 Simulation Results	100
3.3.4 Conclusion	107
3.3.5 Related Publication	108
3.4 Mandatory Lane Change Decision.....	109
3.4.1 Problem Formulation	109
3.4.2 Mandatory Lane Change Algorithm	112
3.4.3 Simulation Results	115
3.4.4 Conclusion	124
3.4.5 Related Publication	125
CHAPTER 4 REAL-WORLD IMPLEMENTATION ANALYSIS	126
4.1 Communication Delay	126
4.1.1 Introduction.....	126
4.1.2 Approach.....	127
4.1.3 Simulation Results	131
4.1.4 Conclusion	135
4.1.5 Related Publication	135
4.2 Real-time Implementation Potential	136
CHAPTER 5 CONCLUSIONS AND FUTURE WORK	139
4.1 Conclusions.....	139
4.2 Future Work	141
LIST OF PUBLICATIONS	144
REFERENCE.....	146

LIST OF TABLES

Table	Page
Table 2.1 Fuel economy and mobility comparison of small scale scenario	44
Table 2.2 Fuel economy and mobility comparison of larger scale scenario.....	48
Table 2.3 Parameters and components of the vehicles	64
Table 2.4 Summary of fuel economy comparison	65
Table 2.5 Summary of average fuel economy of different feedback windows	69
Table 2.6 Summary of fuel economy (MPG) evaluation I	79
Table 2.7 Summary of fuel economy (MPG) Evaluation II	83
Table 3.1 Fuel economy and mobility comparison in the homogeneous scenario	103
Table 3.2 Fuel economy and mobility comparison in the heterogeneous scenario	106
Table 3.3 Summary of vehicle fuel consumption (MPG) and lane change duration.....	123
Table 4.1 Summary of average fuel economy on delay estimation and compensation study	134

LIST OF FIGURES

Figure	Page
Figure 1.1 Connected and automated vehicle technology road map [8].....	2
Figure 1.2 Idealized Hierarchical Control Architecture	5
Figure 2.1 Illustration of the disadvantages of current isolated intersection coordination approaches.....	25
Figure 2.2 The schematic of the longitudinal coordination on traffic lightless intersections	26
Figure 2.3 The hierarchical control architecture of the longitudinal coordination on traffic lightless intersections	27
Figure 2.4 Greenshield model and modified traffic flow model	27
Figure 2.5 Illustration of the notations in Equation (2.3)	32
Figure 2.6 Schematic of the initial simulation setup	37
Figure 2.7 All initial vehicle trajectories on x-direction roads (road 1, road 4 and road 7)	38
Figure 2.8 All initial vehicle trajectories on y-direction roads (road 2 and road 3) of intersection 1	39
Figure 2.9 All initial vehicle trajectories on y-direction roads (road 5 and road 6) of intersection 2	39
Figure 2.10 Relative distance to the intersection of vehicles from road 1 and road 2 of intersection 1 in small scale scenario.....	40

List of Figures (continued)	Page
Figure 2.11 Relative distance to the intersection of vehicles from road 4 and road 5 of intersection 2 in small scale scenario.....	40
Figure 2.12 Randomly selected vehicle velocity tracking performance.....	41
Figure 2.13 (a) Relative distance to the intersection of vehicles form road 1 and road 2 of intersection 1 in larger scale scenario (b) Partial zooming in on intersection area.....	46
Figure 2.14 (a) Relative distance to the intersection of vehicles form road 4 and road 5 of intersection 2 in larger scale scenario (b) Partial zooming in on intersection area.....	47
Figure 2.15 Effects of vehicle type on intersection passing sequence: (a) two vehicles with the same weighting factor (b) two vehicles with different weighting factors	50
Figure 2.16 The schematic of the traffic light intersection problem.....	54
Figure 2.17 Hierarchical control architecture of traffic light intersection problem.....	57
Figure 2.18 Schematic of the target velocity and velocity range lower bound evaluation	58
Figure 2.19 All vehicle trajectories of tr30-tg10 no efficiency feedback (the red dash lines indicate traffic lights).....	65
Figure 2.20 All vehicle trajectories of tr30-tg10 in Gipps car following	66
Figure 2.21 All vehicle trajectories of tr40-tg15 no efficiency feedback (the red dash lines indicate traffic lights).....	66
Figure 2.22 All vehicle trajectories of tr40-tg15 in Gipps car following	67
Figure 2.23 All vehicle velocity profiles of tr30-tg10 no efficiency feedback.....	67
Figure 2.24 All vehicle velocity profiles of tr40-tg15 no efficiency feedback.....	68
Figure 2.25 Average fuel economy of tr30-tg10	70
Figure 2.26 Average fuel economy of tr40-tg15	70

List of Figures (continued)	Page
Figure 2.27 Vehicle No.1 in different feedback time windows of tr30-tg10 case: (a) velocity profiles (b) SOC data	71
Figure 2.28 Vehicle No.7 in different feedback time windows of tr30-tg10 case: (a) velocity profiles (b) SOC data	71
Figure 2.29 Vehicle No.1 in different feedback time windows of tr40-tg15 case: (a) velocity profiles (b) SOC data	72
Figure 2.30 Vehicle No.7 in different feedback time windows of tr40-tg15 case: (a) velocity profiles (b) SOC data	72
Figure 2.31 Schematic of the connected and unconnected vehicles mixed scenario.....	75
Figure 2.32 Vehicle trajectories of all connected vehicle scenario	78
Figure 2.33 Vehicle trajectories of all unconnected vehicle scenario	78
Figure 2.34 Vehicle trajectories when vehicle # 2, 3, 4, and 9 are unconnected.....	80
Figure 2.35 Vehicle trajectories when only vehicle # 4 is unconnected.....	81
Figure 2.36 Vehicle trajectories when only vehicle # 1 is unconnected.....	81
Figure 2.37 Vehicle trajectories when only vehicle # 1 is connected.....	82
Figure 3.1 The schematic of the discretionary lane change problem	91
Figure 3.2 Schematic of the hierarchical control architecture in the discretionary LCD research	91
Figure 3.3 Schematic of the vehicles' relative positions and notations.....	92
Figure 3.4 Reconstructed schematic of the control architecture for discretionary lane change study.....	95

List of Figures (continued)	Page
Figure 3.5 All vehicles' positions when lane changes happen in homogeneous scenario	103
Figure 3.6 All vehicles' positions when lane changes happen under heterogeneous scenario and unconnected vehicles do not change lane	105
Figure 3.7 Schematic of the mandatory lane change problem.....	110
Figure 3.8 Schematic of the proposed hierarchical control architecture for the mandatory lane change.....	111
Figure 3.9 Schematic of the proposed cooperative mandatory lane change algorithm ..	113
Figure 3.10 Initial positions of all the vehicles at $t=0s$ in mandatory lane change study	117
Figure 3.11 All vehicle trajectories on lane 0 without mandatory lane change.....	117
Figure 3.12 All vehicle trajectories on lane 1 without mandatory lane change.....	118
Figure 3.13 Vehicle positions when the mandatory lane change algorithm is about to start ($t=19s$).....	119
Figure 3.14 Vehicle positions when the proposed algorithm ends and the host vehicle is changing the lane ($t=25.5s$).....	119
Figure 3.15 Vehicles positions when the baseline algorithm ends and the host vehicle is change the lane ($t=29.5s$)	120
Figure 3.16 Trajectories of vehicle 2, 3 and 4 under the baseline mandatory lane change algorithm	121
Figure 3.17 (a) Trajectories of vehicle 2, 3 and 4 under the proposed mandatory lane change algorithm (b) Partially zoomed-in plot	122
Figure 4.1 Schematic of the communication delay problem	127

List of Figures (continued)	Page
Figure 4.2 The random delay in the communication network and estimation errors	131
Figure 4.3 All vehicle trajectories in the simulation scenario with ideal communication network (no delay)	132
Figure 4.4 All vehicle trajectories in the simulation scenario with random delay without compensation	133
Figure 4.5 All vehicle trajectories in the simulation scenario with random delay and compensation	133
Figure 4.6 Real-time simulation environment	137
Figure 5.1 Schematic of future experimental validation plan.....	143

CHAPTER 1 INTRODUCTION

There are three aspects of challenges we are facing in today's transportation system: safety, mobility and environmental impact of the vehicles. They are causing significant economic impact, deaths of civilians and waste of natural resources. Millions of crashes happening every year ends up with tens of thousands of deaths [1], which makes safety one of the most critical topics in the transportation system. For example, there were 5.6 million crashes and 32,675 highway deaths in 2014 [2]. Mobility and environment aspects are correlated. The vehicle ownership keeps on growing, especially in the developing countries [3]. At the same time, the vehicle miles traveled has increased annually by an average of 1.7% since 1990 [4]. The widespread use of vehicles makes traffic congestion a growing issue in many metropolitan areas [5]. The cost of traffic congestion in U.S. resulted in 6.9 billion extra hours of travel time for the drivers and \$121 billion economic loss [6]. The environment is also affected. 3.1 billion pounds of additional CO₂ released to the air due to the vehicles stuck and idling on the congested roads [7].

1.1 Connected and Automated Vehicles

The advances in wireless communication and vehicle automation technologies are making the transportation system more intelligent. These technologies have rapidly led to the emergence and development of connected and automated vehicles (CAVs). We can expect full CAVs in the very near future [8].

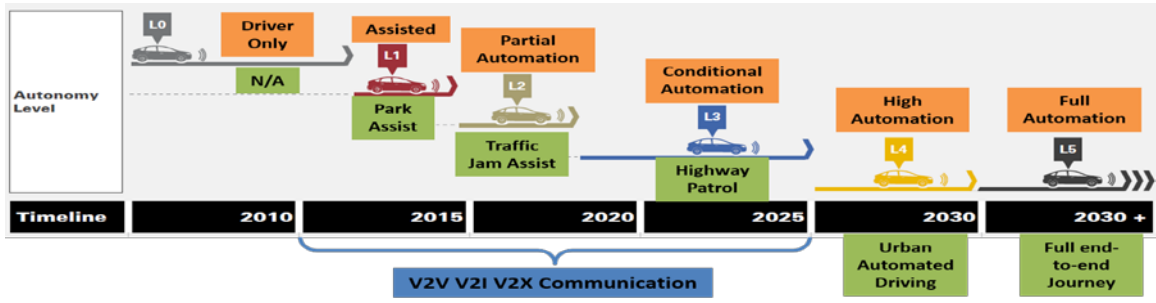


Figure 1.1 Connected and automated vehicle technology road map [8]

According to the U.S. Department of Transportation’s National Highway Safety Administration (NHTSA), the vehicle automation has been defined as five levels [9]. Figure 1.1 shows the connected and automated vehicle technology road map. In this way, Levels 1, 2 and 3 need different level of constant human input and monitoring of the driving environment. Connectivity is available at this stage, including V2V (Vehicle-to-vehicle) and V2I (Vehicle-to-infrastructure). Levels 4 and 5 are the ones corresponding to a fully automated driving mode without requiring any driver intervention.

The CAV technologies offer us another potential solution to the three issues we are dealing with in the current transportation system. In the safety aspect, according to U.S. Department of Transportation (DOT), combined V2V and V2I technology can address about 80% of all vehicle targeted crashes by increasing situational awareness and provide driver warnings or advisories [10]. For mobility and environmental impact of the vehicles, the CAV technologies can maximize transportation system efficiency and minimize traffic congestion by providing real-time traffic data to enable making smart routing choices that reduces travel delay. Also, it can give motorists the real-time information to make “green” transportation choices [11]. In such ways, the mobility of

the traffic system can be improved which also improves the environmental aspect because of the reduction of unnecessary idling time of the vehicles on the roads.

1.2 Urban Roads

Urban roads are one of the most important parts of the transportation system. They are characterized by multiple interconnected intersections where vehicles are moving in different directions with high relative velocity, so the traffic on urban roads is more complex than highway traffic [12]. It has been noted that intersections are major barrier of urban traffic safety and mobility. About 50% of urban crashes and 30% of rural crashes take place at the intersections [13]. Intersections only make up a small portion of transportation system, but they are the major contribution to urban traffic congestion [14].

In the meanwhile, our urban roads infrastructures are also becoming more intelligent. It has been estimated by American Association of State Highway and Transportation Officials (AASHTO) that up to 80% intersections will be V2I-enabled by 2040 [15]. That means the sensor-embedded roadways are able to continuously gather data from passing vehicles [16]. Our smart vehicles are meeting the intelligent roads.

1.3 Research Questions and Research Objective

As we discussed before, the advances in connected vehicle technologies and intelligent road infrastructure are offering us data rich traffic environment. How can we utilize the advantage to improve our transportation system in the sense of fuel economy and traffic mobility? It brings us series of research questions.

- How to control a group of connected vehicles travelling on urban roads, passing through intersections safely and improving fuel economy as well as traffic mobility at the same time.
- How to deal with imperfect connectivity environment with various connected vehicle penetration rate.
- How to make lane change decisions to gain its own benefits with minimum negative impacts on the others.

To answer these questions, the objective of this research is to develop a coordination control strategy for a group of connected vehicles under intelligent traffic environment, which can guide the vehicles passing through the intersections and make smart lane change decisions, with the objective of improving overall fuel economy, traffic mobility and robust to various connected vehicle penetration rate.

1.4 General Introduction of Hierarchical Control Architecture

A Hierarchical control Architecture is a form of control system in which a set of devices and governing software is arranged in hierarchical tree [17]. Figure 1.2 shows an idealized hierarchical control architecture. The unlabeled rectangles represent layers, and the double lines represent information flow. The dotted lines show how the output at one time is the input for the next time. Typically, there are three types of inputs to each layer at each time: previous state, low-level percepts and high-level commands. There are also three types of outputs: next state value, low-level commands and high-level percepts [18].

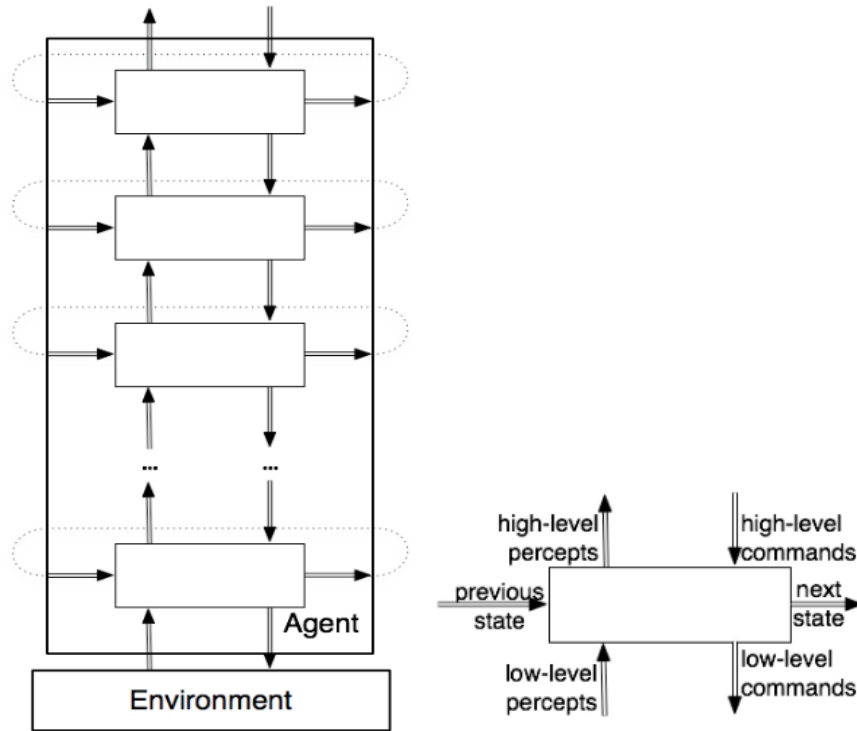


Figure 1.2 Idealized Hierarchical Control Architecture

The idea of hierarchical control architecture is the attempt to partition complex problems by decomposing them into smaller, more manageable subproblems. In such a way, each layer of the subproblems would have lighter computational burden. In this architecture, the subsystems need to interact or combined together to achieve a single task. The hierarchical control architecture is a common control structure to achieve real-time control in the application of manufacturing, robotics and vehicles [19] [20] [21].

Since the scope of this research is controlling a group of connected vehicles on urban roads with multiple interconnected intersections, the system we are dealing with is a large scale and spatially widely arranged system. Also, the vehicles come and leave the control region very frequently. To reduce communication and computation burden and

realize real-time control implementation, it is very appropriate to apply hierarchical control architecture in our problem. More details about the hierarchical control architecture will be further discussed later in the next chapters of this manuscript.

1.5 Novelty and Contribution

The world's first electric traffic signal emerged in about a century ago [22]. Before that, in the earliest days of the automobile, navigating on the America's roads was a chaotic experience with pedestrians, bicycles and horses all competing with motor vehicle for right of way. The situation was alleviated as the development of traffic signals and rules. The mature traffic rules and well-designed traffic signals regulate the vehicles travelling safely on the roads in nowadays.

The emergence of the connected and automated vehicle (CAV) technologies can potentially address the traffic safety, mobility and environment impact, which are the major challenges in today's transportation system [10]. The major automotive OEMs and some technology companies have been focusing on the development of the autonomous vehicles or self-driving cars recently. The target is to enable the vehicle make their own motion planning and decisions, while travelling on the roads, based on the data from the environment captured by the perception system (LIDAR, camera, etc.) [23]. Google's autonomous vehicles have logged nearly 2 million miles of testing and are racking up to 10,000 miles a week learning to drive on public roads [24]. As the efforts from various stakeholders, the CAV technology is expected to become matured and affordable to the public in the near future. It is expected that by 2035, 18 million partially autonomous vehicles could be sold per year globally, which captures 25% of the new car market [25].

However, in the future when most of the vehicles on the roads are CAVs, if they make decisions based only on their own interest and compete the right of way with the others and even with the normal vehicles (non-automated), we will suffer the traffic chaos similar to what we have already experienced about a century ago when the number of automobiles on the roads started growing. The coordination strategies are necessary like today's traffic rules and signals to regulate the CAVs' motion as a group on public road and pursue common objective (e.g., fuel economy, mobility).

In this dissertation work, we focus on the scenario that most of the vehicles involved are CAVs. The control method for coordinating a group of CAVs travelling on urban roads with multiple interconnected intersections has been developed to improve overall vehicle fuel economy and traffic mobility with the focus of individual vehicle trajectory planning. The hierarchical control architecture has been applied in the design of the control method to enable the cooperation among CAVs and intersection controllers. The advantage of the hierarchical control architecture is that it allows to partition complex problems into smaller, more manageable subproblems to enable real-time implementation. Another advantage is that different scope of the problem can be addressed in different layer. For example, in our research, the macroscopic level of traffic density balance can be addressed in the higher-level layer, while the microscopic of the vehicle motion control evaluation can be solved in another vehicle local level layer. Different layers interact and combined to achieve a single task.

The dissertation focuses on two types of intersections: unsignalized and signalized intersection roads. The followings provide brief literature review and motivation of our work in the dissertation. For more details, please refer to the corresponding chapters.

In the first part, we have developed the longitudinal control strategy for a group of CAVs travelling on multiple interconnected unsignalized intersections. A lot of research has focused on the coordination of vehicles at intersections using CAV technologies to avoid vehicle collisions. The coordination approaches at isolated intersection can be categorized as heuristic approaches, reservation-based approaches and optimization-based approaches.

In heuristic approaches, fuzzy logic is a widely used technique. It allows the actions and decisions to be described as simple rules, which is well suited in the complex transportation problems. Milanese *et al.* [26] first presented an intersection detection system with the capability of detecting the position and intention of other cars in its vicinity. The authors then used fuzzy controller to control the throttle and braking of the CAVs based on the distance and speed information. The real-world experiment between one manually driven and the other fully automated vehicles was also provided in [26]. This work was further extended by involving genetic algorithm to tune fuzzy controller parameters [27]. Other heuristic approaches include Wu *et al.* [28] where authors formulated the problem as a mutual exclusion problem. The vehicles could compete for the privilege of passing an intersection. Hafner *et al.* [29] [30] treated the collision avoidance as the problem of keeping the system state always outside the capture set, which is the set where collision is unavoidable given the vehicle dynamics and control

effort's limitations. In general, heuristic approaches only focus on collision avoidance at the intersection and do not consider fuel economy, traffic mobility or environmental impact. Most of the heuristic approaches are decentralized in nature, which means the vehicle local controller only makes the decisions for this corresponding vehicle.

The general idea of reservation-based approaches is that the intersection controller coordinates the time-space reservation based on the request from the vehicles. Dresner and Stone [31] proposed a multi-agent system where each vehicle acts as a driver agent and is responsible for sending the information of its vehicle size, predicted arrival time and velocity to the intersection manager. The intersection manager based on the request and information to coordinate a space-time reservation on the intersection. It will simulate the vehicle's trajectory through the intersection, and check for the conflicts with the previous reservations. In the end, the intersection manager will grant or reject the request and send it back to the driver agent. Fortelle [32] further extended this work by discretizing the intersection into critical points. In doing so, it allowed lower rate of vehicles pass an intersection than the cell-based reservation, but it improved the system scalability and reduced the computational burden. Platoon-based reservation extension can be found in [33]. The disadvantages of the reservation-based approaches are that they don't focus on fuel economy and sometimes the system will suffer from heavy communication requirement because one vehicle may be required to communicate several times until the request is approved. The reservation-based approaches are typical centralized in nature. The intersection manager acts as a centralized controller and makes all the decisions for all the CAVs within the control region.

Since the aforementioned two approaches do not focus on fuel economy or system mobility, researchers came up with optimization-based approach. Lee and Park [34] proposed an algorithm with the objective of minimizing the total overlapped vehicle trajectory length projected in the intersection zone. In doing so, only a limited number of vehicles were inside an intersection at each time instance to avoid collisions. The simulation results in [34] showed significant reduction of total stop and delay time compared to the conventional intersection control mechanisms. Other optimization based approaches aim at minimizing the total travel time. Jin et al. [35] proposed a two-lane intersection scenario which allowed only one vehicle on the intersection at each instance of time. With the information of approaching time of the vehicles, the optimal scheduled departure time of the vehicles was evaluated in [35], while the vehicles chose its appropriate trajectory to follow its prescribed departure time. Yan et al. [36] proposed a more complex scenario with multiple lanes including turning lanes. The CAVs on different lanes were first categorized into different vehicle classes based on their compatibility of coexistence at the intersection area and dynamic programming was used to determine vehicle class passing sequence. Some research effort has been spent on improving more than one aspect of the transportation system, which is multi-objective optimization. Kamal et al. [37] proposed a centralized Model Predictive Control (MPC) strategy with multiple terms in the cost function such as tracking a desired velocity, minimizing acceleration and minimizing the risk of collision. The main disadvantage of such centralized methods is the computational burden issue on the centralized controller to enable real-time operation especially in large-scale systems. Makarem and Gillet [38]

on the other hand, proposed a decentralized MPC method where the cost function and the constraints were similar to [37], but instead of one centralized control unit making decisions for all the involved vehicles, each vehicle is considered to plan its own trajectory and avoid rear end collisions or collisions at the intersection area. Although it would be computational efficiency in this way, the solution will be suboptimal due to the limited information one controller can gather. In order to achieve online real-time optimization, Rios-Torres et al. [39] developed a closed-form formulation for fuel economic control of the vehicles travelling over merging roads, while first-come-first-serve (FCFS) is used to determine vehicle passing sequence. The simulation results presented in [39] showed significant reduction on fuel consumption.

There are numerous research focusing on the coordination of CAVs at isolated intersections, but urban road scenario generally consists of multiple intersections interconnected with each other. In such scenarios, what happens in one single intersection will influence the behavior of the whole intersection network. However, current isolated intersection coordination approaches lack the consideration of downstream traffic information, which means two things: first, once the vehicle clears the intersection, it is out of the consideration of intersection controller; second, whatever traffic status downstream the intersection doesn't influence the intersection coordination strategy. Due to these two shortcomings, we will not get optimal solutions when we extend current isolated coordination approaches to multi-intersection scenarios.

The main contributions (chapter 2.1) of this part of the dissertation are: first, a novel hierarchical control strategy for multiple CAVs, passing through multiple interconnected

unsignalized intersections has been developed, that focuses on the improvement of vehicle fuel economy and system mobility; second, a novel intersection management strategy is proposed where the intersection controller utilizes the traffic density information of the downstream road segment to realize smooth velocity transition of the vehicles between two adjacent roads to further improve the system performance; third, fast model predictive control is employed on vehicle local controller to enable real time operation.

In the second part, we focus on the scenario that the group of vehicles travelling on multiple signalized intersections. The reason why we target on the signalized intersections road is not only because the traffic signals are controlling most of our current intersections, but also because that by assuming fixed signal timing and simple two signal phases, it is possible to allow us focus on one direction roads with limited number of vehicles (e.g., the vehicles on the other direction roads and the vehicles on the left or right turn lane can be ignored). The problem becomes more manageable and easier to solve, which allows us to study different control aspects independently including: longitudinal motion control, lane change decision making, delay estimation & compensation. This allowed us to gain full understanding of each aspect of the problem which can be used to deal with more complex traffic scenarios.

There are generally two categories in the literature to solve the issue of vehicles travelling on signalized intersections. The first one focuses on controller the traffic signal. The research on improving the traffic efficiency at signalized intersections can be categorized into two areas: traffic signal control and connected vehicle coordination. For the traffic

signal control area, Mohamed *et al.* [40] proposed a two-stage fuzzy logic controller to determine whether the current signal phase time interval needs to be extended or terminated. In [41] [42], Model Predictive Control (MPC) is used to determine signal timing with the objective of minimizing the queue lengths in the traffic network. Some other research focused on multiple traffic signal synchronization [43] [44] [45], where the signal timing of a series of interconnected traffic signals is adjusted to make the drivers encounter a long string of green lights. The approach of traffic signal control can be very expensive to implement, because only updating the traffic signal timing across the U.S. is estimated to cost \$ 271 million annually [46]. Besides, even if the traffic signal is well tuned, the scenario could still happen that a vehicle cruises at high speed to a green light, but later suffers a hard brake due to the traffic light sudden change to red. It is inefficient from a fuel economy perspective.

Thus, the problem is better solved on the vehicle side with the knowledge of the traffic signal information. An algorithm minimizing acceleration for a vehicle passing through multiple traffic signal lights is presented by Mandava *et al.* [47]. A machine learning based approach was proposed in [48] where smart phones are used to predict the phase of traffic lights. Asadi and Vahidi in [49] developed a predictive cruise control using traffic signal information to reduce idling time and minimize vehicle's acceleration. This work was later extended by using a probabilistic approach to consider noisy traffic light conditions [50]. In the previous research of our group [51] [52], collaborating with Dr. Vahidi, we utilized the hierarchical control architecture where the intersection controller evaluates the target velocity for each vehicle based on the SPAT information to help the

vehicles minimize red light idling, while the vehicle local controller uses MPC to track the target velocity. We considered two extra terms in our cost function for vehicle longitudinal motion control. The first term is a car following cost, which makes the vehicle maintain desired headway distance and time to its preceding vehicle. The other term is the rate between fuel (conventional vehicle) and power (HEV) consumption per unit distance, which further improves the fuel economy of the vehicles (chapter 2.2).

In this dissertation, we further extend the previous work [51] [52] on vehicle longitudinal motion control reported as in Chapter 2.2 and also performed the connected vehicle penetration rate study and lane change decision evaluation. In chapter 2.2, we built the connection between vehicle local controller and the powertrain controllers. For HEVs, recuperation efficiency feedback is enabled between the optimization problem in the vehicle local controller and the HEV energy management layer. Further fuel economy improvement can be achieved by selecting appropriate efficiency feedback update rate.

In the previous described research efforts, all the subject vehicles under consideration are assumed to be connected, which is a very strong assumption under current stage of connected vehicle development. Furthermore, most of the research on studying the effects of connected vehicle penetration rate are based on statistical analysis at the macroscopic level [53] [54]. The effect of connected vehicle penetration rate studies at a microscopic level involving individual vehicle decision making has not been explored.

The key purpose of the study in Chapter 2.3 is to explore the effects of the presence of the unconnected vehicles in the sense of both connected vehicle penetration rate and the

position of the unconnected vehicles on the convoy. The main contribution in Chapter 2.3 is investigating the vehicles mixed scenarios at a microscopic level focusing on each vehicle's decision making. The key findings include: first, the effect of unconnected vehicles in the convoy on the overall fuel economy has been discovered; second, the discretionary lane change triggering factors have been determined, which will be utilized in LCD study in Chapter 3.

In the aforementioned research, only longitudinal motion coordination is considered. The connected vehicles are assumed to remain on their lane with no lane changes or turns at intersections. However, in a real world driving scenario, the vehicles not only move forward and pass through intersections, but also change lanes. Lane change is one of the unavoidable driver behavior in our traffic environment [55]. Poor lane change decision (LCD) has negative impact of both traffic safety and efficiency. For traffic safety impact, 4% to 10% of the traffic accidents are caused by lane change maneuver [56]. 78% of lane change accidents take place in dense traffic flow with low speed and small inter-vehicle space [57], which is exactly the focus of this dissertation, urban roads. For traffic efficiency impact, lane change could generate a capacity drop with shockwaves in both lanes [58]. It has also been confirmed that aggressive lane changes on highways or urban traffic result in 20-30% extra fuel consumption [59].

The decision to make a lane change can be classified as mandatory lane change and discretionary lane change based on different driving incentives [60]. Mandatory lane change happens when a vehicle has to change lane to follow a specified path or due to the road geometry (i.e. lane merging ahead). For discretionary lane change, it occurs when a

vehicle changes to a lane offering better traffic conditions, i.e. higher speed or lower traffic density, but it does not necessarily happen. The literature on lane change decision can be categorized into three catalogs. In Gipps [61] and Hidas [62] [63], the LCD is made through gap acceptance model based approaches. Lane change is motivated by some triggering factors like the locations of permanent obstructions, the presence of heavy vehicles, special purpose lanes or the intention to turn. The critical or acceptable gap is also defined by either exponential function or normal distribution of certain parameters, like velocity, distance, allowable acceleration and so on. Once the lane change is triggered and the gap on the target lane is greater than the critical gap, lane change will be executed. The Gipps LCD model [61] was later further extended by involving probability theory to make the LCD model more realistic [64]. Some other researchers developed LCD model based on utility theory. The basic idea is to compare the utility of staying on the current lane and the risks associated with lane change. Kesting et al. [65] proposed the LCD model also known as MOBIL (Minimizing Overall Braking Induced by Lane Changes). The authors compared the overall acceleration as the utility of the criteria of lane change. In general, higher overall acceleration means higher velocity and higher traffic mobility. Teloedo et al. [66] proposed a model which is capable of evaluating mandatory and discretionary lane changes and later an explicit target lane model was studied in [67] where the lane with the highest utility is selected as a destination lane. The other catalog of the LCD model is optimization based approach where the longitude motion and LCD are integrated together and the optimization

problem is formulated to determine when and where it is optimal to change lane [68] [69] [70].

For the gap acceptance and utility based model, only the subject vehicle's LCD and action are considered and the reactions and effects of the surrounding vehicles are ignored. Also, the subject vehicle makes decisions independently based on limited information, thus the advantages of connected vehicles have not been fully explored. In some scenarios, the mandatory lane change may not be able to be execute without cooperation due to the short inter-vehicle distance enabled by connected vehicle technology. In the utility based model, LCD is based on utility advantage on the current moment and ignore the sudden changes on traffic conditions, for example traffic signal light changes. For the optimization based approach, the longitudinal motion is continuous while the LCD is discrete. In another words, the frequency for evaluating the longitudinal motion decision is much higher than the LCD evaluation. Thus, integrating these two together into one optimization problem leads to a mixed integer programming problem. Most solution methods for mixed integer programming problems utilize some sort of tree search algorithm and it can be computational inefficient and suffer from poor scalability, especially when the number of subject vehicle increases, which makes them unsuitable for real-time implementation.

The main contributions in Chapter 3 of the dissertation are: first, under hierarchical control architecture, a novel discretionary lane change decision model has been developed for a group of vehicles travelling on signalized intersection roads. Second, the key contribution of the hierarchical control method is that the discretionary LCD is

evaluated at the intersection controller layer and sent to each vehicle local controller. In such a way, the continuous longitudinal motion control and the discrete LCD are decoupled and evaluated at different layers. Thus, our novel LCD model is able to avoid solving the mixed integer programming problem to improve the system scalability and computational efficiency. The LCD at the intersection controller layer is based on offering the subject vehicle higher probability to achieve its target velocity with minimum negative impact on the rest of the vehicles in the group. Another important lane change triggering factor is related to the presence of the unconnected vehicles in the convoy. Third, a novel cooperative mandatory lane change model has been developed. The cooperation during lane change between the host vehicle and the vehicles on the target lane is achieved by modeling a virtual vehicle on the target lane with identical state variables as the host vehicle. With the method developed, the negative impacts caused by the mandatory lane change can be minimized on congested roads.

2.1 Unsignalized Traffic Intersection

2.1.1 Introduction

The importance of the intersection on urban transportation system has already been discussed in the previous section. The intersections are currently controlled by traffic lights, rules and stop signs. Despite the fact that there are numerous research on adaptive traffic lights control over the decades [42] [41] [71], which are focusing on optimizing the traffic light phase switching sequence and period to improve the traffic efficiency, the current intersection control mechanisms will still unavoidably generate vehicles' stop-and-go driving patterns at the intersections. On the other hand, the infrastructures are also under changes to fulfil the goal of Intelligent Transportation System (ITS). The current intersection control mechanisms cannot take the full advantages of the CAVs' capabilities.

Under these circumstances, the research on coordination of CAVs at intelligent intersections becomes an important topic. Recently lots of research has focused on developing coordination strategies that lead CAVs cross the intersections safely. Researchers are trying to potentially remove current intersection control mechanisms (traffic lights, stop signs, etc.) to avoid unnecessary and inefficient stop-and-go driving patterns and solely rely on the cooperation and communication among the connected vehicles and intersection controllers. At the same time, the coordination strategies should

focus on the improvement of different aspects of the transportation system such as reduction of travel time, and the improvement of vehicle fuel economy.

2.1.2 Literature Review

A lot of research has focused on the coordination of vehicles at intersections using CAV technologies to avoid vehicle collisions. In this section, a brief summary of such research is presented. The coordination approaches at isolated intersection can be categorized as heuristic approaches, reservation-based approaches and optimization-based approaches.

In heuristic approaches, fuzzy logic is a widely used technique. It allows the actions and decisions to be described as simple rules, which is well suited in the complex transportation problems. Milanese *et al.* [26] first presented an intersection detection system with the capability of detecting the position and intention of other cars in its vicinity. The authors then used fuzzy controller to control the throttle and braking of the CAVs based on the distance and speed information. The real-world experiment between one manually driven and the other fully automated vehicles was also provided in [26]. This work was further extended by involving genetic algorithm to tune fuzzy controller parameters [27]. Other heuristic approaches include Wu *et al.* [28] where authors formulated the problem as a mutual exclusion problem. The vehicles could compete for the privilege of passing an intersection. Hafner *et al.* [29] [30] treated the collision avoidance as the problem of keeping the system state always outside the capture set, which is the set where collision is unavoidable given the vehicle dynamics and control effort's limitations. In general, heuristic approaches only focus on collision avoidance at

the intersection and do not consider fuel economy, traffic mobility or environmental impact. Most of the heuristic approaches are decentralized in nature, which means the vehicle local controller only makes the decisions for this corresponding vehicle.

The general idea of reservation-based approaches is that the intersection controller coordinates the time-space reservation based on the request from the vehicles. Dresner and Stone [31] proposed a multi-agent system where each vehicle acts as a driver agent and is responsible for sending the information of its vehicle size, predicted arrival time and velocity to the intersection manager. The intersection manager based on the request and information to coordinate a space-time reservation on the intersection. It will simulate the vehicle's trajectory through the intersection, and check for the conflicts with the previous reservations. In the end, the intersection manager will grant or reject the request and send it back to the driver agent. Fortelle [32] further extended this work by discretizing the intersection into critical points. In doing so, it allowed lower rate of vehicles pass an intersection than the cell-based reservation, but it improved the system scalability and reduced the computational burden. Platoon-based reservation extension can be found in [33]. The disadvantages of the reservation-based approaches are that they don't focus on fuel economy and sometimes the system will suffer from heavy communication requirement because one vehicle may be required to communicate several times until the request is approved. The reservation-based approaches are typical centralized in nature. The intersection manager acts as a centralized controller and makes all the decisions for all the CAVs within the control region.

Since the aforementioned two approaches do not focus on fuel economy or system mobility, researchers came up with optimization-based approach. Lee and Park [34] proposed an algorithm with the objective of minimizing the total overlapped vehicle trajectory length projected in the intersection zone. In doing so, only a limited number of vehicles were inside an intersection at each time instance to avoid collisions. The simulation results in [34] showed significant reduction of total stop and delay time compared to the conventional intersection control mechanisms. Other optimization based approaches aim at minimizing the total travel time. Jin et al. [35] proposed a two-lane intersection scenario which allowed only one vehicle on the intersection at each instance of time. With the information of approaching time of the vehicles, the optimal scheduled departure time of the vehicles was evaluated in [35], while the vehicles chose its appropriate trajectory to follow its prescribed departure time. Yan et al. [36] proposed a more complex scenario with multiple lanes including turning lanes. The CAVs on different lanes were first categorized into different vehicle classes based on their compatibility of coexistence at the intersection area and dynamic programming was used to determine vehicle class passing sequence. Some research effort has been spent on improving more than one aspect of the transportation system, which is multi-objective optimization. Kamal et al. [37] proposed a centralized Model Predictive Control (MPC) strategy with multiple terms in the cost function such as tracking a desired velocity, minimizing acceleration and minimizing the risk of collision. The main disadvantage of such centralized methods is the computational burden issue on the centralized controller to enable real-time operation especially in large-scale systems. Makarem and Gillet [38]

on the other hand, proposed a decentralized MPC method where the cost function and the constraints were similar to [37], but instead of one centralized control unit making decisions for all the involved vehicles, each vehicle is considered to plan its own trajectory and avoid rear end collisions or collisions at the intersection area. Although it would be computational efficiency in this way, the solution will be suboptimal due to the limited information one controller can gather. In order to achieve online real-time optimization, Rios-Torres et al. [39] developed a closed-form formulation for fuel economic control of the vehicles travelling over merging roads, while first-come-first-serve (FCFS) is used to determine vehicle passing sequence. The simulation results presented in [39] showed significant reduction on fuel consumption.

2.1.3 Research Gap

There are numerous research focusing on the coordination of CAVs at isolated intersections, but urban road scenario generally consists of multiple intersections interconnected with each other. In such scenarios, what happens in one single intersection will influence the behavior of the whole intersection network. However, current isolated intersection coordination approaches lack the consideration of downstream traffic information, which means two things: first, once the vehicle clears the intersection, it is out of the consideration of intersection controller; second, whatever traffic status downstream the intersection doesn't influence the intersection coordination strategy. Figure 2.1 illustrates an example of aforementioned shortcomings. In Figure 2.1, the intersection controller only control the vehicles from upstream and is not aware of the vehicles downstream are moving slowly because of traffic jam. Due to lack of the

consideration of the downstream traffic jam condition, the vehicle on the upstream may receive the instruction of maintaining current velocity from intersection controller (due to no vehicles on the other direction), which the vehicle will later end up with suffering from sharp deceleration or even collision. Due to these two shortcomings, we will not get optimal solutions when we extend current isolated coordination approaches to multi-intersection scenarios. Additionally, the research on coordination of CAVs at multi-intersection are still on macroscopic level with the focus on traffic flow, average speed and route selection. Wuthishuwong and Treachtler [72] [73] used consensus algorithm to balance the traffic density over a traffic network. Tilg et al. [74] proposed an algorithm to allow vehicles from different directions pass the intersection alternatingly and generate free flow over the network through adjusting the alternating switching frequency. Hauskencht et al. [75] extended the work of [76] by enabling dynamic routing with the help of traffic density information. However, the fuel economy and individual vehicle trajectory planning in presence of multiple-intersection scenarios is not the focus of the aforementioned studies.

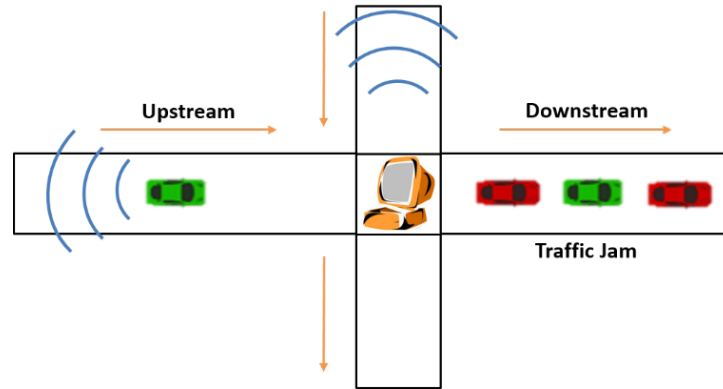


Figure 2.1 Illustration of the disadvantages of current isolated intersection coordination approaches

2.1.4 Approach

In this section, a hierarchical CAVs coordination strategy for multiple interconnected intersections is presented. Figure 2.2 shows the schematic of the focused problem. We assume all the vehicles under consideration are connected vehicles. The vehicles do not change lane or make turns at the intersection. V2V, V2I and I2I communication network is assumed to be available. The major contribution of this work is developing a coordination strategy of connected vehicles at multiple interconnected intersections with the focus of individual vehicle trajectory planning. The coordination strategy also helps improve overall fuel economy and traffic mobility.

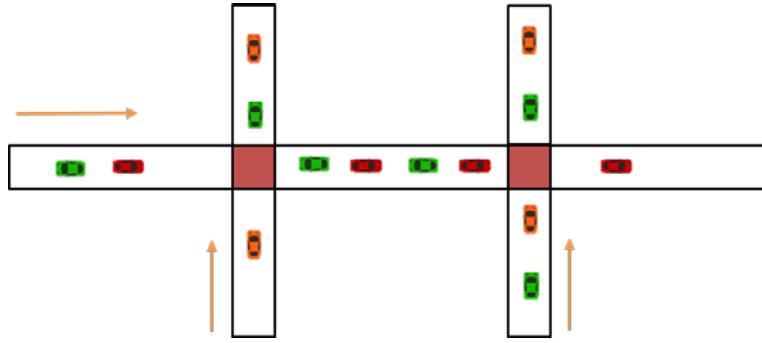


Figure 2.2 The schematic of the longitudinal coordination on traffic lightless intersections

The hierarchical control architecture of this approach is shown in Figure 2.3. At the first layer, the traffic density information is shared between the intersections and consensus algorithm [77] [78] is used to speed up traffic density balance over the network. The second layer is the centralized intersection controller which is responsible for assigning reference velocity for each vehicle on the incoming roads to avoid intersection collisions. At the last, each vehicle local controller utilizes Model Predictive Control (MPC) to track the reference velocity. The details on each of the layers can be found in the next few sections.

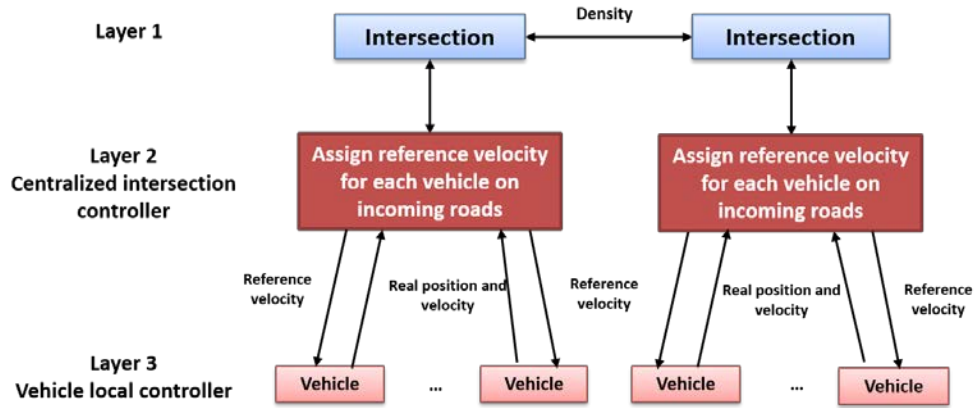


Figure 2.3 The hierarchical control architecture of the longitudinal coordination on traffic lightless intersections

A. Traffic Flow Model and Consensus Algorithm

In real traffic environment, there are three parameters used to describe the traffic behavior in the macroscopic level: average velocity, traffic density and traffic flow. Traffic flow model is designed to present the relationship among these parameters.

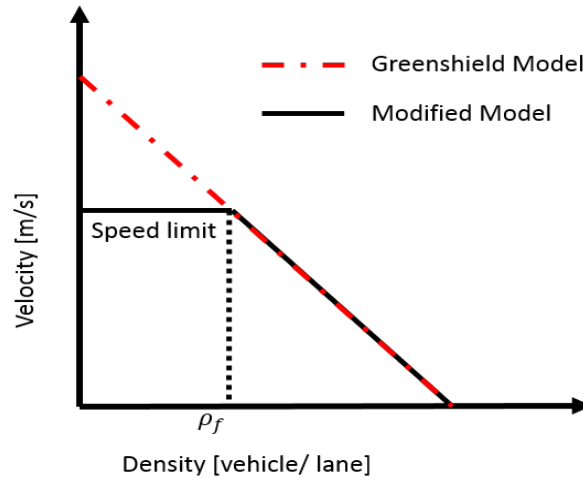


Figure 2.4 Greenshield model and modified traffic flow model

The Greenshield model [79] implies a simple linear function relationship to describe the relationship between average velocity and traffic density. When the traffic density reaches the jam density, the average velocity approaches to zero, which means the vehicles have to stop. As the traffic density decreases, the average velocity grows till the free flow velocity. The Greenshield model considers all conventional vehicles with no communication and automation capabilities, so we made some modifications based on the Greenshield model for our problem with CAVs involved. Figure 2.4 shows the modified relationship between average velocity and density. It can be expressed as:

$$V = f_v(\rho) = \begin{cases} V_f & \rho \leq \rho_f \\ k_s(\rho - \rho_f) + V_f & \rho > \rho_f \end{cases} \quad (2.1)$$

In (2.1), V is the road average velocity and $f_v(\rho)$ is the mapping from road density ρ to road average velocity. When the traffic density ρ on the road is less or equal to the free flow density threshold ρ_f , the road average velocity is considered to be constant V_f , which can be the speed limit for the road. Otherwise, the velocity would drop linearly with a slope k_s as the density increases as shown in Figure 2.4.

We made the modifications based on the assumption that with only a few vehicles, the modern CAV control strategies, such as platoon and connected adapted cruise control (CACC), could enable all the vehicles on the same road travel at a high velocity. It can be assumed that the travelling velocity will decrease slowly due to communication delay and safety consideration when the number of vehicles exceeds a

threshold. We also assume the CAVs will travel as the modified traffic flow, if there is no coordination strategy involved.

In a road network, the traffic status may be different in different roads. When the vehicle travels from one road or intersection to another, it may suffer sudden velocity changes, which is energy inefficient and uncomfortable for the drivers. From fuel economy perspective, minimizing vehicle velocity deviation during the trip generally results in the improvement of fuel consumption [80]. With infrastructure-to-infrastructure communications (I2I), an intersection could be informed about the traffic density at its neighborhood intersections so that it could plan the CAVs' trajectories ahead of time to achieve smooth velocity transitions. For example, if the downstream road is congested and the average velocity is low (Figure 2.1), the vehicles on the upstream road could slow down slowly instead of suddenly deceleration once entering the next road from the minimizing fuel consumption point of view.

Consensus algorithm is implemented in this study to balance the traffic density over multiple intersections and minimize the average velocity difference from road to road. Consensus algorithms are very common in multi-robot formation control problems [77, 81]. It has also been recently studied for the balancing traffic density in the intersection network [72, 82]. The algorithm can be implemented in a decentralized fashion and it naturally gives the convergence properties, which is desirable for large-scale complex system. The new desired road average velocity $V_{CR}^*(k)$ is presented in (2.2).

$$V_{CR}^*(k) = f_v(\rho_{CR}(k)) + \lambda_{CR} (f_v(\rho_{CR}(k)) - f_v(\rho_{ER}(k))) \quad (2.2)$$

It is considering current traffic density ρ_{CR} on its own road CR and the density difference compared with the road ER , where ER is the road the vehicles in CR will finally enter. In (2.2), k indicates the time step and λ_{CR} is a constant factor which indicates how much the velocity will be changed based on its original flow model.

In such a way, we have built the interconnection between the intersection controllers through traffic density information. This is the first layer in our coordination strategy. The new road desired average velocities $V_{CR}^*(k)$ is calculated based on consensus algorithm in this layer to help speed up the density balance process. In next section, we will illustrate how the intersection controller would assign reference velocities for each vehicle within the control region.

B. Optimal reference velocity assignment

Ideally, all the vehicles on the same road should move at the road desired average velocity from (2.2). However, in doing so, there would be a high chance of vehicle collision between the vehicles coming from conflict roads at intersection. The conflict roads here mean the roads with vehicles approaching the same intersection from different directions. To avoid vehicle collision at the intersections, we consider in this paper that the intersection controller adjusts the individual vehicle reference velocity. We formulate it as an optimization problem. The cost function for a single intersection is given by:

$$J = \min_{\bar{v}_{m,p}, \bar{v}_{n,q}} \left(\sum_p w_m w_p (V_m^*(k) - \bar{v}_{m,p}(k))^2 + \sum_q w_n w_q (V_n^*(k) - \bar{v}_{n,q}(k))^2 \right) \quad (2.3a)$$

$$\left| \tau_{m,p} - \tau_{n,q} \right| \geq \tau_0 \quad (2.3b)$$

$$0 \leq \bar{v}_{m,p}(k) \leq V_f \quad (2.3c)$$

$$a_{lb} \leq \bar{v}_{m,p}(k) - v_{m,p}(k-1) \leq a_{ub} \quad (2.3d)$$

$$\tau_{m,p} = \frac{S_{m,p}}{\bar{v}_{m,p}} \quad (2.4e)$$

Here, m and n are the indices of two conflict roads and p and q are the vehicle indices in road m and n respectively. V_m^* and V_n^* represent the road desired velocity obtained from (2.2) of road m and n respectively. In (2.3), $\bar{v}_{m,p}$ and $\bar{v}_{n,q}$ indicate the individual vehicle reference velocities and they are also the decision variables of the optimization problem. The constants w_p and w_q are the weighting factors representing the vehicle types. We want to punish the velocity changes of conventional vehicles and encourage the velocity changes for hybrid electrical vehicles (HEVs), if there is any. The reason behind this is that HEVs could recuperate from braking and accelerate with the power from battery, so maintaining less velocity deviation of conventional vehicles and encouraging HEVs velocity changes would result in better fuel economy. The weighting factors w_m and w_n represent the relative density relation between road m and road n . Figure 2.5 shows the explanation of the notations mentioned above. If $\rho_m > \rho_n$, then $w_m > w_n$, if $\rho_m < \rho_n$, then $w_m < w_n$ and $w_m = w_n$ otherwise. This means, the vehicles on the road with higher density will get the priority and move faster and closer to the road's desired velocity, which would speed up the process of density balancing due to higher

velocity on higher density road. The cost function is subjected to the constraints from (2.3b) to (2.3e). $\tau_{m,p}$ and $\tau_{n,q}$ in (2.3b) are the estimated time of arrival (ETA) to the intersection between roads m and n for the vehicles p and q respectively. For example, the ETA of vehicle p can be expressed as (2.3e) where $S_{m,p}$ denotes the distance of vehicle p on road m to the intersection. Thus, (2.3b) is used to avoid collision at the intersection by guaranteeing there is a time interval of τ_0 between the vehicles on conflict roads arriving at the intersection. The constraints in (2.3c) are making sure that the vehicles reference velocity is within the speed limit range. In (2.3d), a_{ub} and a_{lb} present the maximum and minimum velocity change at each time step while $v_{m,p}(k-1)$ indicates the vehicle real velocity in last time step. The same constraints in (2.3c) are also applied to vehicles p on road m .

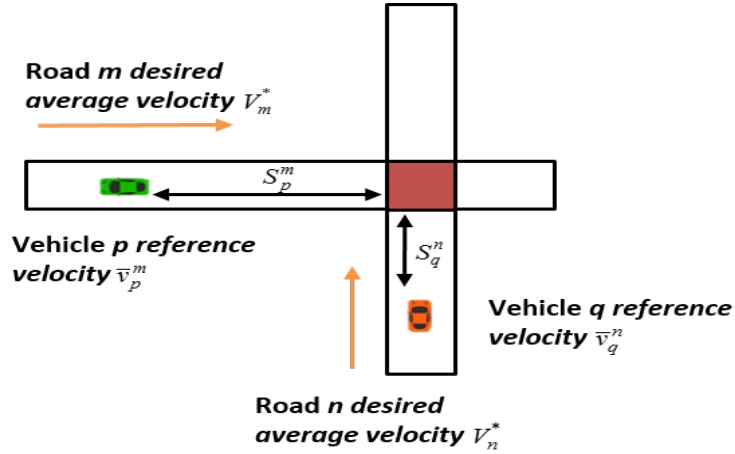


Figure 2.5 Illustration of the notations in Equation (2.3)

The intersection controller utilizes the information of both traffic status (information within its control region and neighborhood intersection) and the states of vehicles (velocity, position and vehicle type) for its decision making. Solving the optimization problem in (3), the intersection controller can assign reference velocity to each individual vehicle with the objectives of avoiding intersection vehicle collisions, improving the fuel economy and speeding up density balancing process. This is the second layer of our coordination strategy. Now in this layer, at each time step, each vehicle will send its velocity and position information to its intersection controller and receive the advisory reference velocity. The next step would be for the vehicle local controller to track its reference velocity while avoiding read end collision with its preceding vehicle.

C. MPC tracking reference velocity assignment

The advantages of model predictive control (MPC) is that it can deal with constrained problems and it allows the current time step to be optimized while keeping future time steps in account. At each time step, the optimal control problem is solved over a finite horizon, but only implements on the current time step [83]. MPC is also very suitable for the application of tracking problem [84].

The longitudinal dynamics of any vehicle index of i is given by [85]:

$$\begin{aligned} \dot{x}_i &= f_i(x_i, u_i) \\ f_i(x_i, u_i) &= \begin{bmatrix} v_i \\ -\frac{1}{2M_h^i} C_D \rho_a A_v^i v_i^2 - \mu g - g \theta + u_i \end{bmatrix} \end{aligned} \quad (2.4)$$

$x_i \in \mathfrak{R}^{n_x}$, $u_i \in \mathfrak{R}^{n_u}$ and $n_x = 2$, $n_u = 1$ in our case. In (2.4), $x_i = [s_i, v_i]$, where s_i is the position of vehicle i and v_i is its velocity. The control input u_i is the traction or braking force per unit mass of a vehicle at any time instance. M_h^i , C_D , ρ_a , A_v^i , μ , g and θ denote the mass of the vehicle, drag coefficient, air density, frontal area of the vehicle, rolling friction coefficient, gravitational constant and road gradient respectively. It should be noted that this vehicle longitudinal dynamic definition is used through the whole thesis.

Once the reference velocity \bar{v}_i for any vehicle i is calculated from (2.3a) in Section 2.1.4B, then the tracking problem is solved as a receding horizon problem. For each vehicle i and a time horizon T , the following cost function is solved at each time step k :

$$J_i = \arg \min_{u_i} \sum_{t=k}^{k+T-1} \left[w_1 \left(v_i(t) - \bar{v}_i(k) \right)^2 + w_2^i(t) R_{ij}^i(t)^2 + w_3 u_i(t)^2 + w_4 \frac{\dot{f}_{fuel}^i(t)}{v_i(t)} \right] \quad (2.5a)$$

$$v_{lb}^i(t) \leq v_i(t) \leq v_{ub}^i(t), \quad \forall t \quad (2.5b)$$

$$u_{lb}^i(t) \leq u_i(t) \leq u_{ub}^i(t), \quad \forall t \quad (2.5c)$$

$$R_{ij}^i(t) = S_0 + t_{hd} \left(v_i(t) - v_j(t) \right) + \left(s_i(t) - s_j(t) \right) \quad (2.5d)$$

In the cost function (2.5a), the first term is used to track the reference velocity $\bar{v}_i(k)$, the second term minimizes the deviation from a desired distance between vehicle i and its preceding vehicle j , and the third term minimizes the control effort. The last term minimizes the fuel consumption rate per unit distance which is the factor how our

proposed approach would realize the improvement on the fuel economy. The definition of $\dot{f}_{fuel}^i(t)$ can be found in the next subsection. In (2.5a), w_1 , w_3 and w_4 are constant weightings, while $w_2^i(t)$, is chosen as a function of the relative distance, $(s_j(t) - s_i(t))$, so it increases as the relative distance decreases and vice versa. The choice of $w_2^i(t)$ is similar to [85]. $v_{lb}^i(t)$ and $v_{ub}^i(t)$ in (2.5b) indicate the speed limits of the road while $u_{lb}^i(t)$ and $u_{ub}^i(t)$ in (2.5c) denote the vehicle's traction and deceleration limits. The problem in (2.5) also needs to be solved considering the constraints of the system dynamics in (2.4). S_0 and t_{hd} in (2.5d) are predefined critical distance and headway time respectively.

D. Fuel consumption evaluation

The rate of fuel consumption for the conventional vehicles is evaluated by the polynomial metamodel proposed in [85]:

$$\dot{f}_{fuel}^i(t) = \dot{f}_{cruise}^i(t) + \dot{f}_{accel}^i(t) \quad (2.6a)$$

$$\dot{f}_{cruise}^i(t) = b_0 + b_1 \cdot v_i(t) + b_2 \cdot v_i(t)^2 + b_3 \cdot v_i(t)^3 \quad (2.6b)$$

$$\dot{f}_{accel}^i(t) = \hat{a}_i \cdot (r_0 + r_1 \cdot v_i(t) + r_2 \cdot v_i(t)^2) \quad (2.6c)$$

$$\hat{a}_i = -\frac{1}{2M_h^i} C_D \rho_a A_v^i v_i^2 - \mu g - g\theta + u_i \quad (2.6d)$$

$\dot{f}_{cruise}^i(t)$ and $\dot{f}_{accel}^i(t)$ denote the fuel consumed by a vehicle travelling at constant velocity and the additional fuel consumption while the vehicle accelerating respectively.

The vehicle and environmental related parameters are taken from [85]: $M_h^i = 1200 \text{ kg}$, $A_v^i = 2.5 \text{ m}^2$, $C_D = 0.32$, $\rho_a = 1.184 \text{ kg/m}^3$ and $\theta = 0$. The polynomial coefficients are equal to: $b_0 = 0.1569$, $b_1 = 2.45 \times 10^{-2}$, $b_2 = -7.415 \times 10^{-4}$, $b_3 = 5.975 \times 10^{-5}$, $r_0 = 0.07224$, $r_1 = 9.681 \times 10^{-2}$ and $r_2 = 1.075 \times 10^{-3}$. If $v_i(t) = 0$ or $u_i < 0$, it means the vehicle is idling. The fuel consumption can be set to be constant as: $\dot{f}_{fuel}(t) = 0.1$.

2.1.5 Simulation Results

In this section, the performance of the proposed approach explained in the previous section is evaluated by two different scale of scenarios. The small scale case contains 38 vehicles initially within the network, while the other one is more complex with 150 vehicles initially. New vehicles will come into the control region in both scenarios.

A. Small scale scenario

The intersection network structure and initial simulation setup is shown in Figure 2.6. The scenario consists of two intersections interconnected with each other. There are 7 one-way roads in total and the length of each road is 500 *m*. Road 1, road 2, road 3 and road 4 belong to intersection 1, while road 4, road 5, road 6 and road 7 belong to intersection 2. Initially, there are 5 vehicles on each road except the interconnecting road (road 4) which contains 8 vehicles. The red arrows in Figure 2.6 indicate the vehicle moving directions. At first we assume all the vehicles are the same type, so $w_p = w_q = 1$.

The effects of different vehicle types mixed driving scenario will be discussed later. There is at least 10 m headway between the two adjacent vehicles in the initial set up and 100 m distance between the intersection and the vehicle closest to the intersection on upstream road, which gives the vehicles enough space to adjust their velocities to avoid collisions at intersection. In every 10 seconds, we consider new vehicles enter the region from 3 different roads (road 2, road 5 and road 7) to make the simulation run continuously. Since we are considering single lane roads, the vehicles do not overtake during the simulation and we assume the vehicles do not turn at the intersections.

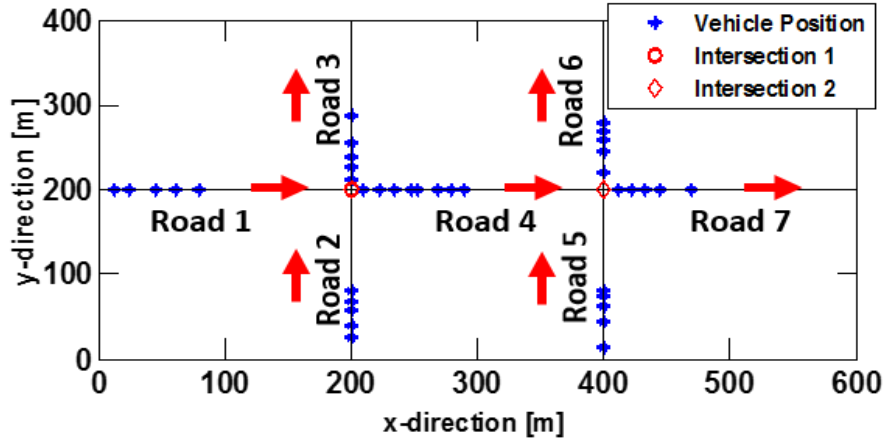


Figure 2.6 Schematic of the initial simulation setup

In the traffic flow model for this case, the free flow density threshold considered is $\rho_f = 5$, speed limit $V_f = 8 \text{ m/s}$, and the slope $k_s = -0.25$. The average road velocity is set to be constant and equal to the speed limit for road 3, road 6 and road 7. The simulation runs for 150 seconds with a prediction horizon $T = 5$ seconds and a time step of $\Delta t = 0.5$ second. The initial velocity of each vehicle i is set to be $v_0^i = 7 \text{ m/s}$. In the simulation, we consider the vehicles and the intersection area are points. The vehicle

length and the area of intersections are taken into account by the parameters of: time interval $\tau_0 = 1 \text{ s}$, critical distance $S_0 = 10 \text{ m}$ and headway time $t_{hd} = 1 \text{ s}$. The other bounding coefficients in the constraints are equal to: $v_{lb}^i(t) = 0 \text{ m/s}$, $v_{ub}^i(t) = 8 \text{ m/s}$, $u_{lb}^i(t) = -2.5 \text{ m/s}^2$, $u_{ub}^i(t) = 2.5 \text{ m/s}^2$, $a_{lb} = u_{lb}(t) \cdot \Delta t$ and $a_{ub} = u_{ub}(t) \cdot \Delta t$.

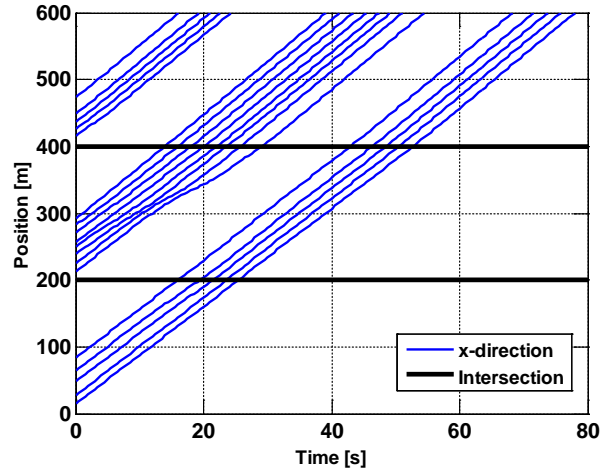


Figure 2.7 All initial vehicle trajectories on x-direction roads (road 1, road 4 and road 7)

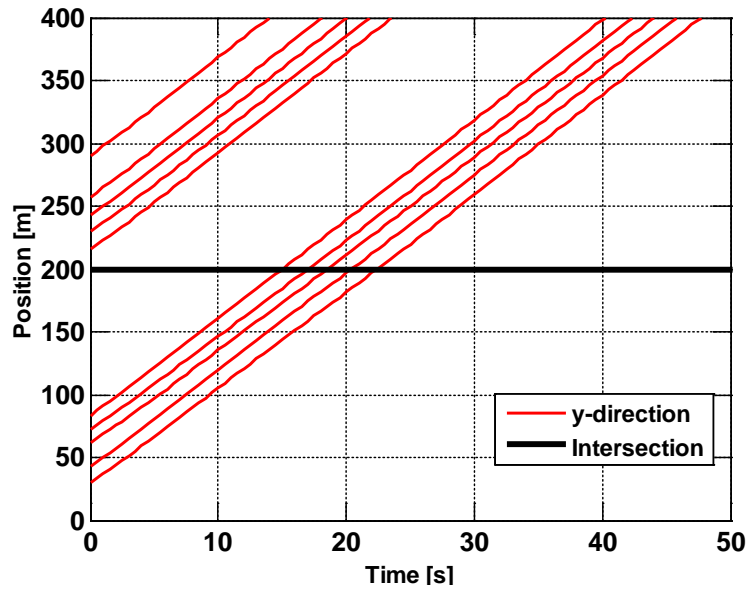


Figure 2.8 All initial vehicle trajectories on y-direction roads (road 2 and road 3) of intersection 1

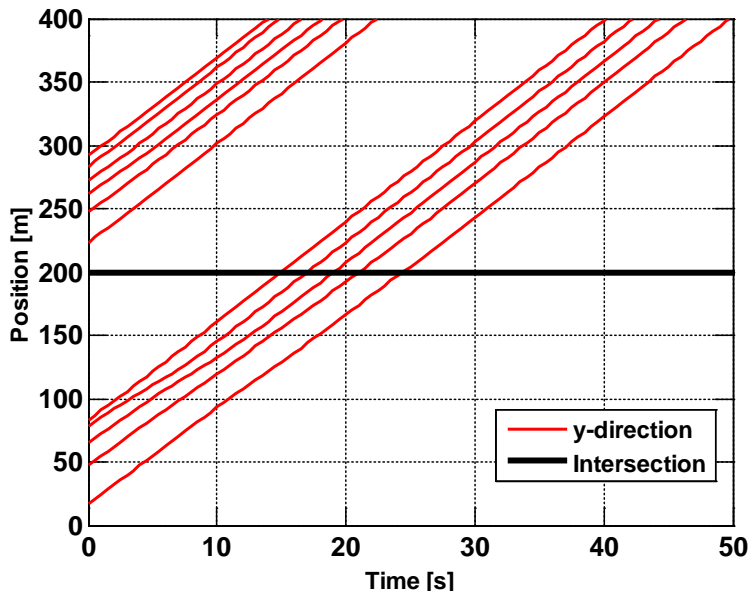


Figure 2.9 All initial vehicle trajectories on y-direction roads (road 5 and road 6) of intersection 2

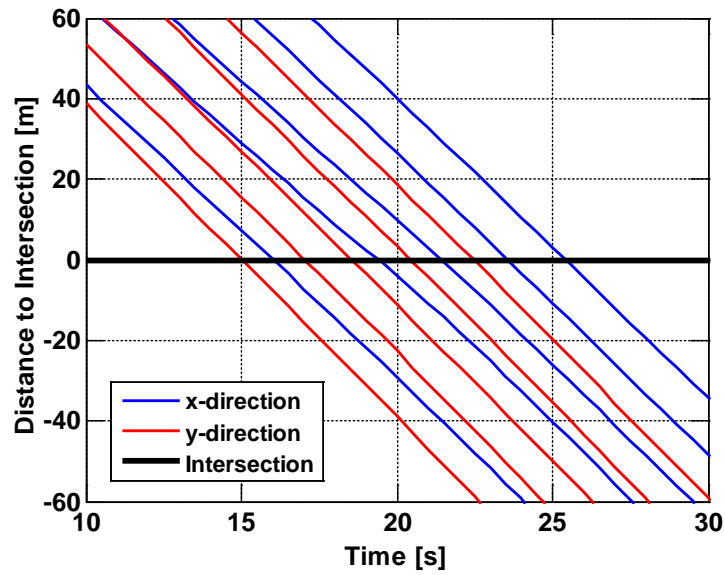


Figure 2.10 Relative distance to the intersection of vehicles from road 1 and road 2 of intersection 1 in small scale scenario

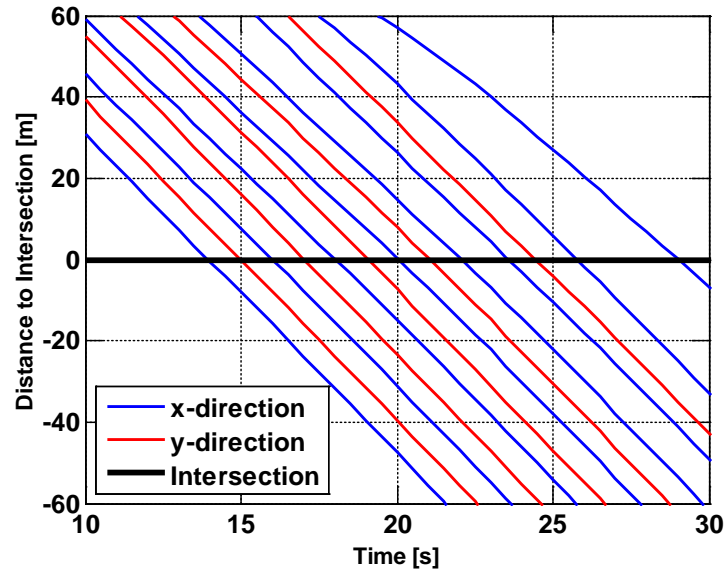


Figure 2.11 Relative distance to the intersection of vehicles from road 4 and road 5 of intersection 2 in small scale scenario

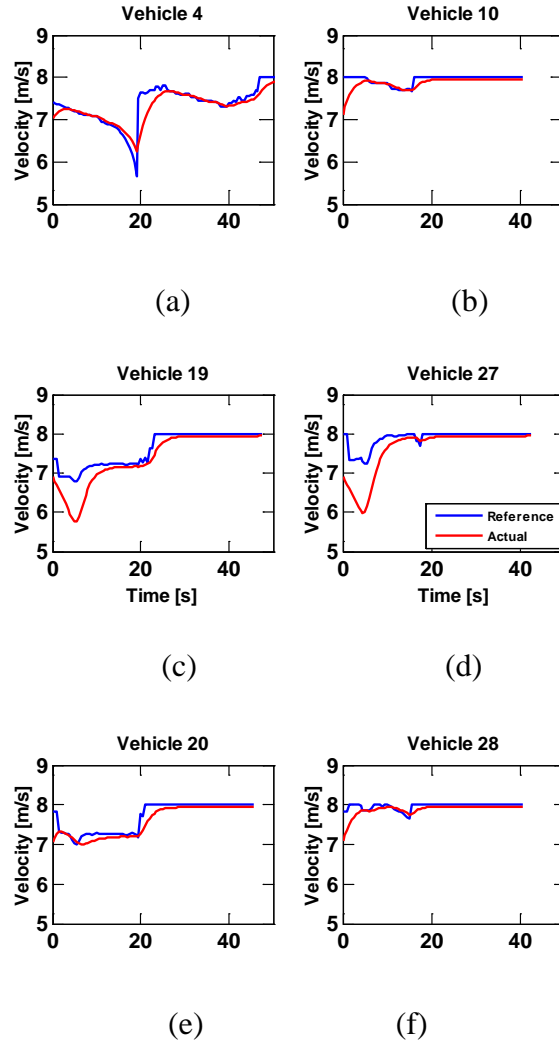


Figure 2.12 Randomly selected vehicle velocity tracking performance

Figure 2.7 to Figure 2.12 show the simulation results of our proposed methodology on the small scale scenario. Figure 2.7 shows the trajectories of all 18 vehicles initially on x-direction roads during the simulation. Figure 2.8 and Figure 2.9 shows the initial 10 vehicle trajectories on y-direction roads of intersection 1 and 2 respectively. The results show no intersection among any of the trajectories, which means there is no rear end collision.

Figure 2.10 and Figure 2.11 show the relative distance of the vehicles coming from different directions to the intersection 1 and 2 respectively. It should be noted that the blue and red lines on the figures indicate the vehicles from different directions and on different roads. The intersections between blue and red trajectories do not mean there is collision. The collision between vehicles from different directions can only happen at the crossroad area. As it can be seen from the Figure 2.10 and Figure 2.11, that collision at the intersections are avoided when using our proposed method.

Figure 2.12 shows the performance of some randomly selected vehicles' local controllers when using MPC to track the reference velocity received from the intersection controller. Figure 2.12a to Figure 2.12d show very good tracking performance. However, in Figure 2.12e and Figure 2.12f, it can be noticed that the vehicles are unable to track the reference velocity very well at the beginning. This is because the vehicles are also constrained by the minimum headway distance and time to its preceding vehicle. The velocity profiles of vehicle 19 and 27 are affected by their preceding vehicles' position and velocity.

To show the advantages of our proposed approach, we designed two baseline methods. The first one is the method without I2I communication (no I2I), which means one intersection does not have the traffic information of its neighborhood intersection. In this method, the road desired velocities (V_m^* and V_n^*) are not calculated from (2.2), but directly from the traffic flow model (2.1). The vehicles will travel as the traffic flow without the consensus algorithm involved, so there is no interconnection between the intersections. The other baseline method is the one without optimally assigning reference

velocity to individual vehicle (no optimization). In this method, the I2I communication is still working. However, we set the cost function in (2.3a) to be constant and the constraints remain the same. Thus, the intersection controller still have the capabilities to avoid vehicle collisions at intersection, but the assigned reference velocity will not be optimal with respect to anything.

We evaluate these approaches on two aspects: fuel economy (miles per gallon (mpg)) and mobility. For fuel economy, we compared the average, maximum, minimum and standard deviation of the fuel economy of all the initial vehicles. The mobility is measured as the total time taken by the initial vehicles to leave the given control region. The results are tabulated in Table 2.1. It should be noted that the results in Table 2.1 are all initial 38 vehicles. Since we fix the incoming times of new vehicles, they are unlikely to change their velocities a lot. It is not necessary to include all the vehicles while conducting the performance comparison.

Table 2.1 Fuel economy and mobility comparison of small scale scenario

Approach	Proposed	No I2I	No Optimization
Average Fuel Economy (mpg)	46.62	45.82	42.98
Maximum Fuel Economy (mpg)	50.12	49.41	49.41
Minimum Fuel Economy (mpg)	41.14	39.85	34.57
Fuel Economy Standard Deviation	2.1353	2.0231	4.2719
All Vehicle Total Travel Time (s)	1503	1523.5	1659

Compared with no optimization method, the proposed approach shows significant reduction on fuel consumption and total travel time. 8.47 % of average fuel economy and 10.28 % of total travel time improvement can be expected. Also, even the minimum fuel economy in our proposed approach is comparable with the average fuel economy of the no optimization method. When compared with no I2I method, the performance of the proposed method is better for both fuel economy and mobility, but the improvement is not very impressive. The reason behind this is that there is a lot of information we can share between the intersection controllers through I2I. Traffic density information is only

one part of all the factors that influence the performance of intersection coordination strategy and it may not be the most critical one, so we can only achieve slight performance improvement by sharing traffic density information. There might be more improvement on the performance if more information is shared. However, as the consequence, the computation and communication burden would increase at the same time and it would be harder to realize the real-time implementation.

B. Small scale scenario

To demonstrate the feasibility and scalability of our methodology, a larger scale scenario with more vehicles has been explored. The traffic network structure remains the same, but the length of each road is extended to 500 m . Initially, there are 20 vehicles on each road except the interconnecting road, where there are 30 vehicles, so there are 150 vehicles in total initially within the control region. Most of the parameters set up are the same with the previous scenario, except that $\rho_f = 20, V_f = 15 \text{ m/s}$ and initial velocity $v_0^i = 12 \text{ m/s}$. Since it is a more complex scenario and it is much more crowded on the interconnecting road (30 vehicles on the middle road), it is very hard to maintain 10 m minimum headway distance, so we set $S_0 = 7 \text{ m}$.

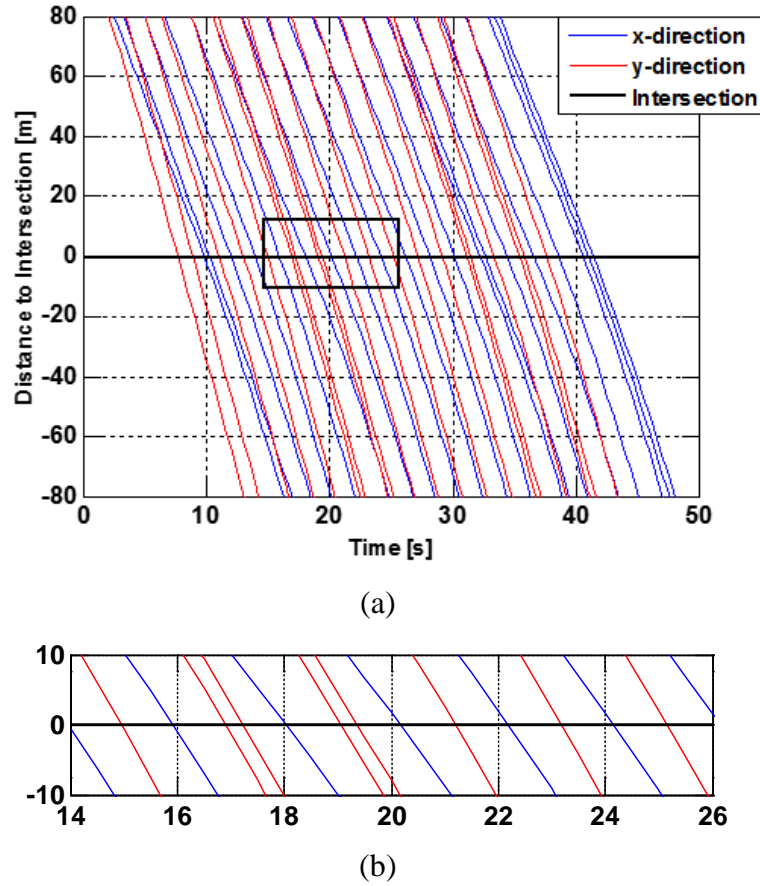
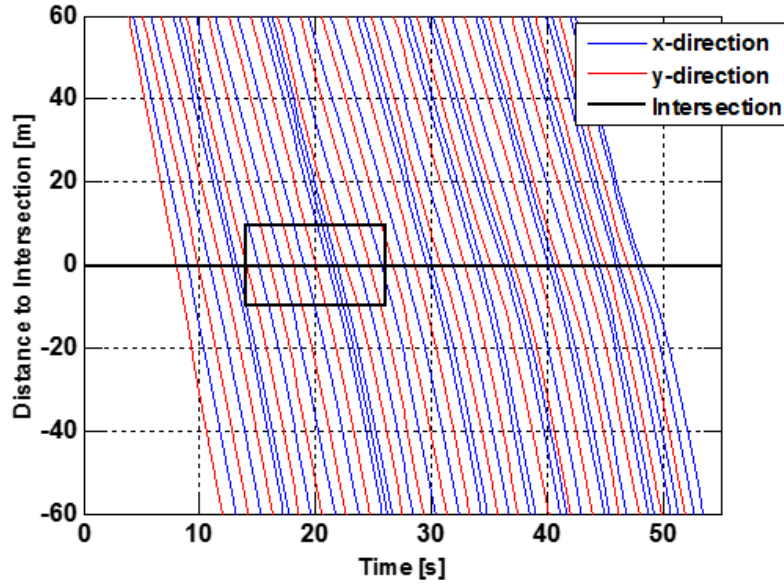


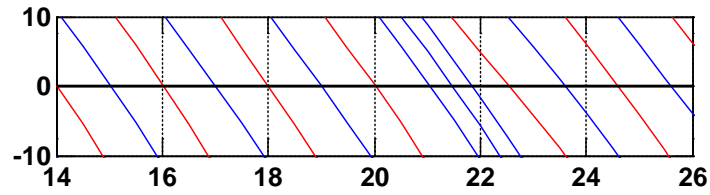
Figure 2.13 (a) Relative distance to the intersection of vehicles from road 1 and road 2 of intersection 1 in larger scale scenario (b) Partial zooming in on intersection area

Figure 2.13 and Figure 2.14 shows the simulation results similar to the previous scenario at intersection 1 and 2 respectively. It can be observed that there is no collision at the intersection areas in this scenario. We also conducted the comparison between our proposed method and the two baseline methods. It should be noted that, while examining the simulation results of fuel economy, we notice that there are a few vehicles that leave the control region very fast because of their initial positions and thus it is meaningless to

evaluate their fuel consumption. Table 2.2 shows the comparison results without taking into account the aforementioned vehicles. The results and conclusions from Table 2.2 are similar to the small scale scenario.



(a)



(b)

Figure 2.14 (a) Relative distance to the intersection of vehicles form road 4 and road 5 of intersection 2 in larger scale scenario (b) Partial zooming in on intersection area

Table 2.2 Fuel economy and mobility comparison of larger scale scenario

Approach	Proposed	No I2I	No Optimization
Average Fuel Economy (mpg)	47.01	46.39	45.62
Maximum Fuel Economy (mpg)	52.32	52.50	50.52
Minimum Fuel Economy (mpg)	41.01	40.75	41.04
Fuel Economy Standard Deviation	2.9676	3.2627	2.2244
All Vehicle Total Travel Time (s)	7581.5	7732.5	8088.5

C. Effects of mixed vehicle types

To study the effects of involving HEVs to our coordination strategy, another scenario has been explored. In this case, we only consider one intersection and two vehicles approaching to the intersection from x-direction and y-direction respective. The initial velocity and distance to the intersection are the same for both vehicles, such that the ETA of the two vehicles to the intersection is the same and they need to adjust their velocities to avoid collision at the intersection. To simplify the simulation, we ignore the

reference velocity tracking using MPC discussed in the previous section and assume the vehicles will travel at the reference velocity exactly at each time step.

We first set $w_p = w_q = 1$, indicating the two vehicles are the same type. Then we set $w_p = 0.8$ and $w_q = 1$, which means the vehicle from x-direction is a HEV and the vehicle from y-direction is a conventional vehicle. We set the weighting factor of HEV is less than the conventional vehicle, because we want to encourage the velocity changes of HEV and maintain less velocity deviation of the conventional vehicle. Since the HEV could recuperate from braking and accelerate with the power from battery, these weighting factors set up would achieve optimal overall fuel economy. Figure 2.15 shows the simulation results. It can be noticed that in the same weighting factor simulation, the controller will increase the velocity of one vehicle and decrease the other one randomly. In the other case, when different weights are used, the velocity of conventional vehicle remains the same during the simulation and the HEV changes its velocity to avoid collision. The vehicle passing sequence are different for the two cases as shown in Figure 2.15. We believe the overall fuel efficiency can be improved by adding appropriate weighting factors representing different vehicle types. However, it is very hard to evaluate the fuel efficiency of the HEV in this case because the HEV only travels for a short distance and time to cross the intersection. Further research effort may worth to expend on this area.

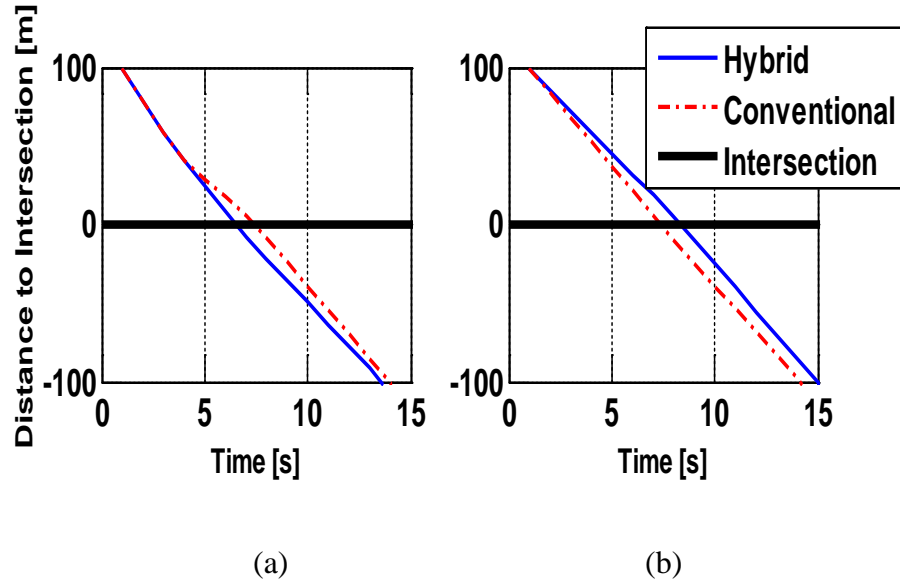


Figure 2.15 Effects of vehicle type on intersection passing sequence: (a) two vehicles with the same weighting factor (b) two vehicles with different weighting factors

2.1.6 Conclusion

In this section, a hierarchical control strategy is presented focusing on the coordination of CAVs at multiple intersections. For the first layer, each intersection is a decentralized controller sharing the neighborhood intersection traffic density information through I2I communication. The intersection controllers generate the average road velocity to assist the traffic density balance over the traffic network. In the second layer, the intersection controllers optimally assign the reference velocity for each individual vehicle based on the objective of minimizing the deviation from average road velocity and avoiding collision at the intersection. In the last layer, each vehicle as a decentralized local controller sends out its position and velocity information and uses MPC to track the

reference velocity sent from the intersection controller. The three layers are interconnected and mutually influence one another. By applying the hierarchical control architecture, we can reduce the computational burden on a single controller to achieve the real-time control of the vehicles at the intersections.

The proposed approach has been implemented on a small scale scenario with fewer vehicles and on a larger scale scenario with more vehicles. The successful implementation on both scenarios demonstrates the feasibility and scalability of our method. In order to prove the advantages of our proposed approach, two baseline methods are designed: no I2I method and no optimization method. The simulation results show the proposed approach outperformed the two baseline methods in both fuel economy and mobility. 8.47 % of average fuel economy improvement and 10.28 % of total travel time reduction can be expected compared with no optimization method from the small scale scenario. The scenario with mixed vehicle types has also been explored. The simulation results show that with the effect of vehicle types, the proposed method can generate a different vehicle passing sequence at the intersection with the objective of optimizing overall fuel economy.

2.1.7 Related Publication

- Du, Z., Chaudhuri, B.H. and Pisu, P., 2016. Distributed Coordination of Connected and Automated Vehicles at Multiple Interconnected Intersections. World Academy of Science, Engineering and Technology, International Journal of Computer, Electrical, Automation, Control and Information Engineering, 10(6), pp.842-848.

- Du, Z., Chaudhuri, B.H. and Pisu, P., Hierarchical Distributed Coordination Strategy of Connected and Automated Vehicles at Multiple Intersections. Journal of Intelligent Transportation Systems: Technology, Planning, and Operations (accepted)

2.2 Signalized Traffic Intersection

2.2.1 Introduction

Although we discussed the development of the coordination strategy for a group of CAVs at unsignalized traffic intersection relying only on the communication and cooperation of involved vehicles and intersection controllers, the traffic lights are still playing an important role in governing our current intersections at current stage of intelligent transportation system. Also, the traffic light controlled intersections would still be functional even at lower connected vehicle penetration rate unlike the traffic lightless intersection coordination strategy. However, poor traffic signal timing accounts for about 5 to 10% of traffic delays or 295 million vehicle-hours of delay on major roadways alone [86], which is very inefficient.

The objective of this research is to develop a coordination strategy for a group of connected vehicle passing through multiple interconnected signalized traffic intersections with the focus of individual trajectory planning. Utilizing the traffic signal phase and timing (SPAT) information to improve fuel economy and traffic mobility for both conventional vehicles and hybrid electric vehicles (HEVs) by avoiding or minimizing red light stops. The coordination strategy should also be robust to various connected vehicle penetration rate. Figure 2.16 shows the schematic of the problem. We assume single lane road with multiple interconnected intersections controlled by traffic lights. Vehicles do not turn or do overtake during the simulation. The traffic lights SPAT information is

assumed to be known. The V2V and V2I communication environment is available among the vehicles and the intersection controllers.

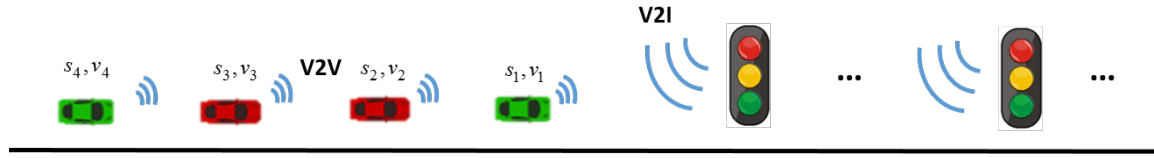


Figure 2.16 The schematic of the traffic light intersection problem

2.2.2 Literature Review

There are generally two categories in the literature to solve the issue of poor signal timing. The first one focuses on controlling the traffic signal. Numerous research efforts have been put on designing the traffic-actuated signals [87] [88], where the traffic signal phase and timing are responsive to the change of the traffic conditions. Some other researchers focus on developing the synchronization of a series of adjacent traffic lights to generate vehicles' free flow or green wave travelling conditions [43] [89] [90]. However, these approaches are very costly to implement and maintain. It is estimated that annually updating the traffic signal timing over the nation would cost about \$217 million [46]. It is even worse that although the traffic signal timing is well designed, vehicles will still often cruise at full speed to a green light and have to come to a sudden halt when the traffic light turns red [91].

Thus, the problem is better to be solved on the vehicle side with the knowledge of the SPAT information. An algorithm minimizing acceleration for a vehicle passing through multiple traffic signal lights is presented in [47]. Asadi and Vahidi in [49] developed a Model Predictive Control (MPC) based strategy using SPAT information to

reduce idling time and minimize vehicle's acceleration. This work was later extended by using a probabilistic approach to consider noisy traffic light conditions [50]. A machine learning based approach was proposed in [48] where smart phones are used to predict the phase of traffic lights.

Since the objective of this work includes improving the fuel economy for both conventional vehicle and HEVs, and we have already discussed the fuel consumption evaluation for conventional vehicles in the last section (Section 2.1.4D), it is better to give a brief review on the HEVs fuel economy research. Hybrid electric vehicles with at least two power sources have attracted great public attention because of the potential of reducing fuel consumption and emission. At any time, the power split between the engine and the alternative power source (e.g. battery) is required optimal to improve fuel economy while satisfying the driver power request at the same time. Thus, the control strategy for HEVs plays an important role of affecting their performance. Brahma et al. [92] proposed to use dynamic programming to control the power split with a given driving profile. The authors in [93] [94] considered driving behavior and real-time road conditions for HEVs, while the authors in [95] [96] have developed energy management strategies for both HEVs and plug-in electric vehicles that uses real-time road grade and trip information. Future driving behavior prediction using historical data can be found in [97] [98].

Most of the literature in HEV energy management research only focuses on controlling the power split and do not consider controlling the driver behavior. For the fuel economy control strategies mentioned above, the focus is only on one single subject

vehicle and do not consider multiple vehicles in the road where behavior of one vehicle affects the others. Also, very few study can be found in the literature on the impact of connected and unconnected vehicle mixed scenario (effects of connected vehicle penetration rate) while focusing on individual vehicle trajectories. The last but not least, most of the work makes single lane assumption without considering lane change. We will discuss the lane change problem in the next section.

2.2.3 Approach

In this section, the hierarchical control strategy for a group of connected vehicles passing through multiple interaction connected traffic light intersections is introduced. Figure 2.17 shows the hierarchical control architecture. At the first layer, the centralized intersection controller assigns target velocity for the vehicles based on SPAT information to help the vehicles avoid or minimize red light idling. In next layer, the vehicle local controller uses MPC to track the reference velocity sent from the intersection controller with the objective to improve fuel economy. If the vehicles are HEVs, another layer is applied to deal with the HEV energy management. Adaptive Equivalent Consumption Minimization Strategy (A-ECMS) is utilized to determine the power split.

The major contribution of this work is developing the coordination strategy for a group of connected vehicles passing through signalized traffic intersections. Utilizing SPAT information to avoid or minimize red light idling to improve the fuel economy and traffic mobility. The study on the effect of connected vehicle penetration rate is also conducted.

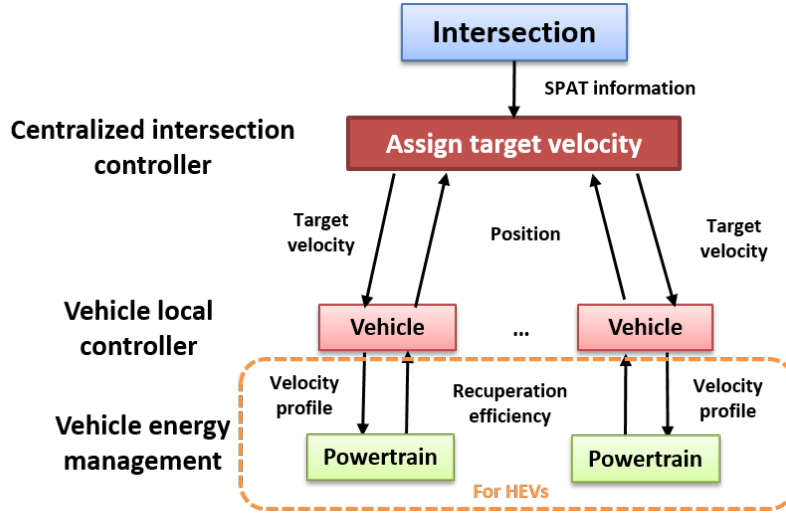


Figure 2.17 Hierarchical control architecture of traffic light intersection problem

A. Target velocity

The target velocity of a vehicle determined by the centralized intersection controller is presented. Rather than simply choosing the target velocity as the speed limit of the road, the target velocity can be chosen based on the SPAT information that helps the vehicle minimize stopping at red light. Similar to [49], the target velocity of each vehicle is calculated at time instance k as:

$$v_{\text{target}}^i(k) = \begin{cases} \frac{d_{ia}(k)}{K_w t_{\text{cycle}} - t_g - k} & \text{if red} \\ v_{\text{max}} & \text{if green and } \frac{d_{ia}(k)}{K_w t_{\text{cycle}} - t_r - k} \leq v_{\text{max}} \\ \frac{d_{ia}(k)}{K_w t_{\text{cycle}} + t_r - k} & \text{if green and } \text{Otherwise} \end{cases} \quad (2.7a)$$

$$\text{light} = \begin{cases} \text{red} & \text{if } 0 < \text{mod}\left(\frac{k}{t_{\text{cycle}}}\right) < t_r \\ \text{green} & \text{if } t_r \leq \text{mod}\left(\frac{k}{t_{\text{cycle}}}\right) \leq t_{\text{cycle}} \end{cases} \quad (2.7b)$$

$$t_{\text{cycle}} = t_g + t_r \quad (2.7c)$$

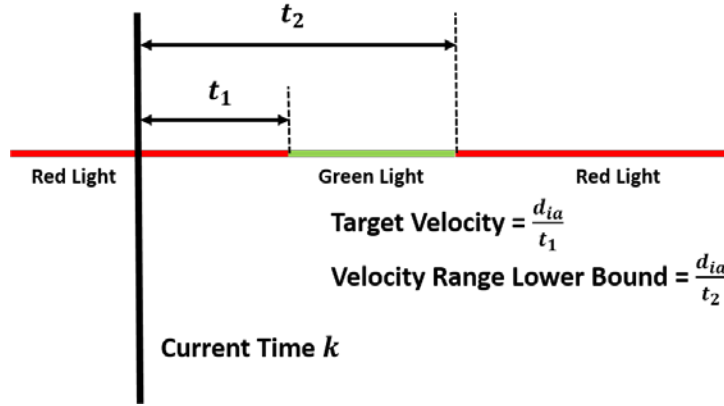


Figure 2.18 Schematic of the target velocity and velocity range lower bound evaluation

Here $d_{ia}(k)$ is the distance between $s_i(k)$ (the position of vehicle i) and the traffic signal a at time instant k , t_r and t_g are the red and green light duration respectively, so the full cycle duration is t_{cycle} . K_w is an integer representing the traffic light cycle number. The function mod in (2.7b) is a modulo function which generates the residue of division k by t_{cycle} . From (2.7a), if the traffic light is green, the speed limit is

chosen as the target velocity unless the constraint $\frac{d_{ia}(k)}{K_w t_{\text{cycle}} - t_r - k} \leq v_{\max}$ is not satisfied. In

that case, the vehicle desires to pass through the traffic signal in the next green light widow as shown in the third case of (2.7a). If no feasible velocity is obtained in the

consecutive green light windows, the vehicle has to stop at the approaching traffic light signal. Figure 2.18 shows the schematic of how our target velocity is evaluated. Basically, the vehicle target velocity is aiming at passing the intersection at the start of the green window. Instead of using zero as the velocity lower bound for the optimization problem later, the velocity lower bound is also evaluated. The calculation of velocity lower bound is similar to the target velocity, but it is targeting at passing the intersection at the end of green window. Both target velocity and the velocity lower bound are sent to each approaching connected vehicle local controller for the MPC optimization problem, such that the vehicle velocity within the range will possibly pass the intersection without stop.

B. MPC tracking target velocity in a fuel efficient way

Once the target velocity of a vehicle is determined, the problem of generation of energy efficient velocity profiles is solved in a model predictive control framework. If the vehicles are conventional vehicle, the MPC problem formulation is presented in (2.8), which is similar to in Section 2.1.4C:

$$J_i = \arg \min_{u_i} \sum_{t=k}^{k+T-1} \left[w_1 \left(v_i(t) - v_{\text{target}}^i(k) \right)^2 + w_2^i(t) R_{ij}(t)^2 + w_3 u_i(t)^2 + w_4 \frac{\dot{f}_{\text{fuel}}^i(t)}{v_i(t)} \right] \quad (2.8)$$

However, if the vehicles are HEVs, our goal is to minimize the power associated with traction force per unit distance for each vehicle by controlling the vehicle traction and braking force. The problem is presented by the following equations (2.9):

$$J_i = \arg \min_{u_i} \sum_{t=k}^{k+T-1} \left[w_1 \left(v_i(t) - v_{\text{target}}^i(k) \right)^2 + w_2^i(t) R_{ij}^i(t)^2 + w_3 u_i(t)^2 + w_4 \frac{P_{\text{trac}}^i(t) \Delta t}{s_i(k+T-1) - s_i(k)} \right] \quad (2.9a)$$

$$P_{\text{trac}}^i(t) = \frac{1}{2} \rho_a C_D A_v v_i(t)^3 + M_h^i g v_i(t) (\mu + \theta) + \beta_1^i \left[v_i(t) M_h^i u_i(t) \right] + \beta_2^i \left[-\eta_{\text{rec}}^i(t) v_i(t) M_h^i u_i(t) \right]$$

$$\beta_1^i = \begin{cases} 0 & \text{if } u_i \leq 0 \\ 1 & \text{otherwise} \end{cases} \quad (2.9b)$$

$$\beta_2^i = \begin{cases} 0 & \text{if } u_i > 0 \\ 1 & \text{otherwise} \end{cases}$$

$$R_{ij} = S_0 + t_{hd} \left(v_i(t) - v_j(t) \right) + \left(s_i(t) - s_j(t) \right) \quad (2.9c)$$

$$v_{\min}^i(t) \leq v_i(t) \leq v_{\max}^i(t) \quad (2.9d)$$

$$u_{\min}^i(t) \leq u_i(t) \leq u_{\max}^i(t) \quad (2.9e)$$

The first term in the cost function in (2.9a) punishes the deviation from the target velocity while the last term minimizes the control effort. It should be noted that the variables recuperation efficiency $\eta_{\text{rec}}^i(t)$ are obtained from our lower level controller. The second term minimizes the deviation from a desirable headway distance and time between vehicle i and its preceding vehicle j . S_0 and t_{hd} in (2.9c) are predefined critical headway distance and time respectively. The first two terms define the desired separation of two following vehicles and the third term in (2.9c) indicates the real distance between the two vehicles. The third term minimizes the power at the wheel per unit distance where $P_{\text{trac}}^i(t)$ can be computed from (2.9b). In (2.9b), P_{trac}^i is the power associated with the traction force derivate from [99] [100]. It can be seen from (2.9a), that the objective is to minimize the power associated with the traction force, such that by applying proper lower level energy management strategy, we can expect fuel economy improvement.

$\eta_{rec}^i(t)$ is the recuperation efficiency for each vehicle i . It is worth to mention that $\eta_{rec}^i(t)$ is obtained from the lower level controller. w_1 , w_3 and w_4 are constant weighting factors respectively. $w_2(t)$ is chosen as a function of the relative distance, so that it increases as the relative distance decreases and vice versa. Equations (2.9d) and (2.9e) indicate the constraints of the velocity and acceleration where v_{\min} and v_{\max} are the minimum and maximum allowable speed respectively, while u_{\min} and u_{\max} are the minimum and maximum possible acceleration of a vehicle i respectively.

C. A-ECMS energy management

If the vehicles are HEVs, the energy management controller maps the velocity evaluated by the vehicle local controller to power request and solves the optimal power split between engine and the battery. At the same time, the recuperation efficiency is fed back to the vehicle local controller layer for future velocity profile evaluation. In this research, the optimization of the power split is realized by using Adaptive Equivalent Consumption Minimization Strategy (A-ECMS) [101]. A-ECMS, similar to ECMS, does not require the knowledge of future driving cycles and has a low computational burden. Apart from that, by using online adaptation of the equivalence factor $s^{eqv}(t)$ instead of constant s^{eqv} in ECMS, better performance can be achieved under various driving conditions while sustaining battery SOC within desired limits. The detailed problem is described by the following equations:

$$\arg \min_{u_i^l} \left[\dot{m}_f(u_i^l(t)) \Delta t + \dot{m}_{f,em}(t) \Delta t \right] \quad (2.10a)$$

$$\dot{m}_{f,em}(t) = s^{eqv}(t) \left[\frac{\gamma}{\eta_{el}(P_{el})} + (1-\gamma) \eta_{el}(P_{el}) \frac{P_{el}}{H_{LHV}} \right] \Delta t \quad (2.10b)$$

$$s^{eqv}(t+1) = 0.5(s^{eqv}(t) + s^{eqv}(t-1)) + c_p(SOC(0) - SOC(t)) \quad (2.10c)$$

$$\gamma = \frac{1 + \text{sgn}(P_{el})}{2} \quad (2.10d)$$

$$SOC(t_f) - SOC(0) \leq \varepsilon_0 \quad (2.10e)$$

Here, $\dot{m}_{f,em}(t)$ is the equivalent fuel consumption rate of the electrical machine, γ is unit step function, η_{el} is the efficiency of the electrical path and P_{el} is the power from the electric machine. $s^{eqv}(t)$ as the equivalent factor is evaluated in (2.10c), where c_p is the step size acting as a proportional feedback gain as mentioned in [101]. It can be noticed that the equivalent factor changes as the battery SOC deviates from its initial SOC. The constraint in (2.10b) has been relaxed to (2.10e) so that the difference between the final SOC and the initial SOC stays within a small bound ε_0 .

In this research, the efficiencies feedback is achieved by the following procedure. The vehicle local controller evaluates the velocity profiles for a certain time window with initial recuperation efficiency. The velocity profiles are then sent to each energy management layer controller. The energy management controllers follow the velocity profiles and optimize the power split. At the same time, the average recuperation efficiency is computed and fed back to the vehicle local controller layer for the future velocity profile evaluations. By doing so we closed the loop between the vehicle local controller layer and energy management controller layer and these two layers are

mutually affecting each other. We name the time window while computing the average efficiencies as feedback time window.

2.2.4 Simulation Results

The simulation results of the proposed method are shown in this section. We run the simulation in MATLAB R2014a. Detailed modeling of the HEVs are developed based on Autonomie software. The description of the HEVs are provided in Table 2.3. We consider a scenario with 10 vehicles in a single lane road with traffic lights at every 500 *m*. Two signal timings are chose to demonstrate the performance of our proposed approach. The first signal timings choice is sampled from a uniform distribution with range 37s to 43s for the red light window (t_r) and 12s to 17s for the green light window (t_g) for each cycle of every traffic signal. For simplicity, we name this signal timings as tr40-tg15, because $t_r = 40s$ and $t_g = 15s$ are the mean value for the range of red light window and green light window respectively. The second choice is called tr30-tg10 with range 27s to 33s for the red light window (t_r) and 7s to 13s for the green light window (t_g).

A 600s simulation time duration is considered for each simulation case. The trajectories of all the vehicles in the tr40-tg15 case and tr30-tg10 case without considering the recuperation efficiency feedback are shown in Figure 2.19 and Figure 2.21 respectively. Here the meaning of without considering the recuperation efficiency feedback is that we use constant $\eta_{rec}^i(t)$ for all the vehicles and all the time instance in (2.9a). As the baseline comparison, Figure 2.20 and Figure 2.22 shows that all the

vehicles are controlled by Gipps car following model [102]. The velocity profiles of all the vehicles for both signal timings cases are shown in Figure 2.23 and Figure 2.24 respectively. The different colors in the figures stand for different vehicles' trajectories. The red bars on the figures indicate the red signal and its duration. It can be observed from the figures that our proposed method enables free flow by generating velocity profiles that helps vehicle reduce the red light idling. In our simulations, only one vehicle suffers a short stop as shown in Figure 2.24. However, the vehicles governed by Gipps car following model suffered lots of stops at red lights during the simulation. The fuel economy results are summarized in Table 2.4

Table 2.3 Parameters and components of the vehicles

Component and Parameters	Description and Value
Vehicle Mass	1360 (kg)
Vehicle Front Area	2.25 (m ²)
Drag Coefficient	0.3
Engine	110 kW and 2.2 L SI gasoline engine
Motor	Permanent Magnet electric motor of the MY04 with continuous power of 25 kW and peak power of 50 kW
Energy Storage	Li-ion Battery with capacity 6 Ah and 75 cells
Transmission	5 speed auto gear box with final drive 4.438
Power Converter	Output voltage 12 V and efficiency 0.95
Wheel	P195/65/R15

Table 2.4 Summary of fuel economy comparison

	Vehicle #	1	2	3	4	5	6	7	8	9	10	Avg MPG
Tr 30s	Proposed	52.62	53.43	50.16	50.41	51.33	52.30	51.97	53.86	53.19	52.64	52.19
Tg 10s	Gipps	30.19	31.92	28.34	29.15	30.95	32.88	33.71	33.87	30.79	31.84	31.37
Tr 40s	Proposed	54.16	51.19	53.09	52.97	51.39	48.87	47.56	47.01	46.00	46.43	49.87
Tg 15s	Gipps	31.62	31.51	31.65	31.83	29.83	28.94	31.82	33.84	35.11	33.97	32.01

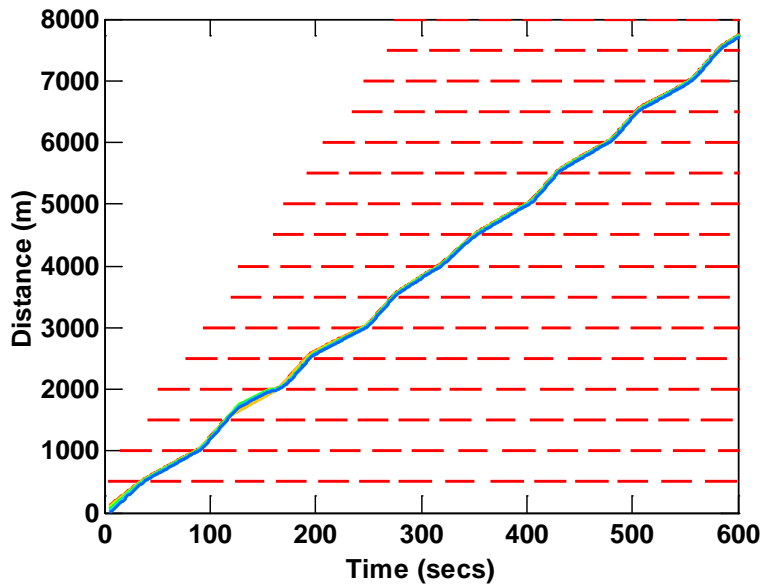


Figure 2.19 All vehicle trajectories of tr30-tg10 no efficiency feedback (the red dash lines indicate traffic lights)

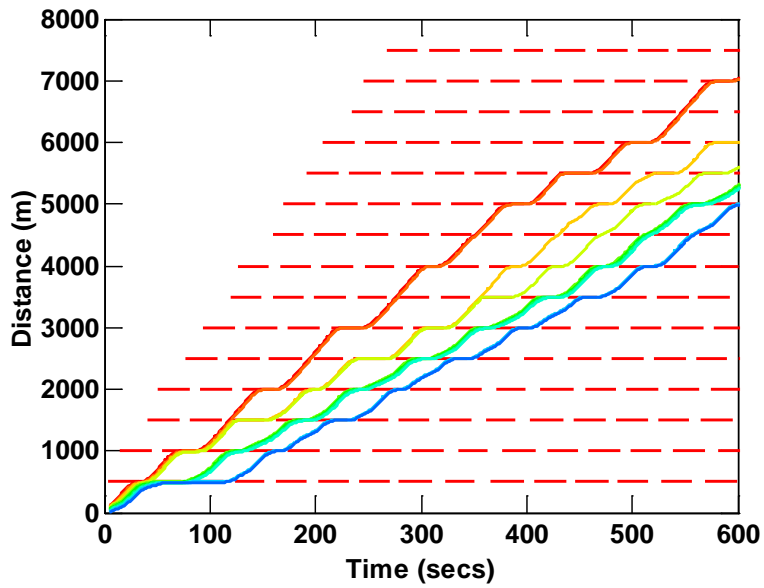


Figure 2.20 All vehicle trajectories of tr30-tg10 in Gipps car following

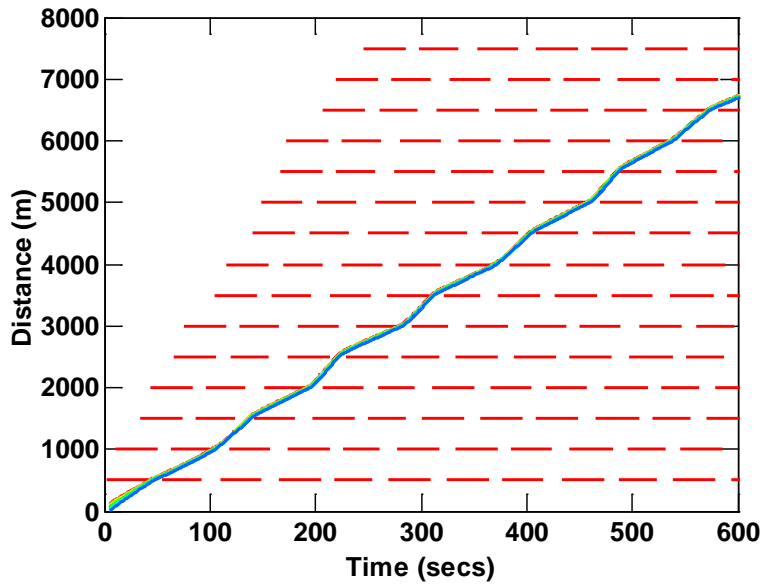


Figure 2.21 All vehicle trajectories of tr40-tg15 no efficiency feedback (the red dash lines indicate traffic lights)

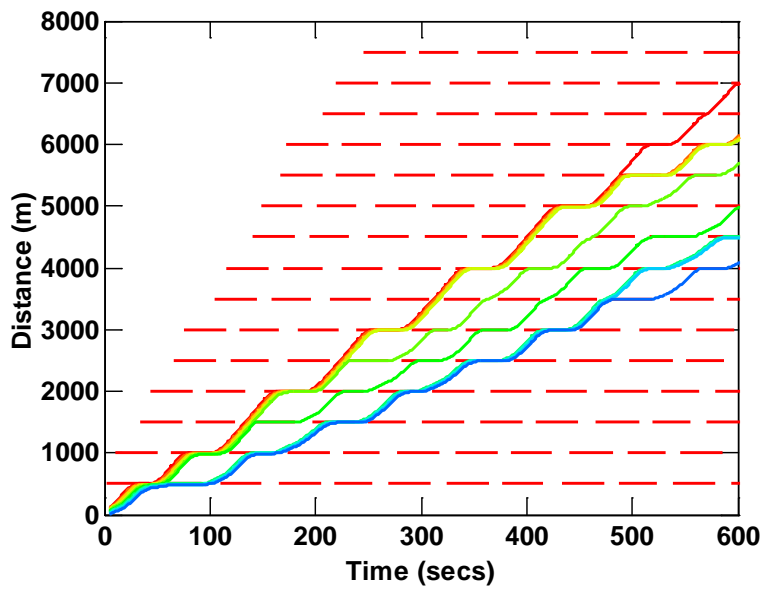


Figure 2.22 All vehicle trajectories of tr40-tg15 in Gipps car following

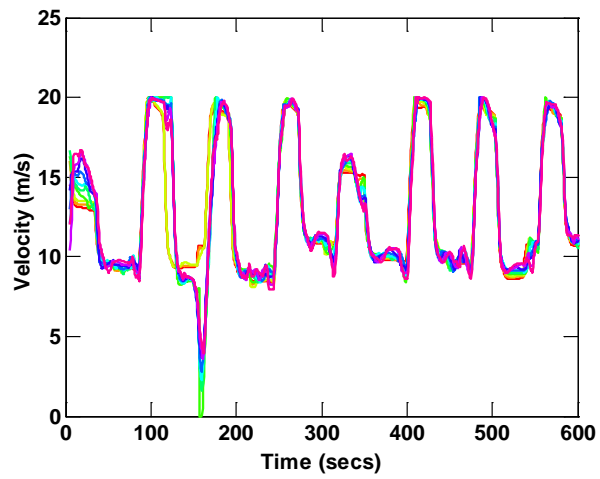


Figure 2.23 All vehicle velocity profiles of tr30-tg10 no efficiency feedback

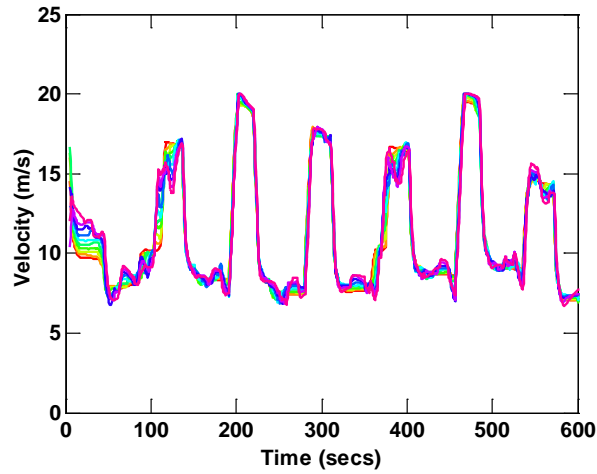


Figure 2.24 All vehicle velocity profiles of tr40-tg15 no efficiency feedback

To demonstrate the performance improvement of the efficiencies feedback proposed in this research, we choose 40s, 60s, 75s, 100s and 200s as our feedback time windows and compare with our baseline (no efficiency feedback) for both aforementioned two signal timings cases. The average fuel economy results for both of the signal timings are presented in Figure 2.25 and Figure 2.26 respectively. The detailed fuel economy results are tabulated Table 2.5. It can be noticed that the fuel economy performance is improved when using the efficiencies feedback proposed in this research compared with baseline where there is no efficiencies feedback. That is because with the efficiencies feedback, the velocity profiles evaluated by the vehicle local controller coincide with the real operating efficiencies of the HEVs, such that the fuel economy is improved. The best performance appears at around 60s to 75s feedback time window which indicates that a proper selection of the feedback time window is important. Figure 2.27 and Figure 2.28 show the velocity profiles and SOC of all the feedback time

windows in tr30-tg10 case for vehicle No. 1 and No. 7 respectively. Figure 2.29 and Figure 2.30 show the velocity profiles and SOC of all the feedback time windows mentioned above in tr40-tg15 case for vehicle No. 1 and No. 7 respectively. It can be seen from the figures that different feedback time windows slightly affect the velocity profiles and the SOC of every vehicle stays within a 2% bound. There is only little final SOC variation among different simulation cases, so the effect of final SOC difference on the fuel consumption evaluation can be negligible. For the sake of simplicity, the velocity profiles and SOC data of the rest vehicles are not presented.

Table 2.5 Summary of average fuel economy of different feedback windows

Signal Timings	Average Fuel Economy (mpg)					
	40s	60s	75s	100s	200s	Baseline
tr40-tg15	51.54	51.71	51.35	50.01	50.41	49.87
tr30-tg10	53.55	53.76	53.14	52.85	52.96	52.19

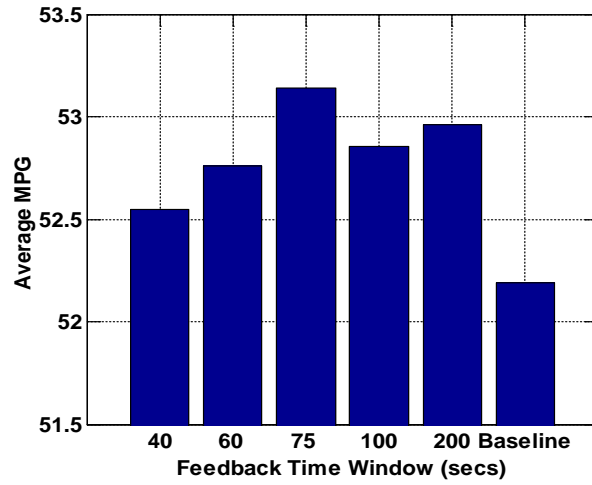


Figure 2.25 Average fuel economy of tr30-tg10

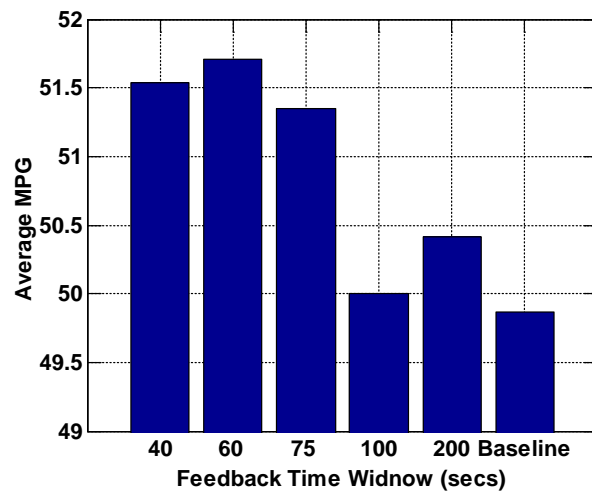
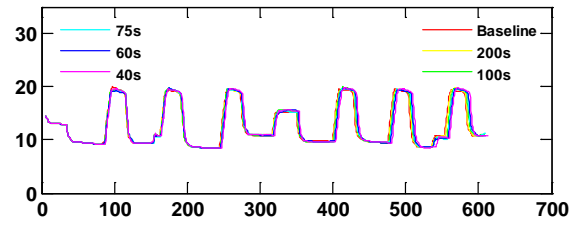
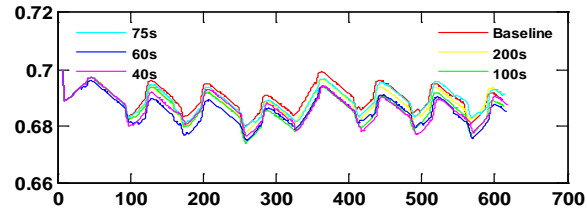


Figure 2.26 Average fuel economy of tr40-tg15

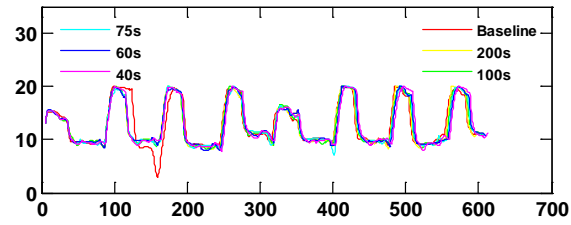


(a)

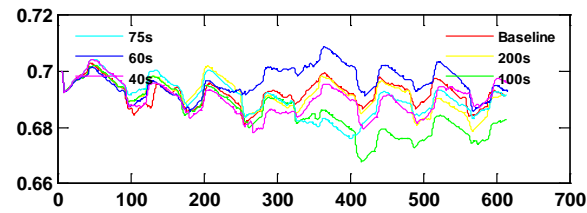


(b)

Figure 2.27 Vehicle No.1 in different feedback time windows of tr30-tg10 case: (a) velocity profiles (b) SOC data

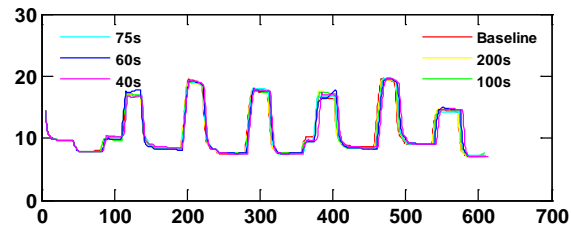


(a)

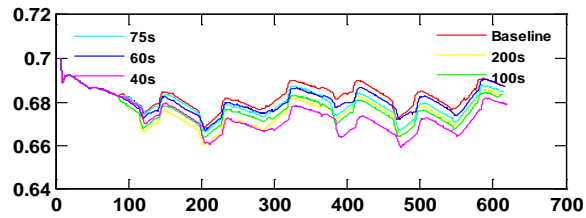


(b)

Figure 2.28 Vehicle No.7 in different feedback time windows of tr30-tg10 case: (a) velocity profiles (b) SOC data

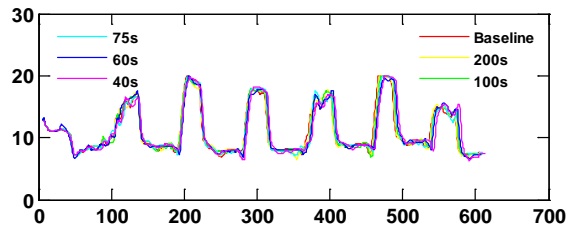


(a)

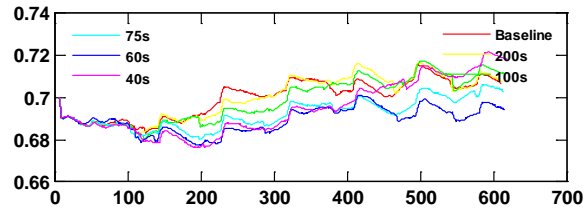


(b)

Figure 2.29 Vehicle No.1 in different feedback time windows of tr40-tg15 case: (a) velocity profiles (b) SOC data



(a)



(b)

Figure 2.30 Vehicle No.7 in different feedback time windows of tr40-tg15 case: (a) velocity profiles (b) SOC data

2.2.5 Conclusion

This section presents a novel hierarchical control architecture where different layers of controllers, although solves different problems, aims at improving fuel economy of a group of HEVs. The different layers of controllers mutually affect each other. The SPAT information is utilized to avoid or minimize red light idling to improve overall fuel economy and traffic mobility. The simulation results show the fuel economy improvement of our proposed approach.

2.2.6 Related Publication

- **Z. Du**, L. Qiu and P. Pisu, Hierarchical Energy Management Control of Connected Hybrid Electric Vehicles on Urban Roads with Efficiencies Feedback, Proceedings of the ASME 2016 Dynamic Systems and Control Conference.
- L. Qiu, **Z. Du**, L. Qian and P. Pisu, Hierarchical Energy Management Control Strategies for Connected Hybrid Electric Vehicles Considering Efficiencies Feedback, Journal of Applied Research and Technology (under review)

2.3 Connected Vehicle Penetration Rate Study

2.3.1 Introduction

In our previous work, we have designed a fuel efficient control strategy for a group of connected vehicles on urban roads with signalized intersections. We assumed that all the vehicles are connected vehicles, which is a very strong assumption under current stage of the connected vehicle development. In this section, we focus on the connected and unconnected vehicles mixed scenario. In the literature, most of the research on connected vehicle penetration rate studies are carried at macroscopic level [53] [54]. The major contribution of the work in this section is that the effects of connected vehicle penetration rate is studied considering individual vehicle decision making at microscopic level, i.e., the control input (acceleration and deceleration in our case) of each vehicle at every time step.

In this section, a simulation study is conducted to find out the effects of various connected vehicle penetration rate and the presence of unconnected vehicles on the convoy. In this study, we assume the connected vehicle can send its position and velocity information to the centralized intersection controller and receive the target velocity at the same time. The connected vehicle longitudinal motion is controlled by our hierarchical control architecture (in Section 2.2.3). The unconnected vehicles do not have the capability of sending or receiving any information from the intersection controller, but its position and velocity information can be captured by the onboard sensors of the connected vehicles and sent to the intersection controller. The unconnected vehicles are also assumed to have a good estimation on the distance between itself and its preceding

vehicle or the approaching traffic lights. The unconnected vehicle longitudinal motion is controlled by the modified Gipps car following model. Figure 2.31 shows the schematic of the simulation scenario.

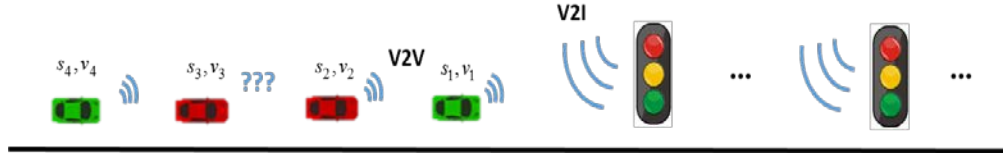


Figure 2.31 Schematic of the connected and unconnected vehicles mixed scenario

2.3.2 Modified Gipps Car Following Model

The Gipps car following model [102] was proposed to estimate the behavior of the preceding vehicle in a stream of traffic. In this section, we modified the original model for controlling the longitudinal motion of the unconnected vehicles travelling on signalized intersection roads with the capability of stopping at the red signal light. For any unconnected vehicle i , if it is following a lead vehicle, the original Gipps car following model is applied as in (2.11):

$$v_i^a(t + \Delta k) = v_i(t) + 2.5 \cdot u_{ub}^i \cdot \Delta k \cdot \left(1 - \frac{v_i(t)}{v_{ub}^i}\right) \cdot \sqrt{0.025 + \frac{v_i(t)}{v_{lb}^i}} \quad (2.11a)$$

$$v_i^b(t + \Delta k) = u_{lb}^i \cdot \Delta k + \sqrt{\left(u_{lb}^i \cdot \Delta k\right)^2 - u_{lb}^i \cdot \left(2[s_{i-1}(t) - S_0 - s_i(t)] - v_i(t) \cdot \Delta k - \frac{v_{i-1}(t)^2}{u_{lb}^{i-1}}\right)} \quad (2.11b)$$

$$v_i(t + \Delta k) = \min(v_i^a(t + \Delta k), v_i^b(t + \Delta k)) \quad (2.11c)$$

In above equations, v_n^a is the maximum speed a vehicle can accelerate to during one time step Δk , while v_n^b is the maximum safe speed for vehicle i with respect to the vehicle in front at time t . The velocity of vehicle i in the next time step is the minimum of v_n^a and v_n^b . The rest parameters are consistent with the definition in Section II. More details about the original Gipps car following model can be found in [102].

If the vehicle is the leading vehicle in the convoy or there is no vehicle between itself and the approaching traffic light, the Gipps car following model is modified as:

if light = red

$$\begin{aligned}
v_i^{a*}(t + \Delta k) &= v_i^a(t + \Delta k) \\
v_i^{b*}(t + \Delta k) &= u_{lb}^i \cdot \Delta k \\
&+ \sqrt{\left(u_{lb}^i \cdot \Delta k\right)^2 - u_{lb}^i \cdot \left(2[s_{light} - s_i(t)] - v_i(t) \cdot \Delta k\right)} \\
v_i(t + \Delta k) &= \min\left(v_i^{a*}(t + \Delta k), v_i^{b*}(t + \Delta k)\right)
\end{aligned} \tag{2.12a}$$

if light = green

$$v_i(t + \Delta k) = v_i(t) + \min\left(0.5 \cdot u_{ub}^i, \left(v_{ub}^i - v_i(t)\right) / \Delta k\right) \cdot \Delta k \tag{2.12b}$$

In this case, when the leading vehicle is approaching a red light, v_i^{a*} remains the same with the original model v_i^a . However, the second equation of (2.12a) is modified, where the position s_{i-1} and velocity v_{i-1} of the preceding vehicle is replaced by the upcoming traffic light with the position of s_{light} and zero velocity. By this modification, the unconnected vehicles governed by the modified Gipps car following model are able to stop at the red light. If the unconnected vehicle is approaching a green light, a constant

acceleration is applied unless its velocity is reaching the speed limit of the road as described in (2.12).

2.3.3 Simulation Results

In this section, we present the simulation study of the connected and unconnected vehicles mixed scenario to find out the effects of the presence of the unconnected vehicles on the convoy. The simulation scenario considered is a single lane road with traffic lights at every 500 m . The baseline duration of the traffic signal green and red are $t_g = 15s$ and $t_r = 40s$, respectively. The traffic signal timing of each traffic light and every cycle varies from the baseline following a uniform distribution and they are assumed to be known by the centralized intersection controllers. The simulation run for 600 s with the sampling time of $k = 0.5s$ and the prediction horizon of $T = 6s$. There are 10 conventional vehicles on the convoy with identical parameters: $M_h^i = 1200kg$, $A_v^i = 2.5m^2$, $C_D = 0.32$, $u_{ub}^i = 3m/s^2$ and $u_{lb}^i = -3m/s^2$. The speed limit of the road $v_{ub} = 20m/s$. We assume the road is flat, so $\theta = 0$ degree. The ten vehicles can be either connected or unconnected depending on the initial set up. Several scenarios have been studied with different connected vehicle penetration rate and different unconnected vehicle positions on the convoy.

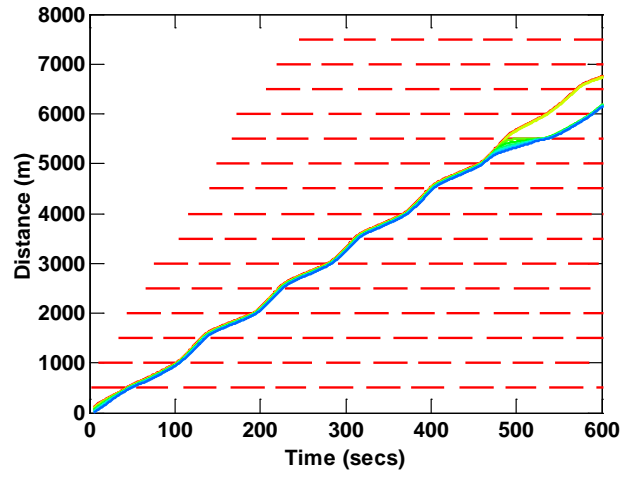


Figure 2.32 Vehicle trajectories of all connected vehicle scenario

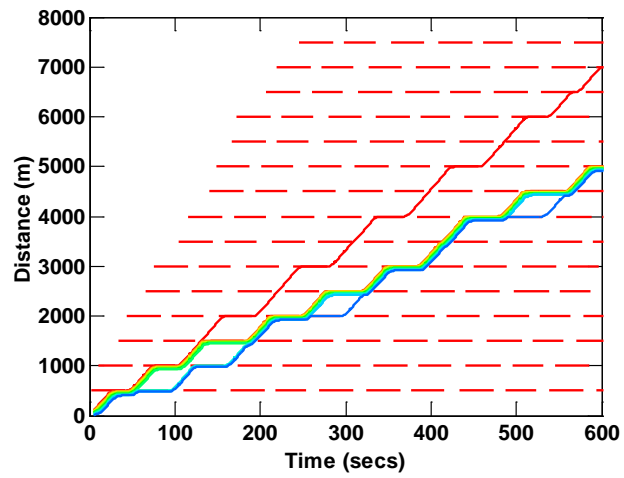


Figure 2.33 Vehicle trajectories of all unconnected vehicle scenario

Vehicle #	All Connected	All Unconnected
1	40.75	24.83
2	40.35	24.20
3	40.49	24.42
4	40.66	24.55
5	39.34	24.59
6	39.58	24.58
7	39.80	24.62
8	40.03	24.08
9	40.19	24.06
10	41.03	23.17
Avg MPG	40.22	24.31
Standard Deviation	0.7304	0.4731

Table 2.6 Summary of fuel economy (MPG) evaluation I

The simulation results of all connected (100% penetration rate) and all unconnected (0 penetration rate) vehicles scenarios are first presented to show the performance and advantages of our proposed connected vehicle longitudinal motion coordination. Figure 2.32 and Figure 2.33 show all the 10 vehicles' trajectories of all connected vehicles scenario and all unconnected vehicles scenario, respectively. The red

horizontal bars on the figures indicate the red light windows of every traffic light and each cycle. Different color of trajectories represents different vehicles. The fuel consumption of the two simulation scenarios are tabulated in Table 2.1. In Figure 2.32, the connected vehicles controlled by our proposed strategy are able to avoid most of the red lights, However, the unconnected vehicles governed by the modified Gipps car following model do not have the capability of red light stop avoidance. The average velocity during the simulation is 10.03 m/s and 8.50 m/s for all connected and all unconnected vehicles scenario respectively, which indicates the better traffic mobility can be achieved by our proposed strategy. At the same time, significant fuel economy improvement is achieved by the connected vehicles as shown in Table 1 due to the pre-knowledge of the SPAT information, minimizing fuel consumption during the trip and mild acceleration/deceleration.

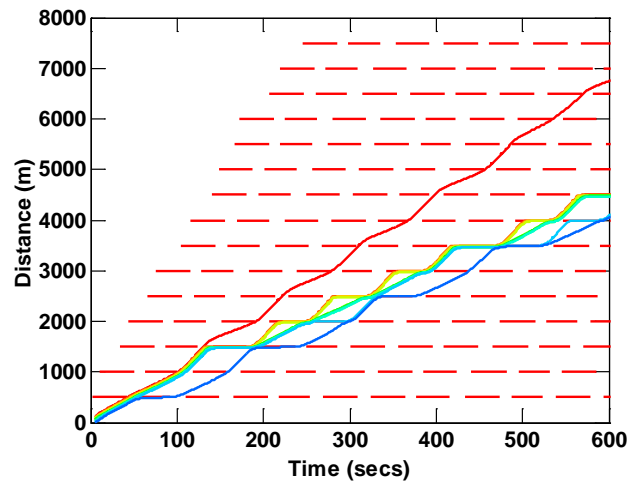


Figure 2.34 Vehicle trajectories when vehicle # 2, 3, 4, and 9 are unconnected

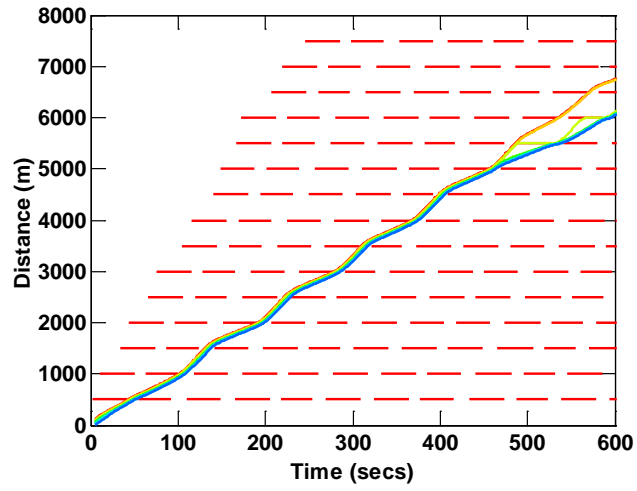


Figure 2.35 Vehicle trajectories when only vehicle # 4 is unconnected

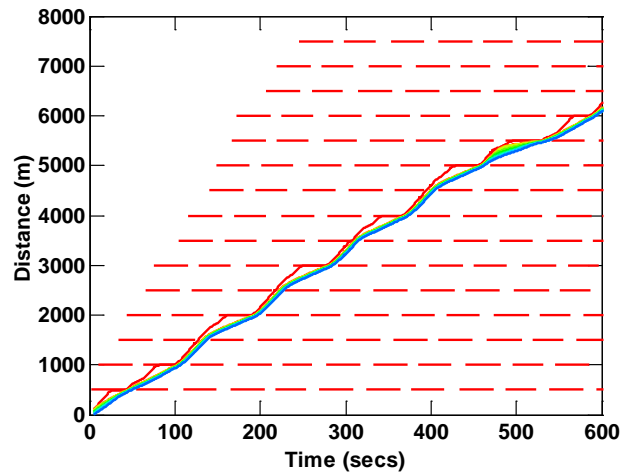


Figure 2.36 Vehicle trajectories when only vehicle # 1 is unconnected

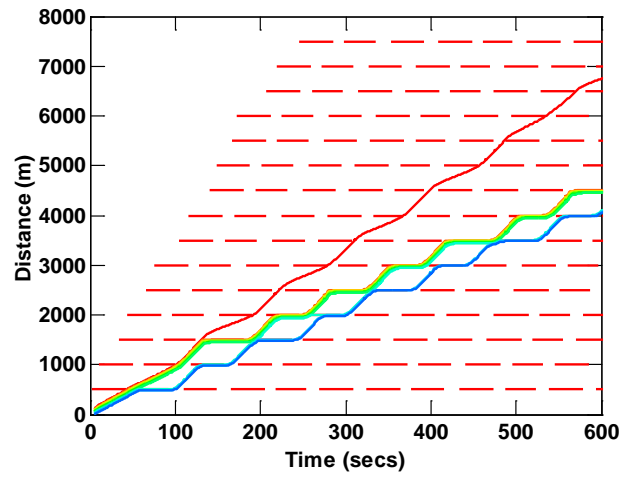


Figure 2.37 Vehicle trajectories when only vehicle # 1 is connected

Vehicle #	# 2 3 4 9 Unconnected	# 4 Unconnected	# 1 Unconnected	# 1 Connected
1	40.75	40.75	24.83	40.75
2	28.18	40.35	38.15	28.17
3	28.32	40.49	38.34	28.32
4	28.44	38.80	38.49	28.44
5	34.12	38.62	38.68	28.53
6	34.40	38.81	39.00	28.48
7	34.57	39.01	39.26	28.53
8	34.85	39.30	35.79	25.91
9	30.43	39.33	36.63	25.02
10	32.87	40.43	37.95	25.16

Avg MPG	32.69	39.59	36.71	28.73
STD	3.9549	0.8233	4.3083	4.4678

* The bold MPG numbers indicate the vehicles are unconnected

Table 2.7 Summary of fuel economy (MPG) Evaluation II

Figure 2.34 to Figure 2.37 show all the vehicles' trajectory under various connected and unconnected vehicles mixed scenarios and the fuel consumption evaluation is summarized in Table 2.7. The vehicle is numbered as shown in Figure 2.31, where vehicle # 1 is the leading vehicle on the convoy. For the sake of simplicity, we define the connected vehicle which is following an unconnected vehicle as CFU (connected following unconnected), while the unconnected vehicle which is following a connected vehicle as UFC (unconnected following connected).

From the mixed scenario simulation results, a few conclusions can be made. First, the fuel economy of UFC is improved compared with all unconnected vehicles scenario (Table 2.6). The reason behind this is the unconnected vehicles are following an optimal trajectory generated by the connected vehicles for at least a while before they are stopped by the red light. For instance, the unconnected vehicle # 2, 3 and 9 in Figure 2.34 follow the optimal trajectory of connected vehicle #1, thus the fuel economy gets improved. Another example is the unconnected vehicle # 4 in Figure 2.35, which follows the connected vehicles and avoid most of the red lights during the simulation, thus the fuel economy of vehicle # 4 in Figure 2.35 improves significantly. Secondly, the fuel economy of CFU is better than unconnected vehicles, but it is not as good as the

performance in all connected vehicles scenario. For example, vehicle # 5, 6, 7 and 10 in Figure 2.34, these connected vehicles controlled by our proposed strategy can still avoid most of the red lights even following the unconnected vehicles which stop frequently, but they unavoidably suffer a couple of stops due to following the bad trajectories of its preceding unconnected vehicles. That explains the performance degradation for the CFU.

Additionally, from the simulation study, we find the connected vehicle penetration rate does not necessarily relate to the average fuel economy of the convoy particularly in our no lane change setup. The scenarios in Figure 2.35 and Figure 2.36 have the same connected vehicle penetration rate (90%, only one vehicle is unconnected in both scenarios). However, the average MPG (third and fourth column in Table 2.7) is quite different. That is because the unconnected vehicle # 4 in Figure 2.35 like we discussed before follows the connected vehicles adequately for most of the simulation due to its initial position and traffic signal timing. Also, it only affects the fuel economy of the rest 6 vehicles behind it. In the other case, the vehicle # 1 in Figure 2.36 is unconnected and it affects all the rest 9 vehicles on the convoy, thus the overall fuel economy decreases. In Figure 2.37, even there is only one vehicle is connected (vehicle # 1), but the only connected vehicle is the leading vehicle on the convoy. It improves the fuel economy of all the rest unconnected vehicles and increases the average fuel economy of the convoy.

From the above simulation study and analysis, it can be concluded that the connected vehicle penetration rate does not necessarily relate to the average fuel economy performance of the convoy, but the position of the unconnected vehicle on the

convoy matters. From the fuel economy perspective, the connected vehicle should not follow an unconnected vehicle which will decrease the fuel economy of the connected vehicle. This conclusion gives us a very important triggering factor of discretionary lane change when the single lane assumption is removed. Other than the discretionary lane change triggering factors like seeking better traffic conditions or get higher velocity, the presence of unconnected vehicle is another important triggering factor we will consider in the following lane change study.

2.3.4 Conclusion

In this section, the Gipps car following model is modified for the unconnected vehicles on the signalized intersection roads. The scenarios of connected and unconnected vehicles mixed scenario have been simulated where the connected vehicles are controlled by our proposed hierarchical control architecture and the unconnected vehicles are governed by the modified Gipps car following model. From the simulation results, we conclude that the connected vehicles do not want to follow unconnected vehicles from the fuel consumption perspective. Also, under our single lane assumption, the connected vehicle penetration rate does not relate to the average fuel economy of the group of vehicles directly. The position of the unconnected vehicle on the convoy affects the average fuel economy significantly.

2.3.5 Related Publication

- **Z. Du**, B. HomChauduri and P. Pisu, Coordination Strategy for Vehicles Passing Multiple Signalized Intersections: A Connected Vehicle Penetration Rate Study,

Proceedings of 2017 American Control Conference (ACC), Seattle, WA, May 2017.

- **Z. Du**, B. HomChauduri and P. Pisu, The Discretionary Lane Change Decision Study for a Group of Vehicles on Urban Roads under Imperfect Connected Vehicle Penetration Rate, IEEE Transactions on Intelligent Transportation Systems (under review)

CHAPTER 3 LANE CHANGE DECISION

3.1 Introduction on Lane Change Decision (LCD)

We assume all the vehicles do not change lane or make turns at the intersections in our previous research setup. However, in the real world driving scenario, the vehicles not only move forward and pass through intersections but also perform lane change. Lane change is one of the basic driver behaviors, which can never be avoid in real traffic environment [55]. Poor lane change decision has negative impact of both traffic safety and efficiency. For traffic safety impact, 4% to 10% of the traffic accidents are caused by lane change maneuver [56]. Also, 78% of lane change accidents take place in dense traffic flow with low speed and small inter-vehicle space [57], which is, exactly the focus of our research, urban areas. For traffic efficiency impact, lane change could generate a capacity drop with shockwaves in both lanes [58]. It has also been confirmed that aggressive lane changes on highways or urban traffic, result in consuming 20- 30% extra fuel [59].

The lane change is classified as mandatory lane change and discretionary lane change based on different driving incentives [60]. Mandatory lane change occurs when a vehicle must change lane to follow a specified path or due to the road geometry (i.e., lane merging ahead). On the other hand, discretionary lane change occurs when a vehicle changes to a lane perceived to offer better traffic conditions i.e., higher speed or moving to a lane with lower traffic density, but it does not necessarily happen.

3.2 Literature Reviews

The literature on LCD can be categorized into three catalogs. In Gipps [61] and Hidas [62] [63], the LCD is made through gap acceptance model based approaches. Lane change is motivated by locations of permanent obstructions, the presence of heavy vehicles, special purpose lanes or the intention to turn. The critical or acceptable gap is defined by either exponential function or normal distribution of certain parameters, like velocity, distance, allowable acceleration and so on. Once the lane change is motivated and the gap on the target lane is greater than the critical gap, lane change will be executed. The Gipps LCD [61] was later extended by involving probability theory to make the LCD model more realistic [64]. Some other researchers developed LCD model based on utility theory. The basic idea is to compare the utility of staying in the current lane and the risks associated with lane change. Kesting *et al.* [65] proposed the LCD model known as MOBIL (Minimizing Overall Braking Induced by Lane Changes). The authors compared the overall acceleration as the utility of the criteria of lane change. Basically, higher overall acceleration means higher velocity and higher traffic mobility. Other utility theory based LCD models include Ahmed [103], Toledo [67] [66] and so on. The other catalog of the LCD model is optimization based approach where the longitude motion and LCD are integrated together and the optimization problem is formulated to determine when and where it is optimal to change lane [69] [55] [68].

For the gap acceptance and utility based model, only the subject vehicle's LCD and action are considered and the reactions and affection of surrounding vehicles are ignored. Additionally, the subject vehicle makes decisions independently. The advantages

of connected vehicles have not been fully taken. Sometimes the mandatory lane change may not be able to be executed independently due to short inter-vehicle distance enabled by connected vehicle technologies. In the utility based model, LCD is made based on the utility advantage on the current moment ignoring the sudden changes on the traffic conditions, like the traffic light changes in our research. For optimization based approach, since the longitudinal motion is continuous while the LCD is discrete, integrating these two together into one optimization problem ends up with a Mixed Integer Programming Problem. Most solution methods for Mixed Integer Problem apply some form of tree searching and it can be very computational inefficient and with poor scalability especially when the number of subject vehicle increases, which makes it unrealistic for real-time implementation.

3.3 Discretionary Lane Change Decision

In this section, our approach of discretionary LCD is introduced. We initiate our research on LCD by starting with discretionary LCD, because it is easier to handle compared with mandatory LCD. No cooperation among the connected vehicles is necessary. Once we get enough experience dealing with the discretionary LCD, we can move on to study the mandatory LCD, which is more challenging.

3.3.1 Problem Formulation

In this research, we focus on a connected vehicle environment with a group of connected and unconnected vehicles on a road with two identical lanes. The vehicles can make discretionary LCD to gain benefits such as higher velocity or better fuel economy.

We assume the vehicles only pass through and do not make turns at any signalized intersection. In this connected vehicle framework, the information of position and velocity of a particular connected vehicle is assumed to be available to its near neighborhood via V2V communication. The information of all the connected vehicles within a certain region (e.g., within the range of Dedicated Short Range Communications (DSRC)) is available to the centralized intersection controller. Figure 3.1 shows the schematic of our research scenario. The vehicle with question marks is an unconnected vehicle, i.e., the vehicle which does not share or receive any information from other vehicles or traffic infrastructure. The rest vehicles in Figure 3.1 are connected and under the control of our proposed algorithm. Similar to our previous research [51] [104] [52], we attempt to formulate and solve the problem in the hierarchical control architecture, such that the problem is decomposed and resolved in different layers in order to reduce the computational complexity and realize the real-time implementation. Figure 3.2 shows the schematic of the hierarchical control architecture, where the centralized intersection controller evaluates the target velocity for each vehicle approaching to the intersection based on the SPAT information to help the vehicles minimize red light idling. At the vehicle local controller level, each vehicle tracks the target velocity from the intersection controller in a fuel efficient manner by using MPC. At the same time the vehicles avoid rear-end collisions and seeking discretionary lane change opportunities.

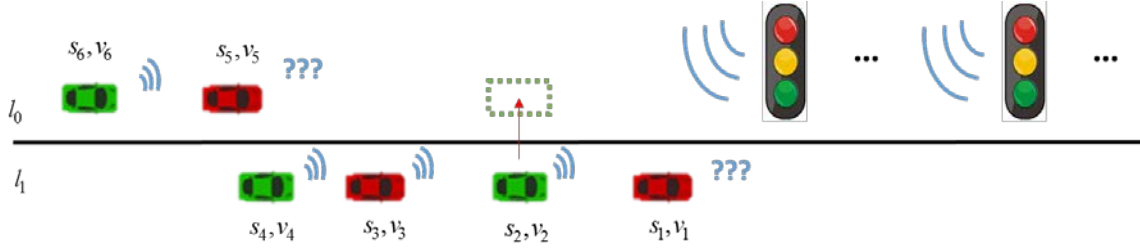


Figure 3.1 The schematic of the discretionary lane change problem

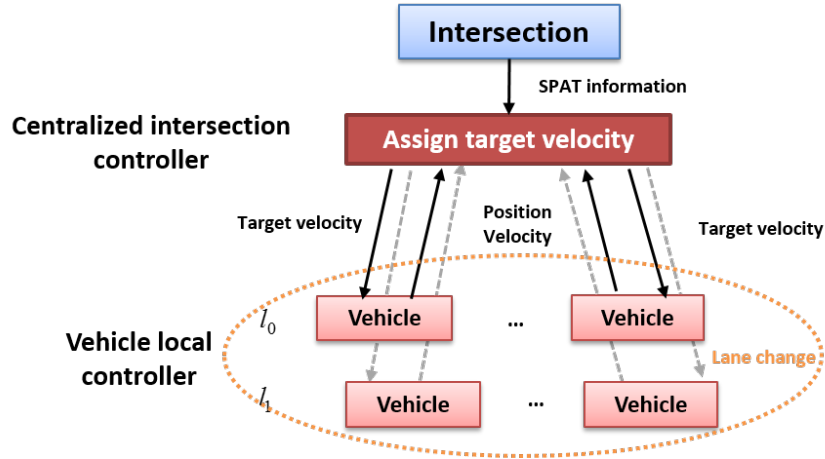


Figure 3.2 Schematic of the hierarchical control architecture in the discretionary LCD research

In our two-lane scenario, similar to [68], we define $l_i \in \{l_0, l_1\}$ that indicates two different lane. The lane change decision variable for any vehicle i at each time step k is defined as $\delta_i(k) \in \{0, 1\}$. $\delta_i(k) = 0$ and $\delta_i(k) = 1$ represent the decision of “stay on the current lane” and “change to the adjacent lane”, respectively. It worth to be mentioned that we only focus on the discretion LCD making in this research. The lateral dynamics of the vehicle is ignored and we assume an instant jump for the vehicle from one lane to the other.

To integrate the discretionary LCD with our previous research about longitudinal motion coordination on multiple interconnected traffic light intersections with single lane road, the optimization problem can be formulated as followings:

$$J_i = \arg \min_{u_i, \delta_i} \sum_{t=k}^{k+T-1} \left[w_1 \left(v_i(t) - v_{\text{target}}^i(k) \right)^2 + w_3 u_i(t)^2 + w_4 \frac{\dot{f}_{\text{fuel}}^i(t)}{v_i(t)} + \left((1 - \delta_i(k)) \cdot w_2^{ij^c} \cdot R_{ij^c} + \delta_i(k) \cdot \left(w_2^{ij^t} \cdot R_{ij^t} + w_5 J_{\text{change}} \right) \right) \right] \quad (3.1a)$$

$$v_{lb}^i(t) \leq v_i(t) \leq v_{ub}^i(t), \quad \forall t \quad (3.1b)$$

$$u_{lb}^i \leq u_i(t) \leq u_{ub}^i, \quad \forall t \quad (3.1c)$$

$$R_{ij^*}(t) = S_0 + t_{hd} \left(v_i(t) - v_{j^*}(t) \right) + \left(s_i(t) - s_{j^*}(t) \right) \quad (3.1d)$$

Here, the term $R_{ij^*}(t)$ in (3.1d) is used to avoid rear-end collision and maintain desired headway distance and time for vehicle i and its preceding vehicle j^* . j^* can be either j^c or j^t , which represents the preceding vehicle of vehicle i on the current or target lane respectively. The notations are shown in Figure 3.3. In Figure 3.3, vehicle j^c is the preceding vehicle of vehicle i on the current lane, while vehicle j^t and q^t are vehicle i 's preceding and following vehicle on the target lane respectively.

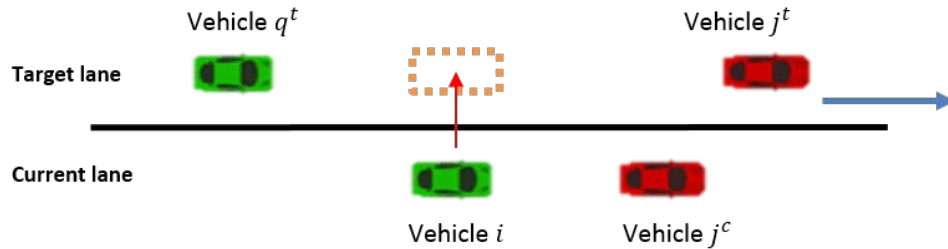


Figure 3.3 Schematic of the vehicles' relative positions and notations

In (3.1a), the first term is used to track the target velocity obtained from the intersection controller. The second term minimizes the longitudinal control effort to achieve mild acceleration and deceleration. The third term penalizes the fuel consumption per unit distance. The fourth and fifth term minimize the deviation from the desired headway distance and time between vehicle i and its preceding vehicle j^c on the current lane or vehicle j^t on the target lane respectively. J_{change} in the fifth term consists of extra cost that punishes the lane change and $\left(R_{q^t i}(t)\right)^2$ (similar to the definition in (3.1d)), which represents the effects on the following vehicle q^t when vehicle i moves to the target lane. At every time step, only one term exists in the cost function between the fourth and fifth term. For example, if the lane change decision variable $\delta_i(k)=0$, it means the vehicle will not change lane and travel on its current lane. Then the fifth term is zero and vice versa. w_1 , w_3 and w_4 are constant weighting factors respectively. $w_2^{\bar{y}^*}(t)$ is chosen as a function of the relative distance, so that it increases as the relative distance decreases and vice versa. The definition of j^* is the same with the j^* in $R_{\bar{y}^*}(t)$. Equation (3.1b) and (3.1c) indicate the constraints on vehicle velocity and acceleration, respectively.

This optimal control problem formulation ends up with a mixed integer programming problem, because the decision variable of longitudinal acceleration u_i is considered to be continuous, while the lane change decision δ_i (0 or 1) is discrete. Most solution methods for mixed integer programming problem apply some form of tree search, which is computationally inefficient and poor on scalability [105].

In our hierarchical control architecture, the centralized intersection controller has all the connected vehicles' velocity and position information within its region. These information is sufficient to make the centralized intersection controller capable of making a discretionary LCD for any connected vehicle. If the lane change decision is made in the intersection controller, the decision variable δ_i in (3.1a) becomes an input from the intersection controller. In such a way, the optimal control problem can be reformulated to avoid solving the mixed integer programming problem.

3.3.2 Approach

To avoid solving the mixed integer programming problem discussed in the previous, the optimization problem is reformulated. The centralized intersection controller has the position and velocity information of the approaching connected vehicles. The information of unconnected vehicles can be captured by the onboard sensors of the surrounding connected vehicles and sent to the centralized intersection controller. Since the centralized intersection controller has sufficient information, it has the capability of making the discretionary lane change decision for the connected vehicles. Figure 3.4 shows the reconstructed schematic of the control architecture. Instead of making the lane change decision among the vehicle local controllers, the decision is made by the intersection controller and sent to each connected vehicle. In such a way, our approach is able to decrease the computational complexity and improve the system feasibility and scalability. Our approach works in three phases: first, the target velocity of

each connected vehicle is evaluated, which remains the same as described in the previous research. Second, the lane change decisions are made to help the connected vehicle gain more opportunity to travel at its target velocity. The reason behind is that the connected vehicle travelling at the target velocity has less chance to be stopped by a red light, which will improve its mobility and fuel economy. These above two phases are completed at the centralized intersection controller. Finally, each vehicle controller uses a reformatted MPC to track the target velocity and follow the lane change instruction.

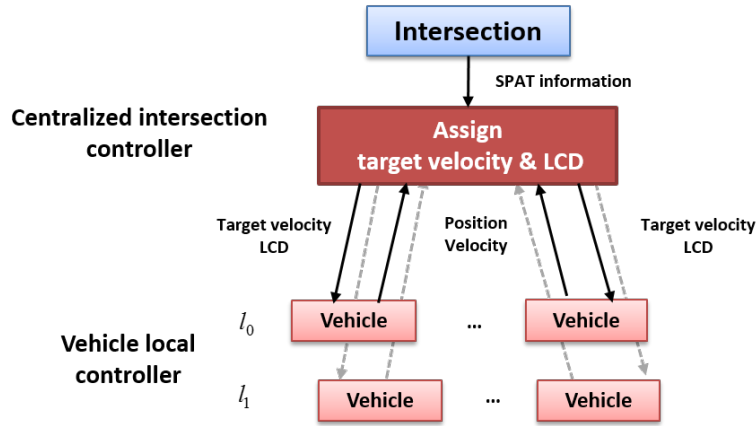


Figure 3.4 Reconstructed schematic of the control architecture for discretionary lane change study

A. Discretionary lane change decision

The discretionary lane change decisions of the connected vehicles in our proposed approach are made at the centralized intersection controller. There are several discretionary LCD triggering factors the centralized intersection controller would consider during the decision making:

1. The ability to track the target velocity.

2. Minimum impact on the lag vehicles on the target lane
3. Lane traffic density balance
4. The vehicle position in the convoy.
5. The presence of the unconnected vehicles.

The first objective is to allow a connected vehicle gain higher opportunity to achieve its target velocity through lane change. Considering the first and last cases in (2.7a) of the target velocity evaluation equation, the target velocity of a subject vehicle is always higher than its preceding vehicle if there any. The subject vehicle here means the vehicle which is under the evaluation of lane change by the centralized controller. However, the subject vehicle may never achieve its target velocity due to the constraints of maintaining minimum headway distance and time to its preceding vehicle. Under this circumstance, if the lane beside the subject vehicle is available, the subject vehicle would receive the lane change instruction to change lane and achieve its target velocity. For the second factor, when a subject vehicle changes lane, it may cause negative impact on the lag vehicles on the target lane. This impact needs to be minimized. In the third factor, the density of different lanes needs to be balanced for better traffic efficiency, so the vehicle should be punished if it changes lane from a lower density lane to a higher density lane. In the fourth point, the more rear of a vehicle's position in the convoy, it has more chance to be stopped by the red lights. It is true in both of our research or real traffic environment, so the vehicle rear in the convoy should have more desire to change lane. Additionally, based on the connected vehicle penetration rate study, the lane change decision will also help the subject vehicle avoid following an unconnected vehicle. By

doing so, the discretionary lane change behavior of the connected vehicle will not only improve its own but also the overall group performance in the sense of traffic mobility and fuel economy.

Instead of making lane change decisions from the MPC among the vehicle local controllers, the centralized intersection controller would compare the cost of travelling on the current lane and on the target lane for each connected vehicle and then make the lane change decisions. The lane change decisions will be sent to each vehicle as the input of the MPC problem. The computation of the lane change at time instance K is presented as:

$$J_i^c(K) = w_4^{ij^c} \cdot \tilde{R}_{ij^c}(K) + J_{unconn} \quad (3.2a)$$

$$J_i^t(K) = w_4^{ij^t} \cdot \tilde{R}_{ij^t}(K) + w_4^{q^ti} \cdot \tilde{R}_{q^ti}(K) + J_{density} + J_{unconn} \quad (3.2b)$$

$$J_{density} = \begin{cases} 0 & \text{if } \rho_c(K) - \rho_t(K) \geq 0 \\ \varepsilon_{density} & \text{if } \rho_c(K) - \rho_t(K) < 0 \end{cases} \quad (3.2c)$$

$$J_{unconn} = \begin{cases} \varepsilon_{unconn} & \text{if vehicle } j^c \text{ or } j^t \text{ is unconnected vehicle} \\ 0 & \text{otherwise} \end{cases} \quad (3.2d)$$

$$\delta_i(K) = \begin{cases} 1 & \text{if } J_i^c(K) - J_i^t(K) > J_{critical} \\ 0 & \text{otherwise} \end{cases} \quad (3.2e)$$

Here, the time step ΔK of the time instance K while the lane change decision evaluation is much greater than the time step Δk of the time instance k in the MPC problem mentioned previously. That is because the frequency of lane change is much lower than the longitudinal dynamics. Equation (3.2a) and (3.2b) evaluate the cost of maintaining target velocity while running on the current lane and on the target lane

respectively. The definition of \tilde{R} in (3.2a) and (3.2b) is similar to (3.1d), but we use the target velocity instead of the real velocity of a connected vehicle. For example,

$$\tilde{R}_{ij^c}(K) = S_0 + t_{hd} \left(v_{\text{target}}^i(K) - v_{\text{target}}^{j^c}(K) \right) + \left(s_i(K) - s_{j^c}(K) \right)$$

The notation of j^c , j^t and q^t are consistent with (3.1), and the definition of \tilde{R}_{ij^t} and $\tilde{R}_{q^t i}$ are similar to \tilde{R}_{ij^c} . The first term in (3.2a) penalizes the vehicle i getting too close to its preceding vehicle while maintain its target velocity. The second term represents an additional cost if vehicle i is following an unconnected vehicle. J_{unconn} is 0, if the preceding vehicle is connected. Otherwise, $J_{\text{unconn}} = \varepsilon_{\text{unconn}}$, which is a constant cost as shown in (3.2d). The first term in (3.2b) is similar to (3.2a), while the second term indicates the impact of lane change to the vehicle q^t behind the vehicle i on the target lane. The effect here means that the vehicle q^t may not be able to maintain its target velocity due to vehicle i ' lane change and headway distance of vehicle q^t is decreased. The third term penalizes the vehicle from a higher density lane changing to a lower density lane as shown in (3.2c), which will balance the traffic density between the two lanes and maximize the traffic efficiency. ρ_c and ρ_t in (3.2c) represent the traffic density on the current and target lane respectively. $\varepsilon_{\text{density}}$ is a constant cost associated with the third term of (3.2b). The last term in (3.2b) prevents the vehicle i changes to a lane that will end up with following an unconnected vehicle. At the end, the lane change decision is made by comparing the cost of running on the current lane and on the target lane in (3.2e), where J_{critical} is constant threshold. In a special scenario that both a vehicle

and its preceding vehicle could make discretionary lane change after the evaluation by the centralized intersection controller. In such scenario, the centralized intersection would decision to make the vehicle behind to change lane due to the fourth triggering factor mentioned before and it is pointless to make both vehicles change lane.

In such an approach, the discretionary lane change decisions for the connected vehicles motivated by gaining higher opportunity of marinating the target velocity and avoiding following an unconnected vehicle have been made by the centralized intersection controller. The discretionary LCD along with the target velocity will be sent to the vehicle local controller and fed into the MPC problem.

B. Reformulated MPC problem

Since the lane change decisions have already been made at the centralized intersection controller previously, the decision variable of δ_i can be removed from (3.2). Thus, we can reformulate the mixed integer programming problem to a nonlinear optimization problem. The reformulated optimization problem for each vehicle i for a finite time horizon T is presented as:

$$J_i = \arg \min_{u_i} \sum_{t=k}^{k+T-1} \left[w_1 \left(v_i(t) - v_{\text{target}}^i(k) \right)^2 + w_2 u_i(t)^2 + w_3 \frac{\dot{f}_{\text{fuel}}^i(t)}{v_i(t)} + (1 - \delta_i(k)) \cdot w_4^{ij^c} \cdot R_{ij^c} + \delta_i(k) \cdot w_4^{ij^t} \cdot R_{ij^t} \right] \quad (3.3a)$$

$$\text{where } \delta_i(k) = \begin{cases} \delta_i(K) & \text{if } k = K \\ 0 & \text{if } \textit{otherwise} \end{cases} \quad (3.3b)$$

$$v_{lb}^i(t) \leq v_i(t) \leq v_{ub}^i(t), \quad \forall t \quad (3.3c)$$

$$u_{lb}^i \leq u_i(t) \leq u_{ub}^i, \quad \forall t \quad (3.3d)$$

In above equations, the lane change decision $\delta_i(k)$ is obtained from (3.2) only when the time instance k of the MPC problem matches the lane change evaluation time instance K , otherwise $\delta_i(k) = 0$ as shown in (3.3b). Equation (3.3c) and (3.3d) are consistent with (3.1b) and (3.1c).

In our approach, the discrete lane change decision is evaluated by the centralized intersection controller and fed into the MPC problem instead of solving among the vehicle local controllers. By doing so, we can avoid solving the mixed integer programming problem to improve the computational efficient, system scalability and feasibility. The performance of our proposed approach is presented through the simulation in the next subsection.

3.3.3 Simulation Results

The simulation setup here is almost similar to the connected vehicle penetration rate study, except that the single lane road is replaced by a road with two-identical-lane. The time step for target velocity evaluation and MPC remains $\Delta k = 0.5 s$, while the lane change decision is evaluated at the time step of $\Delta K = 15 s$. There are 15 vehicles in total. Initially, there are 10 vehicles on lane 0 and 5 vehicles on lane 1.

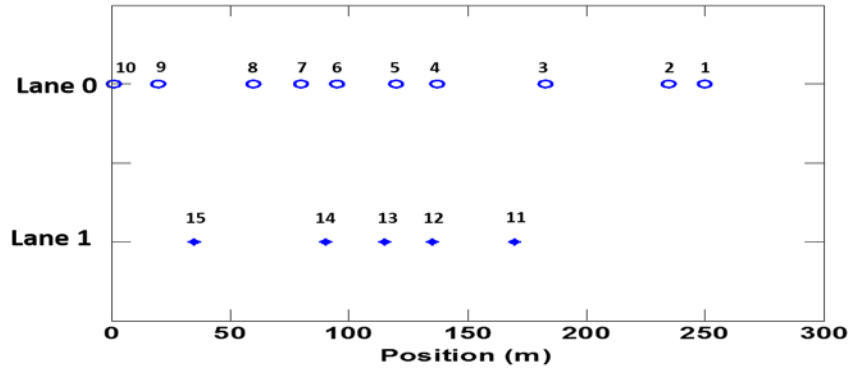
To demonstrate the advantages of our proposed discretionary LCD approach, we have two different simulation setups. One is called homogenous scenario where all the

involved vehicles are connected vehicles. The other is heterogeneous scenario which is a connected and unconnected vehicle mixed scenario

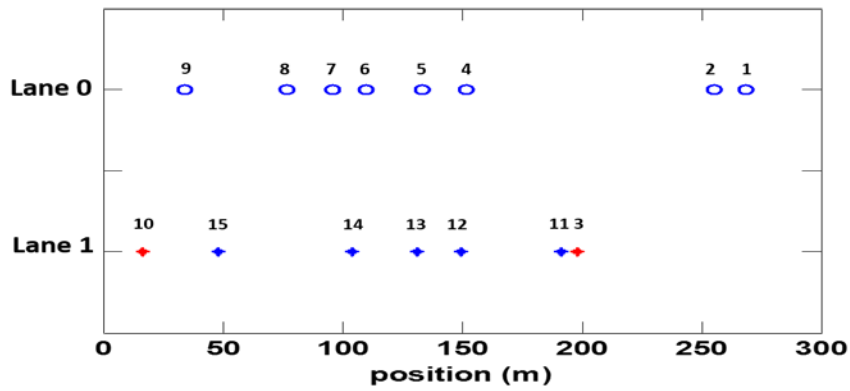
A. Homogenous scenario

In the homogenous scenario, all the vehicles are connected. We compared our proposed approach with the case which all the vehicles are not allowed to make lane change. Figure 3.5 shows the positions of all the vehicles at the time instance when the lane changes happen. The positions in red in the figures mean the vehicle just made a lane change. The initial positions of all the connected vehicles are shown in Figure 3.5a. It worth to be mentioned that at $t=1s$ in Figure 3.5b, both vehicle # 2 and 3 are feasible to change lane. However, it doesn't make sense to make two following vehicles to change lane together, and based on the fourth lane change triggering factor, the rear vehicle (vehicle # 3) receives the lane change instruction at this time instance. The vehicle # 3 at the next lane change evaluation timing ($t=16s$) is still feasible to change lane as shown in Figure 3.5c. It should be noted that there are not many lane changes happened during the simulation. That is because after several lane changes and the method of target velocity evaluation, the vehicles will move beside each other on the two lanes and there is no further room to make lane changes as it can be seen from Figure 3.5d. The fuel economy and mobility performance compared our proposed approach and the case with no lane changes are tabulated in Table 3.1. There is slightly improvement on each aspect over the baseline. The reason behind this it that it is a homogenous scenario where all the connected vehicles are identical and the fuel economy is already an optimal solution.

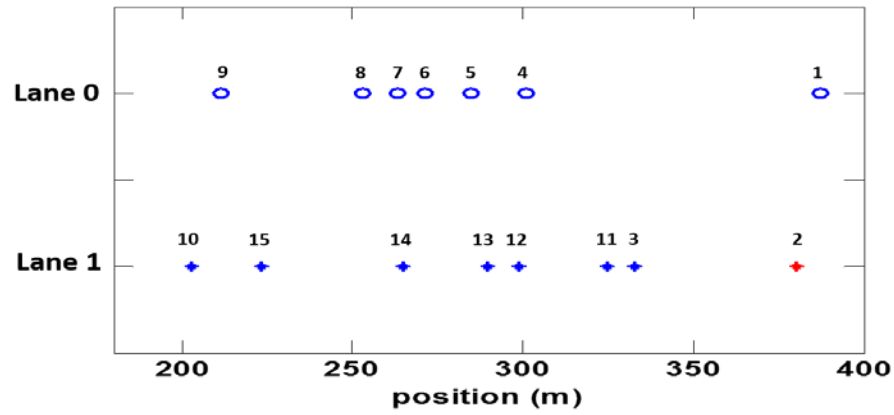
Furthermore, the lane changes only happen on a few vehicles. There is not much room for the further improvement on the performance. However, the performance is still impressive given the aforementioned reasons and considering the average is over 15 vehicles.



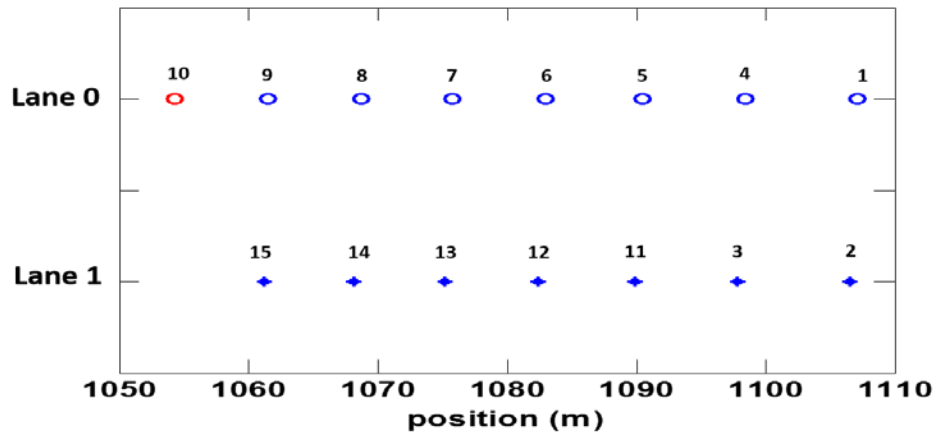
(a) $t=0s$



(b) $t=1s$



(c) $t=16s$



(d) $t=106s$

Figure 3.5 All vehicles' positions when lane changes happen in homogeneous scenario

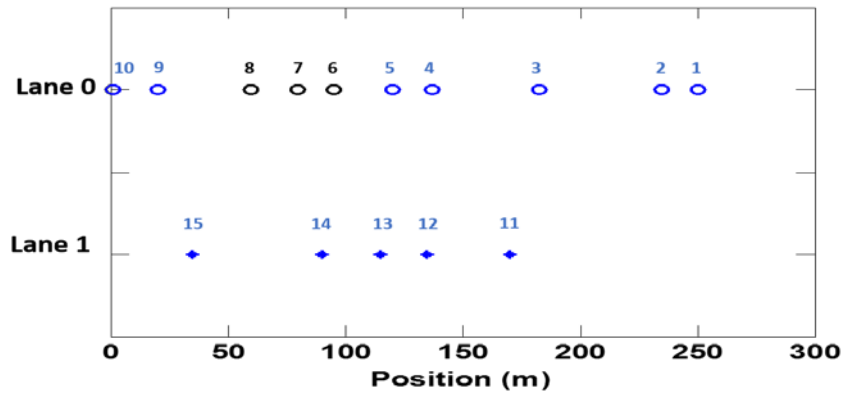
Approach	Total red light idling (s)	Average velocity (m/s)	Average MPG
No lane change	105	10.54	41.78
Proposed approach	93.5	10.66	41.88

Table 3.1 Fuel economy and mobility comparison in the homogeneous scenario

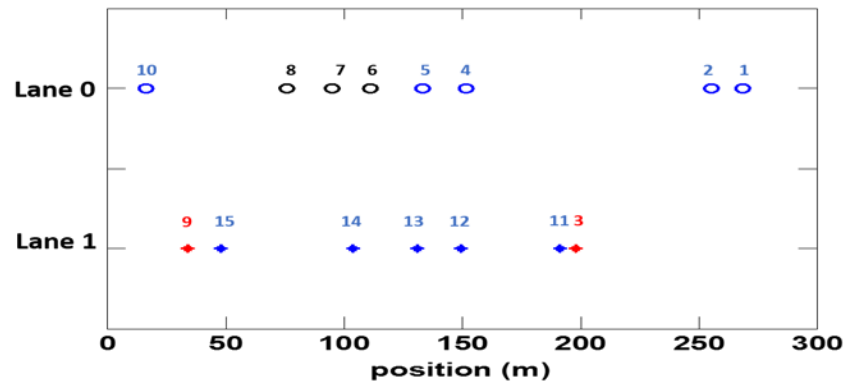
B. Heterogeneous scenario

In the heterogeneous scenario, the simulation setup is the same with the previous homogeneous scenario, except that the vehicle # 6, 7 and 8 on lane 0 are defined to be unconnected. All the vehicle parameters are still considered to be identical. For the connected vehicles, the longitudinal motion and the discretionary LCD are controlled by the approaches described in thesis. The longitudinal motion of the unconnected vehicles, similar to the previous section, is controlled by the modified Gipps car following model. For the LCD model of the unconnected vehicles, a simplified probability based LCD model [106] is applied, where the probability of the unconnected vehicle lane change is assumed to be linear distribution with the available gap length on the target lane.

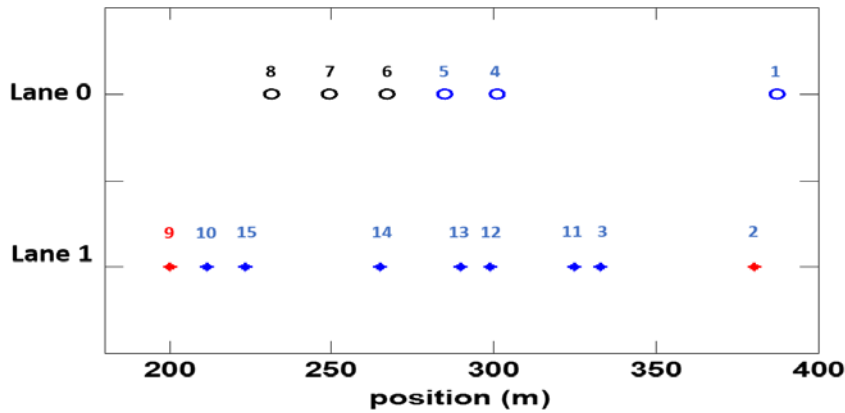
There are three cases we have studied. The first one is all the vehicles are not allowed to change lane. The second one is unconnected vehicles do not change lane while the connected vehicles can make lane changes based on our approach. The last one is that the unconnected vehicles use the probability based LCD model and the connected vehicles are governed by our proposed approach. Figure 3.6 shows the positions of all the vehicles at the time instance when the lane changes happen under the scenario of unconnected vehicles do not change lane. The positions in black represent the unconnected vehicle # 6, 7 and 8 respectively. The rest results of the fuel economy and mobility performance are summarized in Table 3.2. In the third cases, since it involves the probability based method, the results in the corresponding row of Table 3.2 are averaged over multiple simulations.



(a) $t=0s$



(b) $t=1s$



(c) $t=16s$

Figure 3.6 All vehicles' positions when lane changes happen under heterogeneous scenario and unconnected vehicles do not change lane

Approach	Total red light idling (s)	Average velocity (m/s)	Average MPG
(All vehicles) No lane change	490	10.13	38.32
Unconnected no lane change & connected proposed lane change	293.5	10.62	40.89
Uncounted probability lane change & connected proposed lane change (average)	256	10.52	40.14

Table 3.2 Fuel economy and mobility comparison in the heterogeneous scenario

The case of the unconnected vehicles no lane change and the connected vehicles using our proposed approach offers the best performance. The improvement is much more significant in this heterogeneous. Most of the improvement on the fuel economy comes from the vehicle # 9 and 10 which initially follow the unconnected vehicles, because these vehicles (vehicle # 9 and 10) would follow the unconnected vehicles during the entire trip without proper lane change, which will affect the performance as discussed in Section. III. The case where the unconnected vehicles make lane change by the probability based approach suffers certain level of performance degradation. That is because the probability based LCD model of the unconnected vehicles gives non-optimal LCD most of the time and the random behavior of the unconnected vehicles will have negative impact of the overall performance.

3.3.4 Conclusion

In this section, a hierarchical control architecture is proposed to coordinate the longitudinal motion and evaluate the discretionary LCD for the connected vehicles is proposed. We focus on the scenario of a group vehicles under imperfect connected vehicle penetration rate (connected and unconnected vehicles mixed scenario) travelling on a multiple-lane road with signalized intersections. The SPAT information is utilized by the centralized intersection controller to evaluate the target velocity for the connected vehicles in order to help minimize red light idling. The vehicle local controllers use MPC for the longitudinal motion to track the target velocity in a fuel efficient manner. A novel discretionary LCD approach is proposed in this research. The centralized intersection with sufficient vehicle information would evaluate the LCD for the connected vehicles and send to the connected vehicles along with the evaluated target velocity. In such an approach, we avoid solving the mixed integer programming problem to decrease the computational complexity and improve the system scalability and feasibility. The LCD in our approach are made based on offer the subject vehicle higher possibility to achieve its target velocity and with minimum negative impact on the rest of the vehicles in the group at the same time. Another important lane change triggering factor, which is the presence of the unconnected vehicles on the convoy, discovered in the connected vehicle penetration rate study is also involved. In the simulation study of the discretionary lane change behavior, both homogeneous and heterogeneous scenario have been provided. The simulation results show the improvement of the group performance.

The future research direction includes the development of lane change strategies for the connected vehicles on the roads with asymmetric lanes where the mandatory lane changes could happen. That would require the collaboration work of a subgroup of vehicles involved. Other future research could be the experimental validation of our proposed approach on the robotic cars which offer us a safe and cost-effective way to validate the real-time implementation potential of our strategies.

3.3.5 Related Publication

- **Z. Du** and P. Pisu, A Fuel Efficient Control Strategy for Connected Vehicles in Urban Roads with Multiple-lane, in the proceedings of, the 55th IEEE Conference on Decision and Control
- **Z. Du**, B. HomChauduri and P. Pisu, The Discretionary Lane Change Decision Study for a Group of Vehicles on Urban Roads under Imperfect Connected Vehicle Penetration Rate, IEEE Transactions on Intelligent Transportation Systems (under review)

3.4 Mandatory Lane Change Decision

In our previous research, we have developed the fuel efficient [52] [107] [108], control strategies for a group of connected vehicles (both conventional and hybrid electric vehicles) on urban roads utilizing SPAT information. Later the work has been extended to a multiple lane scenario where the connected vehicle discretionary lane change has been enabled [109]. In this paper, we extend our previous work and investigate the connected cooperative mandatory lane change behavior. In our approach, the intersection centralized controller sends out target velocities to each approaching connected vehicles and the vehicle decentralized controller uses MPC to track the target velocity. The vehicles with mandatory lane change request (host vehicles) would cooperate with the vehicles on the target lane (the lane that the host vehicle needs to change to) to complete the lane change process.

3.4.1 Problem Formulation

In this research, we focus on a connected vehicle environment with a group of connected vehicles travelling on signalized intersection roads. Some of the vehicles need to make mandatory lane change in order to make a turn at the intersection. The objective of this research is to develop a cooperative mandatory lane change strategy where the host vehicle is able to cooperate with the vehicles on its target lane to accomplish the lane change process in a safe and efficient manner. Figure 3.7 shows the schematic of the problem. Vehicle 2 needs to change to lane 1 to make a right turn at the intersection. However, the inter-vehicle distance is too short to make a safe lane change. In such case, Vehicle 2 needs to cooperate with the vehicles (e.g., probably Vehicle 5 and 6) on lane 1.

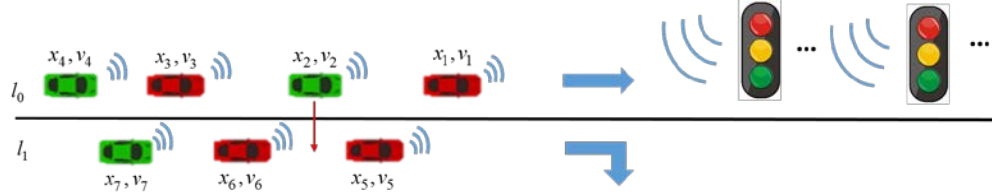


Figure 3.7 Schematic of the mandatory lane change problem

The problem we are addressing in this section is in a large scale system where the connected vehicles and intersection controllers are spatially widely arranged. The connected vehicles approach and leave the control region of the intersection controllers all the time. Besides, one connected vehicle could be under the control of multiple different intersection controllers during its trip. The fully centralized or decentralized control architecture suffers poor scalability while handling such system. The hierarchical control architecture is applied in this research for the purpose of reducing communication and computational burden, improving the system scalability and realizing real-time implementation. The general idea of hierarchical control architecture is to decompose complex problems into some smaller more manageable sub-problems. The subsystems collaborate with each other to achieve one common task [19] [20].

Figure 3.8 shows the schematic of our proposed hierarchical control architecture. The centralized intersection controller gathers the SPAT information from the traffic lights and the connected vehicle positions. With these information, the centralized intersection controller evaluates the target velocity for each approaching connected vehicle to aid the connected vehicles avoid red light stop. For the longitudinal motion of the connected vehicles, each decentralized vehicle controller uses MPC to track the target

velocity evaluated by the centralized intersection controller in a fuel efficient manner. Once some criteria are met, the host vehicle who has prescribed path and need to do the mandatory lane change would seek and cooperate with vehicles on its target lane.

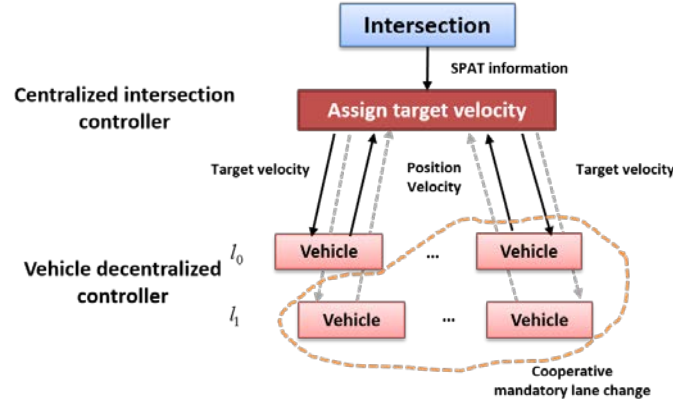


Figure 3.8 Schematic of the proposed hierarchical control architecture for the mandatory lane change

In this section, we focus on a connected vehicle environment with a group of connected vehicles on a road with two lanes. The host vehicles are able to perform mandatory lane change. The vehicle discretionary lane change for the purpose of gaining better traffic conditions is not considered in this paper. In this connected vehicle framework, the information of position and velocity of a particular vehicle is considered to be available to the vehicles' neighborhood through vehicle-to-vehicle communication. The information of all the vehicles within a certain region is available to the centralized intersection controller. The SPAT information of each traffic light and every cycle is assumed to be available to the centralized intersection controller. In this research, we

assume the lane change process as an instant jump. The lateral dynamics of a vehicle and the vehicle's behavior after mandatory lane change is out of the scope of this research. We also assume that the vehicles on the target lane are all willing to cooperative with host vehicles.

3.4.2 Mandatory Lane Change Algorithm

The longitudinal motion of the vehicles is controlled by our hierarchical control architecture, which is the same with previous research. For the sake of simplicity, it is not repeated it here. In this section, the cooperative mandatory lane change algorithm is explained. In our algorithm, we assume that when the host vehicle whom needs to change lane reaches a certain distance to the intersection, the mandatory lane change algorithm will be initiated and the host vehicle will start to cooperate with the surrounding vehicles on the target lane. The vehicles on the target lane are also assumed to be willingly cooperative, once they get the request from the host vehicle. It should be noted that in this research, the host vehicle will straightly cooperate with the vehicles right beside itself at the moment the distance criteria are met. Other types of cooperation are not considered in this work.

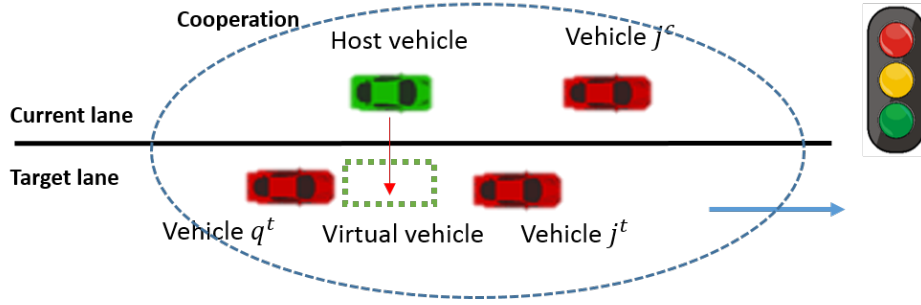


Figure 3.9 Schematic of the proposed cooperative mandatory lane change algorithm

Figure 3.7 shows the schematic of the proposed mandatory lane change algorithm. The notations in the algorithm are also shown in Figure 3.7. Vehicle j^c indicates the host vehicle's preceding vehicle on the current lane. Vehicle j^t and q^t represent the preceding and following vehicle of the virtual vehicle on the target lane, respectively. The detailed algorithm is listed as follows:

- Step 1: If $d_{ia}^{host} \leq d_{criteria}$, go to Step 2. Otherwise, skip this algorithm. d_{ia}^{host} is the distance between the host vehicle and the intersection, while $d_{criteria}$ is the predefined critical distance where the algorithm is initiated.
- Step 2: A virtual vehicle $\hat{x}_{host} = [\hat{s}_{host} \quad \hat{v}_{host}]^T$ with the same position and velocity of the host vehicle is placed on the target lane ($\hat{x}_{host} = x_{host}$).
- Step 3: For the host vehicle, replace the R_{ij} in the cost function

$$J_i = \arg \min_{u_i} \sum_{t=k}^{k+T-1} \left[w_1 \left(v_i(t) - v_{target}^i(k) \right)^2 + w_2^i(t) R_{ij}(t)^2 + w_3 u_i(t)^2 + w_4 \frac{\dot{f}_{fuel}^i(t)}{v_i(t)} \right]$$

(2.8) in Section 2.2.3B by $R_{host_j} = \max(R_{host_j^c}, R_{host_j^t})$, where

$$R_{host_j^c}(t) = S_0 + t_{hd} \left(v_{host}(t) - v_{j^c}(t) \right) + \left(s_{host}(t) - s_{j^c}(t) \right) \quad \text{and} \quad \text{similarly,}$$

$$R_{host_j^t} = S_0 + t_{hd} \left(v_{host}(t) - v_{j^t}(t) \right) + \left(s_{host}(t) - s_{j^t}(t) \right).$$

The host vehicle is constrained by both vehicle j^c and j^t , so we choose the one contributes more one the cost function.

- Step 4: As the host vehicle approaching the intersection, Additional weighting is added to the second term of the cost function for the host vehicle and vehicle q^t on the target lane in order the speed up the process of generating space for the host vehicle. In such a way, the host vehicle can complete the lane change before the intersection.
- Step 5: if $R_{q^t_virtual} \leq -r_0$ and $R_{virtual_j^t} \leq -r_0$, the algorithm ends. r_0 is a predefined positive value close to zero. At this moment, it means there is enough space for the host vehicle's lane change maneuver on the target lane. The host vehicle can finish the lane change safely. Otherwise, go to Step 2. The definition of $R_{q^t_virtual}$ and $R_{virtual_j^t}$ are similar to the definition of R_{ij} in the cost function (2.8) in Section 2.2.3B and Step 3.

The basic idea of the above algorithm is that by inserting a virtual vehicle with the same state variables on the target lane, the second term of cost function (2.8) in Section III.B which maintains the desired headway distance will generate enough headway distance and time between vehicle q^t and the virtual vehicle as well as the virtual vehicle

and vehicle j^t . In such a way, there would be enough space for the host vehicle to make the lane change maneuver safely. For Step 3, because the host vehicle and the virtual vehicle are constrained by two different preceding vehicles (vehicle j^c and j^t respectively), we use one with larger second term of cost function (2.8) for the host vehicle to guarantee safety. The simulation results compared with the baseline method showing the advantage of our proposed method can be found in the next section.

3.4.3 Simulation Results

In this section, the simulation results of the methodology explained in the last sections are presented. The simulation scenario in this work is a two-lane straight road with traffic signal lights at every 500 *m*. The time step for target velocity evaluation, MPC and the cooperative lane change algorithm is $k = 0.5$ *s*. The prediction horizon $T = 6$ *s* of the MPC problem is used. All the vehicles are considered to be connected and automated vehicles with identical parameters. The vehicle parameters and the coefficients associated with fuel consumption evaluation is the same with the previous research. The signal timing of each traffic signal light and every cycle varies from the baseline of $t_g = 15$ *s* and $t_r = 40$ *s* following a uniform distribution.

To demonstrate the advantages of our proposed cooperative lane change algorithm, we develop a baseline mandatory lane change strategy without cooperation with any other vehicles. The general idea of the baseline strategy is that once the host vehicle meets the criteria in Step 1, it will start to look for the available gap on the target lane. If the gap is enough, the host vehicle will make the lane change. Otherwise, the host

vehicle will decelerate and even stop if necessary when it is close enough to the intersection until it finds the available gap for the lane change. The gap mentioned here is defined in terms of both inter-vehicle distance and relative velocity, similar to Step 5. The aforementioned baseline strategy describes the behavior of real world drivers when they have to make mandatory lane change to follow a prescribed path.

In the simulation scenario, there are 14 vehicles in total. Initially, there are 8 vehicles on lane 0 and 6 vehicles on lane 1. Vehicle 2 is the host vehicle which has to change from lane 0 to lane 1 before reaching to the first intersection (at 500 *m*). Figure 3.10 shows the initial positions of all the vehicles. To show that our longitudinal coordination strategy with the SPAT information is capable of helping the connected vehicles minimize the red light idling, the host vehicle is first set not to change lane, and only move straight at this time. Figure 3.11 and Figure 3.12 show the vehicle trajectories on lane 0 and lane 1, respectively. The red bars on the figures indicate the red signal and its duration. The figures show the connected vehicles avoid the red light stop through tracking the target velocity evaluated by the centralized intersection controller. For more detailed results on this topic, please refer to our previous work [52] [107] [108].

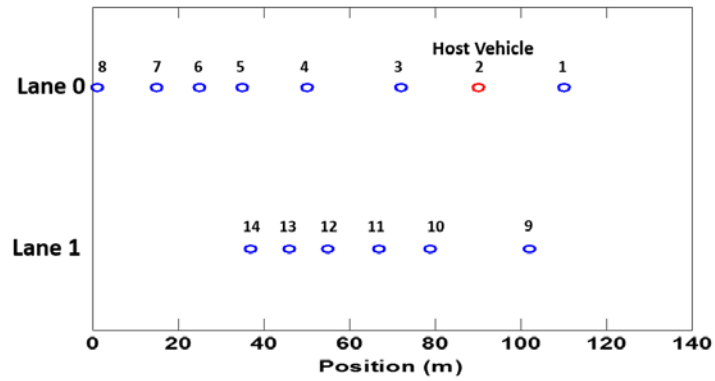


Figure 3.10 Initial positions of all the vehicles at $t=0s$ in mandatory lane change study

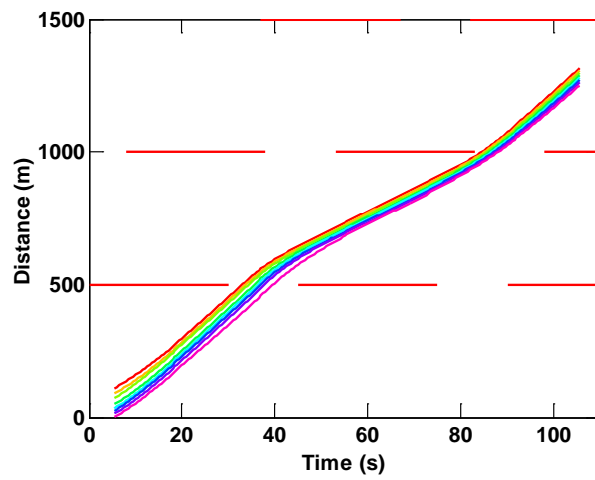


Figure 3.11 All vehicle trajectories on lane 0 without mandatory lane change

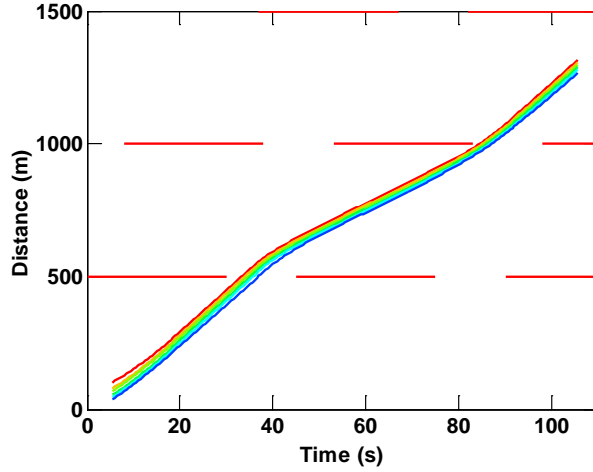


Figure 3.12 All vehicle trajectories on lane 1 without mandatory lane change

Now the mandatory lane change of the host vehicle 2 is enabled and it has to compete the lane change from lane 0 to lane 1 before the first intersection at 500 *m*. Figure 3.13 shows the positions of all the vehicles when the lane change algorithm is about to start as the host vehicle is approaching the criteria $d_{\text{criteria}} = 150\text{m}$. Figure 3.14 and Figure 3.15 show the vehicle positions for the proposed and baseline strategy when the algorithms terminate and the host vehicle is ready to change lane, respectively. In Figure 3.14, as our proposed cooperative lane change algorithm is designed for the host vehicle to cooperate with the vehicles right beside itself (vehicle 9 and 10 in this scenario), a virtual vehicle is inserted between vehicle 9 and 10. After the algorithm runs for 6.5s, enough space is generated through the cooperation and the host vehicle is ready to change lane. However, in Figure 3.15, as there is no cooperation in the baseline algorithm, the host vehicle has to keep on decelerating, because there is not enough space on the target lane. The host vehicle can only change after all the vehicles on the target

lane passing itself due to tight inter vehicle distance. It should be noted that there seems to be quite a lot space between vehicle 13 and 14 in Figure 3.15. However, the host vehicle has been kept on decelerating, there is high velocity difference between the host vehicle and vehicle 14. It is not safe for the host vehicle to move into the gap between the vehicle 13 and 14.

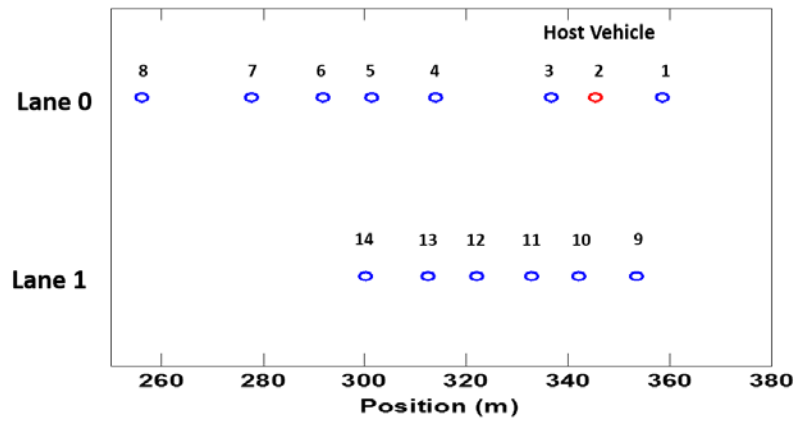


Figure 3.13 Vehicle positions when the mandatory lane change algorithm is about to start ($t=19s$)

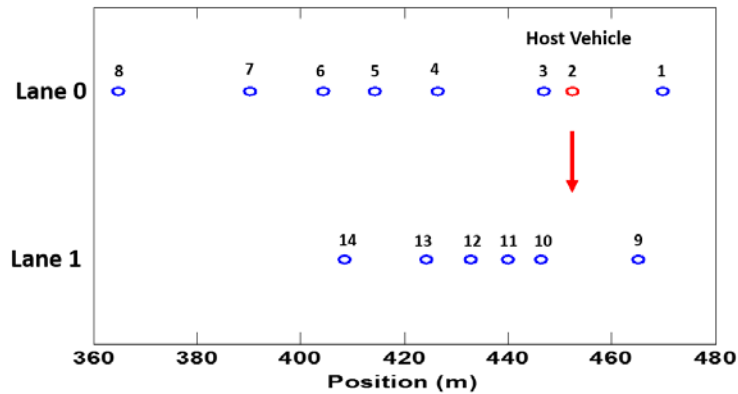


Figure 3.14 Vehicle positions when the proposed algorithm ends and the host vehicle is changing the lane ($t=25.5s$)

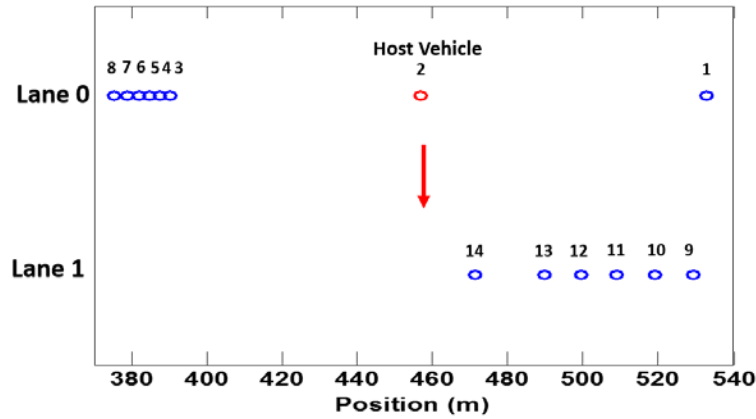


Figure 3.15 Vehicles positions when the baseline algorithm ends and the host vehicle is change the lane ($t=29.5s$)

In Figure 3.15, it can be seen that vehicle 3, 4, 5, 6, 7 and 8 on lane 0 are far away from vehicle 2. Due to vehicle 2's deceleration, its following vehicles (vehicle 3 to 8) are unable to track their target velocity very well, therefore missing the opportunity to pass the intersection within the upcoming green light window. Our longitudinal coordination strategy forces them to slow down to stop at the intersection and wait for the next green window. Figure 3.16 shows the trajectories of vehicle 2, 3 and 4 under the baseline lane change algorithm. The solid red trajectory indicates vehicle 2 is moving on lane 0, while the dash red trajectory means vehicle 2 completes its lane change and travels on lane 1. Because of the deceleration of vehicle 2, vehicle 3 and 4 cannot track their target velocity and are forced to stop at the intersection and wait for the next green light window. Figure 3.17 shows the trajectories of vehicle 2, 3 and 4 under the proposed cooperative lane change algorithm. It can be noticed that the host vehicle's following vehicle 3 and 4 are

not affected a lot and they can still track their target velocity and pass the intersection without stopping.

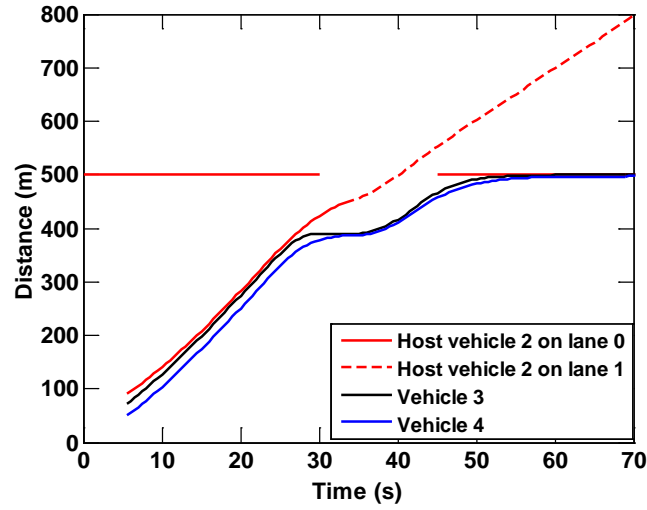
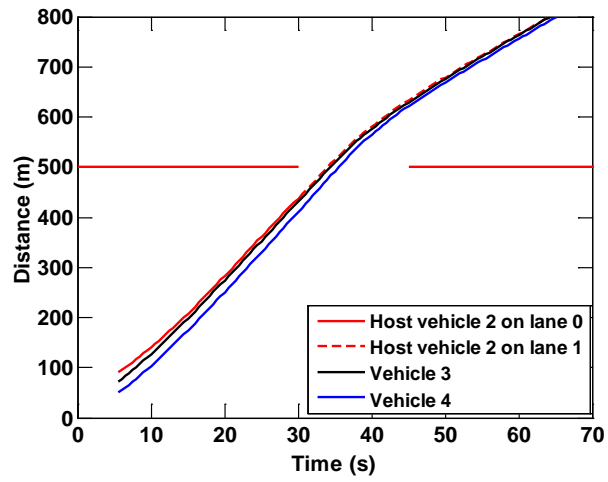
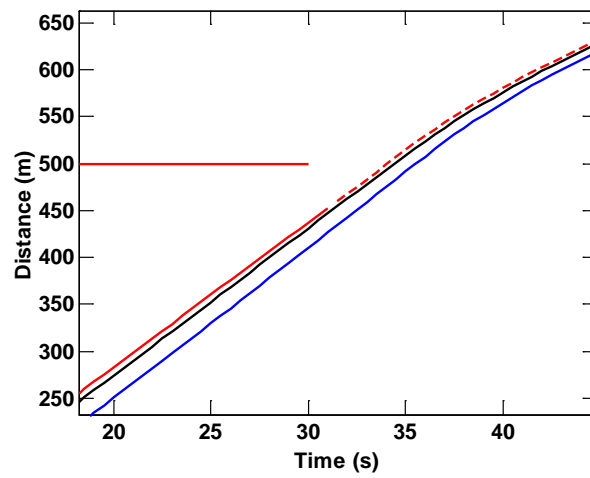


Figure 3.16 Trajectories of vehicle 2, 3 and 4 under the baseline mandatory lane change algorithm



(a)



(b)

Figure 3.17 (a) Trajectories of vehicle 2, 3 and 4 under the proposed mandatory lane change algorithm (b) Partially zoomed-in plot

		Proposed	Baseline
Lane 0	Vehicle 2 (HV)	41.54	37.41
	Vehicle 3	43.21	24.33
	Vehicle 4	43.98	24.40
	Vehicle 5	44.78	25.93
	Vehicle 6	45.35	26.99
	Vehicle 7	44.26	27.31
	Vehicle 8	45.52	30.26
Lane 1	Vehicle 10	42.77	44.03
	Vehicle 11	46.63	47.08
	Vehicle 12	43.62	44.32
	Vehicle 13	43.86	44.60
	Vehicle 14	48.01	47.70
	Avg MPG	44.46	35.36
	Lane change duration (s)	6.5	10.5

Table 3.3 Summary of vehicle fuel consumption (MPG) and lane change duration

The vehicle fuel efficiency and lane change duration for both the proposed and baseline algorithm are summarized in Table 3.3. The first vehicles (vehicle 1 and 9) on both lanes are not shown in the table, because the behavior of these vehicles are identical in both methods. From the table, it can be seen that the vehicles on lane 0 of the baseline

method suffer significant fuel efficiency degradation compared with the proposed method. In the proposed method, there is only slightly fuel efficiency degradation for the vehicles on lane 1 due to the effect of cooperating with the host vehicle. The measurement of lane change duration indicates the time lane change algorithm runs. It takes much longer for the host vehicle in the baseline method to complete the mandatory lane change without cooperation compared with the proposed method. That means our proposed method is more efficient.

3.4.4 Conclusion

In this research, the scenario of a group of vehicles moving on signalized intersection roads is studied, where some vehicles have to make mandatory lane change to follow a prescribed path. For the connected vehicle longitudinal coordination, the fuel efficient control strategy utilizing SPAT information is utilized to help the connected vehicles minimize red light stop, thus reducing the fuel consumption. Apart from that, a cooperative mandatory lane change algorithm has also been proposed. The host vehicle cooperates with the vehicles on the target lane to complete its mandatory lane change. The algorithm is realized through inserting a virtual vehicle on the target lane which has identical state variables with the host vehicle. Simulation results show the advantages of the cooperation during the lane change in the aspects of both fuel and system efficiency. One of the future research direction includes integrating both mandatory and discretionary lane change to study the reactions of the connected vehicles triggered by mandatory lane change. Other future research can be considering the communication latency to be more realistic.

3.4.5 Related Publication

- **Z. Du** and P. Pisu, Cooperative Mandatory Lane Change for Connected Vehicles on Signalized Intersection Roads, 2018 American Control Conference (ACC) (in preparation)

4.1 Communication Delay

4.1.1 Introduction

Our proposed hierarchical control method for both the signalized and unsignalized intersections study relays on the wireless communication including V2V, V2I and I2I. We assume our previous research is under ideal communication environment with on communication delay. However, in the real-world implementation, while the wireless communication allows the connected vehicles to receive sufficient information to make optimal control decisions, it also introduces delays into the control loop due to the intermittencies and packet drops. Current designated short range communication (DSRC) protocols broadcast messages in every 100 *ms* and the packet delivery ratio varies depending on distance and geography [110]. It has also been shown that a high number of channel access requests, either due to a high number of communicating vehicles or high data volumes produced by these vehicles, may result in dropped packets and unbounded delays. The arising delays may significantly change the traffic dynamics leading to instabilities at the linear and nonlinear levels [111] [112].

In this section, we focus on the scenario similar to Section 2.2 with a group of connected conventional vehicles travelling on single lane signalized intersection roads. However, we introduce the random bounded delay into the communication network to make the simulation scenario more realistic. The delay estimation method has been proposed and we have also developed an approach utilized the delay estimation to

compensate the negative impacts on the system performance caused by the involved random bounded delay in the communication network.

Figure 4.1 shows the schematic of the problem. We assume the delay τ at any instance of time is the same all over the communication network including V2V and V2I. The dash line in Figure 4.1 indicate the information is transmitted through wireless communication, while the sold line represents the information is obtained from vehicle onboard sensors. Any vehicle i measures the position and velocity of its preceding vehicle $i-1$ from the onboard sensors and receives the position information of vehicle $i-1$ via V2V as well. Each vehicle i sends its position information to the intersection controller and receives the reference velocity through V2I. The communication delay exists on both ways.

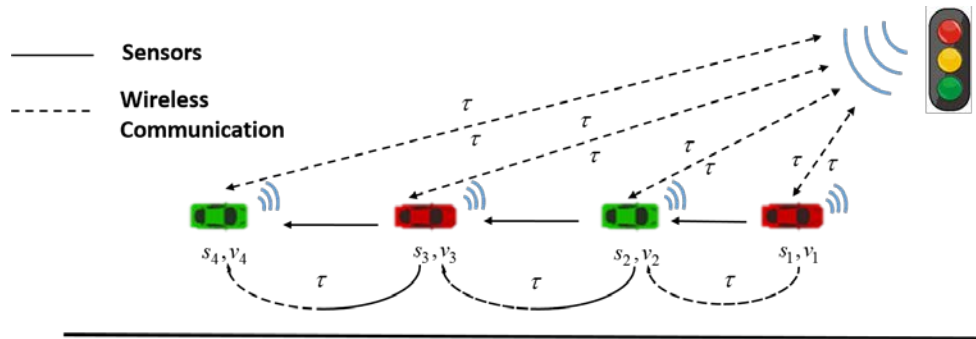


Figure 4.1 Schematic of the communication delay problem

4.1.2 Approach

In this section, two aspects of this problem have been addressed: first, we describe the method used to estimate the delay in the communication network; second, with the estimation, the approach we used to compensate the delay and maintain the proper function and performance of our algorithm is presented.

A. Delay estimation

In this research, we assume the delay in the communication network (V2V and V2I) is consistent at any instance of time. The stochastic delay τ is defined as:

$$\tau = l \cdot \Delta k, \quad l \in \{0, 1, \dots, l_{\max}\} \quad (4.1)$$

where Δk is the sampling time of the system and l follows a uniform distribution between 0 to l_{\max} .

Taylor series expansion technique [113] is often used to approximate delayed systems by ordinary differential equations in different engineering and biological applications. If the delay is sufficient small compared to the characteristic time of the system then replacing the delayed term by zeroth-order or first-order expansion provides a good approximation [114] [115]. The first-order approximation is also often used for stochastic time-delay systems to eliminate the delay from the equation [116]. The Taylor series approximation can also be valid for large delays as well. In human balancing models with reflex delay, the delayed terms are often approximated by either first-order [117] or second-order [118] [119] Taylor series expansion.

In this research, the second-order Taylor series expansion is applied here to approximate the delay τ . For any vehicle i at any time t , it has the position $s_{i-1}(t)$ and velocity $v_{i-1}(t)$ information of the preceding vehicle $i-1$ from its own onboard sensors and the information are assumed to be accurate and non-delayed. The vehicle i also receives the position information $\bar{s}_{i-1}(t-\tau)$ from vehicle $i-1$ through wireless

communication and it comes with delay τ . The delayed position information is expanded by second-order Taylor series similar to [120] as:

$$\begin{aligned}\bar{s}_{i-1}(t-\tau) &= s_{i-1}(t) - \tau \cdot \dot{s}_{i-1}(t) + \frac{1}{2} \cdot \tau^2 \cdot \ddot{s}_{i-1}(t) \\ \dot{s}_{i-1}(t) &= v_{i-1}(t) \\ \ddot{s}_{i-1}(t) &= (v_{i-1}(t) - v_{i-1}(t - \Delta k)) / \Delta k\end{aligned}\tag{4.2}$$

Here, $s_{i-1}(t)$ is the position of vehicle $i-1$ coming from the onboard sensor of vehicle i . The first-order derivative $\dot{s}_{i-1}(t)$ is the velocity $v_{i-1}(t)$ of vehicle $i-1$, which is obtained from the onboard sensor of vehicle i . The second-order derivative $\ddot{s}_{i-1}(t)$ is the acceleration of vehicle $i-1$ which can be either obtained from the wireless communication or approximated by the derivative of the velocity. In this research, we chose the second option and differentiate the velocity information from the onboard sensor. $\bar{s}_{i-1}(t-\tau)$ is the delayed position information broadcasted by vehicle $i-1$ via wireless communication. At any time t , as we have the value of $\bar{s}_{i-1}(t-\tau)$, $s_{i-1}(t)$, $\dot{s}_{i-1}(t)$, $\ddot{s}_{i-1}(t)$, we can solve the following second-order differential equation for τ , such that the delay can be approximated.

$$\frac{1}{2} \cdot \tau^2 \cdot \ddot{s}_{i-1}(t) - \tau \cdot \dot{s}_{i-1}(t) + s_{i-1}(t) - \bar{s}_{i-1}(t-\tau) = 0\tag{4.3}$$

B. Delay compensation

In our hierarchical control method, the control input of each vehicle is determined from the MPC at the vehicle local controller. One of the advantages of the MPC is that it allows the current time step to be optimized while keeping future time steps in account.

At each time step, the optimal control problem is solved over a finite horizon, but only implements the control of the first step. If the prediction horizon is greater than the maximum delay in the communication network, the rest of the control evaluated within the finite horizon besides the first one can be utilized to compensate the delay. For the MPC problem with the prediction horizon of T , at any instance of time k , instead of only implementing the control $u(k+1)$, the rest predictions from $u(k+2)$ to $u(k+T-1)$ are also saved for the purpose of delay compensation.

In the hierarchical control architecture, the vehicle local controllers send the vehicle position to the centralized intersection controller. The intersection controller evaluates the target velocity for each vehicle based on the received position and SPAT information and then send it back to the vehicle local controller. That is a two-way communication between the vehicle local controller and the intersection controller. If the estimated delay in the communication network is $\hat{\tau}$, the vehicle local control would receive the target velocity from the intersection controller with the delay of $2\hat{\tau}$. Since the delay τ can be estimated based on the approach proposed in the last subsection, to compensate the communication delay at any instance of time k , instead of sending the position $s_i(k)$ to the intersection controller, we can send $s_i(k+2\hat{\tau})$, which can be evaluated from the controls within the prediction horizon and vehicle dynamics model. In such a way, the communication delay can be compensation and minimize the negative impacts of the delay on the performance of our system.

4.1.3 Simulation Results

In our simulation setup, the sampling time $\Delta k = 0.5\text{ s}$ and $l_{\max} = 3$, which means the delay τ follows a uniform distribution between 0 to 1.5 s. The prediction horizon of the MPC problem $T=6\text{ s}$, which makes $T > 2\tau_{\max}$, such that the prediction horizon can cover two times of the maximum delay in order to compensate the delay. The simulate is set to run for 400 s. Three simulation scenarios are shown in this section including the simulation with ideal communication network (no delay), the simulation with random delay as described above and the simulation with both delay and delay compensation.

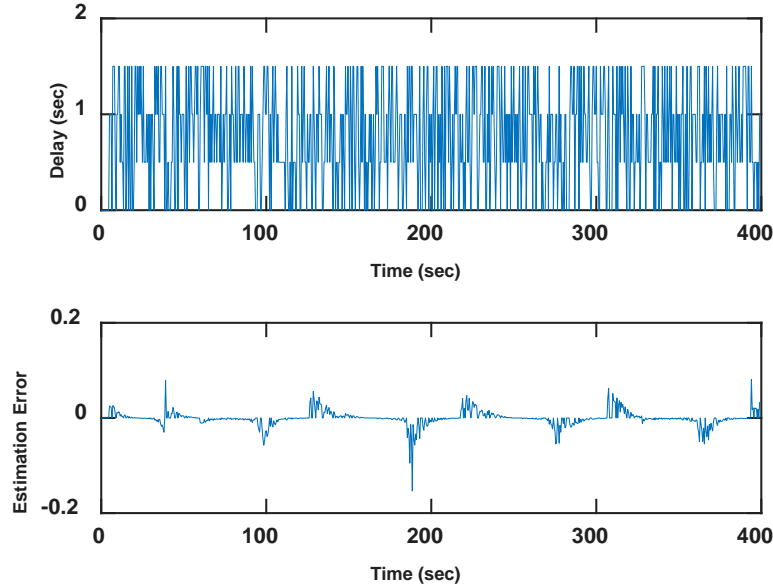


Figure 4.2 The random delay in the communication network and estimation errors

The upper plot in Figure 4.2 shows the delay we injected into the system distributed from 0 to 1.5 s with 0.5 s as the increment. The lower plot in Figure 4.2 shows the error compared with the estimation from our proposed approach in Section 4.1.2A.

The errors are all within 0.2 s which is acceptable. It should be noted that there are a few spikes on the estimation error in the figure at time instance when the traffic signal light change from red to green or the otherwise. The reason behind is that the vehicle control input has a jump either from acceleration to deceleration or vice versa at the time instances when the traffic signal light change the status. The second-order Taylor series expansion approach to approximate the delay involves the vehicle acceleration terms, and that may be the reason of existing spikes on the estimation error. It indicates the Taylor series expansion may not be a good way for the delay estimation. Future research includes seeking different delay estimation approaches for our problem.

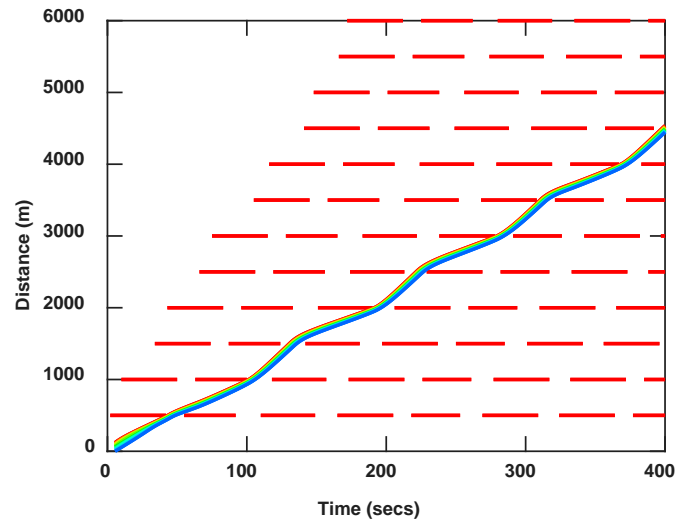


Figure 4.3 All vehicle trajectories in the simulation scenario with ideal communication network (no delay)

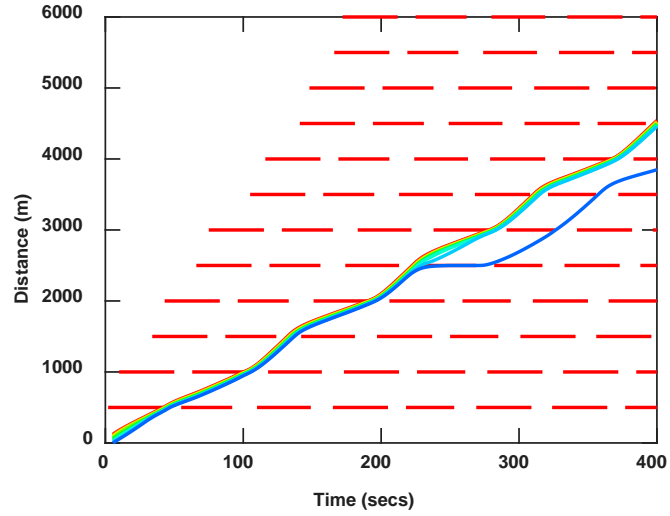


Figure 4.4 All vehicle trajectories in the simulation scenario with random delay without compensation

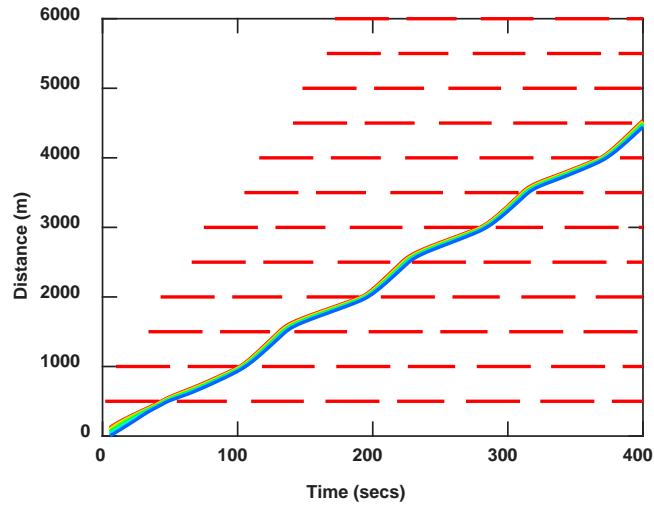


Figure 4.5 All vehicle trajectories in the simulation scenario with random delay and compensation

Figure 4.3 shows all the vehicle trajectories under ideal communication network work without any delay. The simulation results are similar to our previous research.

Figure 4.4 shows all the vehicle trajectories under random delay in the communication network without compensation. In this scenario, some vehicles are stopped by the red light, because the target velocity evaluated by the centralized intersection is based on the delayed position information. It should be noted that even under the delayed communication scenario, there would be no rear-end collisions happen, because the information the preceding vehicle can be obtained from the onboard sensors of the following vehicle and it is considered to be accurate without delay. Figure 4.5 shows all the vehicle trajectories when the communication network is under the same delay, but our proposed compensation approach is involved. It can be seen that the trajectories are almost the same with the ones in Figure 4.3 where there is no delay. The fuel economy performance of the three scenarios are summarized in Table 4.1. The performance of the delay compensation scenario is almost the same compared with the ideal case.

	Average Fuel Economy (MPG)	Standard Deviation
No delay	40.42	0.5322
Random delay	38.66	0.4961
Random delay & compensation	40.41	0.5478

Table 4.1 Summary of average fuel economy on delay estimation and compensation study

4.1.4 Conclusion

In this section, a more realistic simulation scenario with random communication delay is investigated. The delay estimation utilizing second-order Taylor series expansion is presented. We also take the advantage of the MPC optimization and use the prediction within the time horizon to compensate the delay. The simulation results show the effectiveness of our proposed approaches. Future research direction may include seeking other delay estimation method which is suitable for our hierarchical control method.

4.1.5 Related Publication

- **Z. Du**, Z. Abdollahi and P. Pisu, The Hierarchical Control Method for a group of connected vehicles travelling on signalized intersection roads with stochastic communication delay, 2018 American Control Conference (in preparation)

4.2 Real-time Implementation Potential

To evaluate the real-time implementation potential of our hierarchical control method and prepare for the future experimental validation, the following simulation study is conducted.

We integrate our hierarchical control algorithm for the connected vehicles on traffic signalized intersections into MATLAB SIMULINK. The MPC optimization problem at the vehicle local controller level is solved at a faster rate by exploiting the system structure and the approximation methods similar to [121] [122] [123] and the approach in Section 2.1.4. The solution method is called Fast-MPC, which is targeting on improving the computational efficient for real-time implementation. A 3D vehicle dynamics animation model is also integrated for better visualization. Our hierarchical control algorithm is used to control the longitudinal dynamics of the two vehicles in the 3D animation model. The simulation is implemented under the Simulink Desktop Real-Time block. The Simulink Desktop Real-Time provides a real-time kernel for executing Simulink models on laptop or desktop. If the algorithm is too slow and missing ticks exceeds the maximum allowance, it reports error and stops the simulation. Figure 4.6 shows the simulation environment.

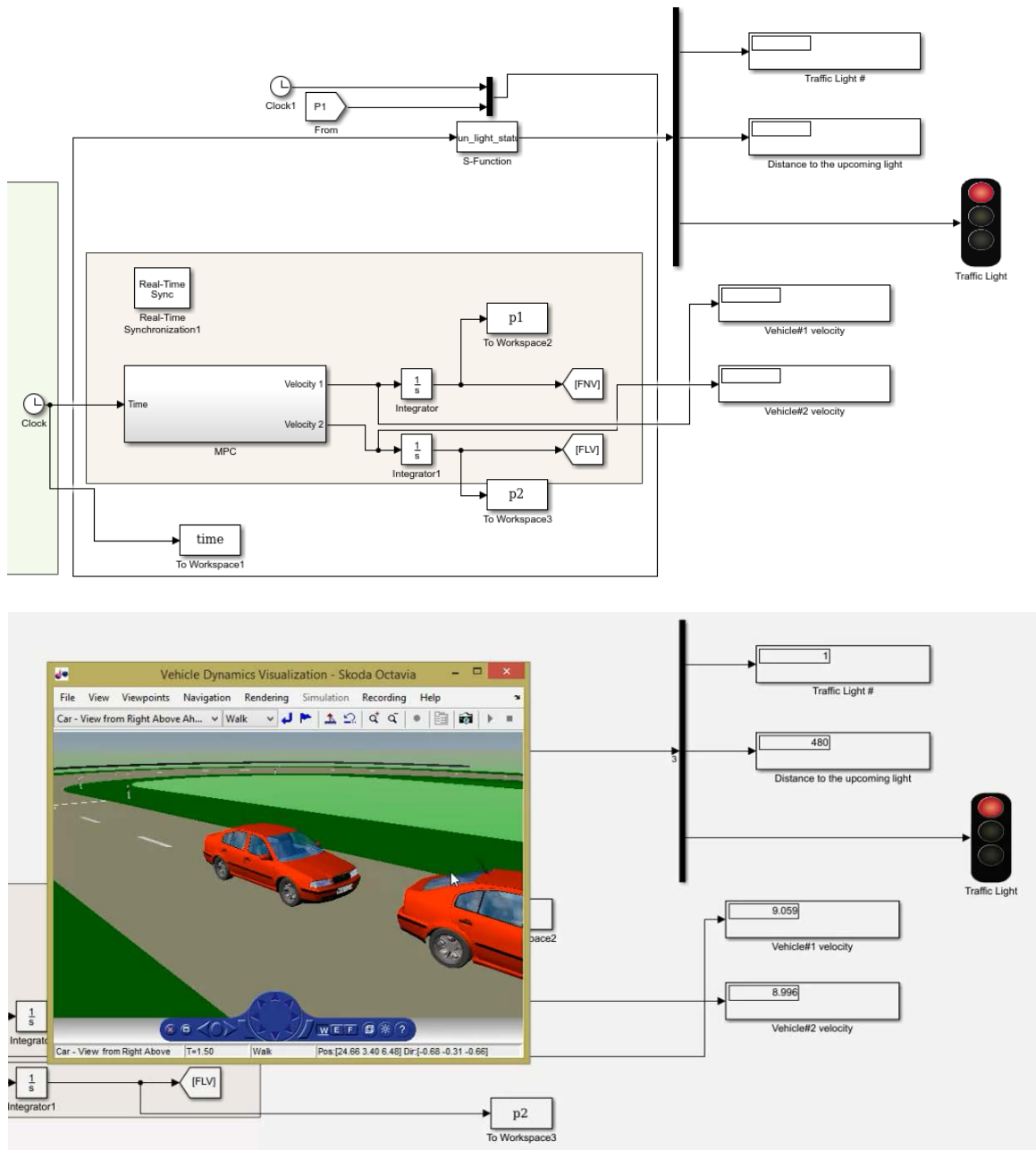


Figure 4.6 Real-time simulation environment

The successful execution of this simulation proves that our algorithm has the capability of real-time implementation. It should be noted that we used only one laptop

and run the MPC for the control of both vehicles in the 3D animation model. In the real-world implementation, we are expecting the decentralized control for each vehicle and the MPC would be executed parallelly in separate control unites, so further computational burden decrease can be expected.

As we have shown the capability of real-time implementation of our algorithm in the simulation, one of the future research is to conduct the real-world experimental validation based on the Arduino robot cars, which will be further discussed in section of our future work.

4.1 Conclusions

This dissertation work proposes the hierarchical control method for coordinating a group of connected vehicles travelling on urban roads. The hierarchical control strategy can guide the vehicles passing through the intersections and make smart lane change decisions, with the objective of improving overall fuel economy, traffic mobility and robust to various connected vehicle penetration rate. Our approach also has great potential for real-world implementation.

In chapter 2, the connected vehicle longitudinal motion coordination is exploited. In section 2.1, we focus on the connected vehicle travelling on multiple interconnected unsignalized intersection roads. The intersection area vehicle collision avoidance relies on the communication and cooperation among the connected vehicles and the intersection controllers. Our control strategies successfully guarantees the vehicle collision avoidance at the intersection area. Rapid traffic density balance and smooth vehicle transition from different roads have also been achieved. In section 2.2, the scenario has been changed to the signalized intersection roads. The centralized intersection controller evaluates the target velocity for each approaching connected vehicle based on their position and the traffic SPAT information to help the vehicles minimize red light idling. The vehicle local controllers apply MPC to track the target velocity in a fuel efficient manner. The simulation results compared with the baseline method where the longitudinal dynamics of the vehicles are controlled by modified Gipps care following model show the fuel

economy improvement of our proposed approach. In section 2.3, the effects of the connected vehicle penetration rate have been explored. we find that the connected vehicle penetration rate does not relate to the average fuel economy of the group of vehicles directly. The position of the unconnected vehicle on the convoy affects the average fuel economy significantly. Also, under our single lane assumption, the connected vehicles do not want to follow unconnected vehicles from the fuel consumption perspective. The simulation results offer us another motivation for the study of the connected vehicle lane change behavior.

In chapter 3, the connected vehicle discretionary and cooperative mandatory lane change decision have been studied. In section 3.3, the discretionary LCD in our proposed approach is made based on offering the subject vehicle higher possibility to achieve its target velocity and with minimum negative impact on the rest of the vehicles in the group at the same time. Another important lane change triggering factor the presence of the unconnected vehicles on the convoy, which is discovered in the connected vehicle penetration rate study is also involved. In the simulation study of the discretionary lane change behavior, both homogeneous and heterogeneous scenario have been provided. The simulation results show the improvement of the group performance under the proposed algorithm. In section 3.4, the cooperative mandatory lane change algorithm has been proposed. The host vehicle cooperates with the vehicles on the target lane to complete its mandatory lane change. The algorithm is realized through inserting a virtual vehicle on the target lane which has identical state variables with the host vehicle.

Simulation results show the advantages of the cooperation during the lane change in the aspects of both fuel and system efficiency.

Finally, in chapter 4, several aspects of real-world implementation our proposed method is facing have been investigated. In section 4.1, we have studied the effects of random communication delay on our hierarchical control method. The delay estimation approach based on second-order Taylor series has been proposed. The control predictions in the MPC horizon are utilized to compensate the delay. Simulation results show that with the delay estimation and compensation, the system performance are comparable with the ideal communication network case. In section 4.2, we investigate the real-time implementation potential of our algorithm with the help of Simulink desktop real-time. The simulation proves the algorithm have the capability of real-time implementation, which is critical for the future real-world experimental validation.

4.2 Future Work

The present research work can be extended in different directions as suggested below.

For the coordination strategy at unsignalized intersections, it is proposed as future work to consider sharing other information besides the traffic density between the adjacent intersection controllers. The most critical information which affects the system performance needs to be exploited in order to improve the overall performance without increasing too much communication and computation burden.

For the lane change decision study, it would be more realistic to include the lane change process. In our previous work, we ignored the vehicle lateral motion and assume

instant jump from current lane to the target lane for the sake of simplicity. However, lane change may take around 4s which may vary based on velocity and traffic conditions. We also need to consider maintaining the collision avoidance constraints on both lane during the process. For the cooperative mandatory lane change study, exploring the optimal lane change initiation point may be one of the future research direction. In our current work, we set a fixed lane change algorithm start point, which may not be the optimal one.

One of the future research direction may also include seeking other communication delay estimation and compensation approaches to overcome the shortcomings of the Taylor series expansions.

The experimental validation of our hierarchical control method is another future research. We are building the experimental test platform based on Arduino robot cars with the capability of wireless communication, indoor GPS localization and lane recognition & tracking. Figure 5.1 shows the schematic of the future experimental validation plan. The traffic signal lights send their SPAT information to our algorithm. At the same time, the Arduino robot cars also send their GPS position and velocity to our algorithm via UDP communication protocol. Our algorithm based on the information gathered evaluates the control input for the robot cars to help them minimize red light idling time.

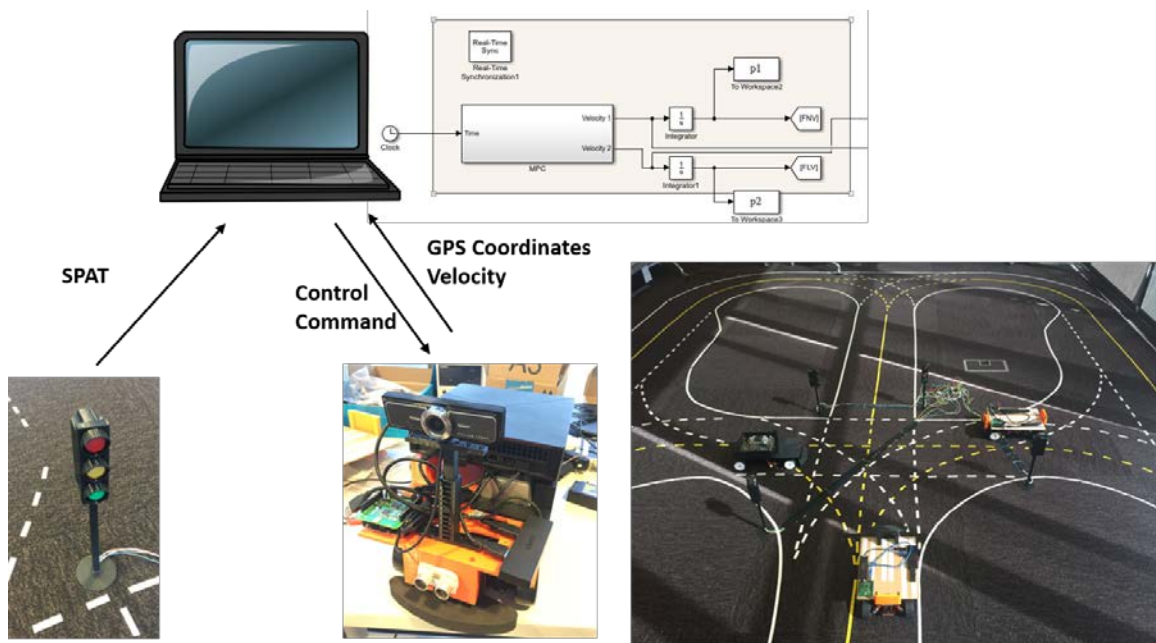


Figure 5.1 Schematic of future experimental validation plan

LIST OF PUBLICATIONS

- **Z. Du**, B. HomChaudhuri, and P. Pisu, 2016. Distributed Coordination of Connected and Automated Vehicles at Multiple Interconnected Intersections. World Academy of Science, Engineering and Technology, International Journal of Computer, Electrical, Automation, Control and Information Engineering, 10(6), pp.842-848.
- **Z. Du**, B. HomChaudhuri and P. Pisu, Hierarchical Distributed Coordination Strategy of Connected and Automated Vehicles at Multiple Intersections. Journal of Intelligent Transportation Systems: Technology, Planning, and Operations (accepted)
- **Z. Du**, B. HomChaudhuri and P. Pisu, The Discretionary Lane Change Decision Study for a Group of Vehicles on Urban Roads under Imperfect Connected Vehicle Penetration Rate, IEEE Transactions on Intelligent Transportation Systems (under review)
- L. Qiu, **Z. Du**, L. Qian and P. Pisu, Hierarchical Energy Management Control Strategies for Connected Hybrid Electric Vehicles Considering Efficiencies Feedback, Journal of Applied Research and Technology (under review)
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- **Z. Du** and P. Pisu, A Fuel Efficient Control Strategy for Connected Vehicles in Urban Roads with Multiple-lane, in the proceedings of, the 55th IEEE Conference on Decision and Control, Las Vegas, NV, 2016
- **Z. Du**, B. HomChauduri and P. Pisu, Coordination Strategy for Vehicles Passing Multiple Signalized Intersections: A Connected Vehicle Penetration Rate Study, Proceedings of 2017 American Control Conference (ACC), Seattle, WA, May 2017.
- **Z. Du** and P. Pisu, Cooperative Mandatory Lane Change for Connected Vehicles on Signalized Intersection Roads, 2018 American Control Conference (ACC) (in preparation)
- **Z. Du**, Z. Abdollahi and P. Pisu, The Hierarchical Control Method for a group of connected vehicles travelling on signalized intersection roads with stochastic communication delay, 2018 American Control Conference (in preparation)
- **Z. Du** and P. Pisu, The Lane Change Decision for A Group of Connected Vehicles on Asymmetric Multiple Lanes Urban Roads (in preparation)

REFERENCES

- [1] NHTSA, "2014 Motor Vehicle Crashes: Overview," 2014.
- [2] NHTSA, "Traffic Safety Facts," 2014.
- [3] P. Sillaparcharn, "Vehicle ownership and trip generation modelling: a case study of Thailand," *IATSS research*, vol. 31, pp. 17-26, 2007.
- [4] U. BTS, "Transportation statistics annual report 2012," 2013.
- [5] R. O'Toole, "Solving the Problem of traffic Congestion," 2012.
- [6] T. A. M. T. Insitute, "2015 Urban Mobility Scorecard," 2015.
- [7] D. Schrank, B. Eisele, and T. Lomax, "TTI's 2012 urban mobility report," *Texas A&M Transportation Institute. The Texas A&M University System*, 2012.
- [8] KPMG, "Connected and Autonomous Vehicles - The UK Economic Opportunity," 2015.
- [9] NHTSA, "U.S. Department of Transportation Releases Policy on Automated Vehicle Development " 2013.
- [10] ITSJPO, "Connected Vehicle Research in the United States," 2015.
- [11] ITSJPO, "How Connected Vehicles Works," 2015.
- [12] A. Böhm, "Delay-sensitive wireless communication for cooperative driving applications," 2013.
- [13] R. Margiotta and D. Snyder, "An Agency Guide on How to Establish Localized Congestion Mitigation Programs," 2011.
- [14] T. R. Neuman, *Guidance for Implementation of the AASHTO Strategic Highway Safety Plan: A guide for addressing unsignalized intersection collisions* vol. 4: Highway Research Board of the Division of Engineering and Industrial Research, National Academy of Sciences, National Research Council, 1965.
- [15] J. Wright, J. K. Garrett, C. J. Hill, G. D. Krueger, J. H. Evans, S. Andrews, *et al.*, "National Connected Vehicle Field Infrastructure Footprint Analysis," 2014.
- [16] R. Radhakrishnan and P. Satyavolu, "Connected Lives Where Smart Vehicles Meet the intelligent Roads," *Cognizanti an annual journal produced by Cgnizat*, vol. 9, 2016.
- [17] Wikipedia. *Hierarchical control system*. Available: https://en.wikipedia.org/wiki/Hierarchical_control_system
- [18] A. I. F. o. C. Agents. *Hierarchical Control* Available: http://artint.info/html/ArtInt_37.html
- [19] G. i. Yasuda, "Implementation of real-time distributed control for discrete event robotic systems using Petri nets," *Artificial Life and Robotics*, vol. 16, pp. 537-541, 2012.
- [20] J. Borges de Sousa, K. H. Johansson, J. Silva, and A. Speranzon, "A verified hierarchical control architecture for co - ordinated multi - vehicle operations," *International Journal of Adaptive Control and Signal Processing*, vol. 21, pp. 159-188, 2007.
- [21] O. J. Ogunlowore, "Realtime Motion Planning for Manipulator Robots under Dynamic Environments: An Optimal Control Approach," 2013.

- [22] M. Bellis, "The History of roads and asphalt," *About. Com*, vol. 24, 2007.
- [23] J. M. Lutin, A. L. Kornhauser, and E. L.-L. MASCE, "The revolutionary development of self-driving vehicles and implications for the transportation engineering profession," *Institute of Transportation Engineers. ITE Journal*, vol. 83, p. 28, 2013.
- [24] J. M. Anderson, K. Nidhi, K. D. Stanley, P. Sorensen, C. Samaras, and O. A. Oluwatola, *Autonomous vehicle technology: A guide for policymakers*: Rand Corporation, 2014.
- [25] BCG. (2017). *Autonomous Vehicle Adoption Study*.
- [26] V. Milanés, J. P. Rastelli, E. Onieva, and C. González, "Controller for urban intersections based on wireless communications and fuzzy logic," *IEEE Transactions on Intelligent Transportation Systems*, 2010.
- [27] E. Onieva, V. Milanés, J. Villagra, J. Pérez, and J. Godoy, "Genetic optimization of a vehicle fuzzy decision system for intersections," *Expert Systems with Applications*, vol. 39, pp. 13148-13157, 2012.
- [28] W. Wu, J. Zhang, A. Luo, and J. Cao, "Distributed mutual exclusion algorithms for intersection traffic control," *IEEE Transactions On Parallel and Distributed Systems*, vol. 26, pp. 65-74, 2015.
- [29] M. Hafner, D. Cunningham, L. Caminiti, and D. Del Vecchio, "Automated vehicle-to-vehicle collision avoidance at intersections," in *Proceedings of World Congress on Intelligent Transport Systems*, 2011.
- [30] M. R. Hafner, D. Cunningham, L. Caminiti, and D. Del Vecchio, "Cooperative collision avoidance at intersections: Algorithms and experiments," *IEEE Transactions on Intelligent Transportation Systems*, vol. 14, pp. 1162-1175, 2013.
- [31] K. Dresner and P. Stone, "A multiagent approach to autonomous intersection management," *Journal of artificial intelligence research*, vol. 31, pp. 591-656, 2008.
- [32] A. de La Fortelle, "Analysis of reservation algorithms for cooperative planning at intersections," in *Intelligent Transportation Systems (ITSC), 2010 13th International IEEE Conference on*, 2010, pp. 445-449.
- [33] Q. Jin, G. Wu, K. Boriboonsomsin, and M. Barth, "Platoon-based multi-agent intersection management for connected vehicle," in *Intelligent Transportation Systems-(ITSC), 2013 16th International IEEE Conference on*, 2013, pp. 1462-1467.
- [34] J. Lee and B. Park, "Development and evaluation of a cooperative vehicle intersection control algorithm under the connected vehicles environment," *Intelligent Transportation Systems, IEEE Transactions on*, vol. 13, pp. 81-90, 2012.
- [35] Q. Jin, G. Wu, K. Boriboonsomsin, and M. Barth, "Multi-Agent Intersection Management for Connected Vehicles Using an Optimal Scheduling Approach," in *Connected Vehicles and Expo (ICCVE), 2012 International Conference on*, 2012, pp. 185-190.

- [36] F. Yan, M. Dridi, and A. El Moudni, "Autonomous vehicle sequencing algorithm at isolated intersections," in *Intelligent Transportation Systems, 2009. ITSC'09. 12th International IEEE Conference on*, 2009, pp. 1-6.
- [37] M. Kamal, A. Samad, J.-i. Imura, A. Ohata, T. Hayakawa, and K. Aihara, "Coordination of automated vehicles at a traffic-lightless intersection," in *Intelligent Transportation Systems-(ITSC), 2013 16th International IEEE Conference on*, 2013, pp. 922-927.
- [38] L. Makarem and D. Gillet, "Model predictive coordination of autonomous vehicles crossing intersections," in *Intelligent Transportation Systems-(ITSC), 2013 16th International IEEE Conference on*, 2013, pp. 1799-1804.
- [39] J. Rios-Torres, A. Malikopoulos, and P. Pisu, "Online Optimal Control of Connected Vehicles for Efficient Traffic Flow at Merging Roads," Oak Ridge National Laboratory (ORNL); National Transportation Research Center (NTRC)2015.
- [40] M. B. Trabia, M. S. Kaseko, and M. Ande, "A two-stage fuzzy logic controller for traffic signals," *Transportation Research Part C: Emerging Technologies*, vol. 7, pp. 353-367, 1999.
- [41] A. Yazici, G. Seo, and U. Ozguner, "A model predictive control approach for decentralized traffic signal control," *IFAC Proceedings Volumes*, vol. 41, pp. 13058-13063, 2008.
- [42] J. Lei and U. Ozguner, "Decentralized hybrid intersection control," in *Decision and Control, 2001. Proceedings of the 40th IEEE Conference on*, 2001, pp. 1237-1242.
- [43] D.-w. Huang and W.-n. Huang, "Traffic signal synchronization," *Physical Review E*, vol. 67, p. 056124, 2003.
- [44] J. A. Hillier and R. Rothery, "The synchronization of traffic signals for minimum delay," *Transportation Science*, vol. 1, pp. 81-94, 1967.
- [45] M. Wiering, J. Van Veenen, J. Vreeken, and A. Koopman, "Intelligent traffic light control," *Institute of Information and Computing Sciences. Utrecht University*, 2004.
- [46] R. W. Denney Jr, "The National Traffic Signal Report Card," *Institute of Transportation Engineers. ITE Journal*, vol. 82, p. 22, 2012.
- [47] S. Mandava, K. Boriboonsomsin, and M. Barth, "Arterial velocity planning based on traffic signal information under light traffic conditions," in *Intelligent Transportation Systems, 2009. ITSC'09. 12th International IEEE Conference on*, 2009, pp. 1-6.
- [48] E. Koukoumidis, L.-S. Peh, and M. R. Martonosi, "SignalGuru: leveraging mobile phones for collaborative traffic signal schedule advisory," in *Proceedings of the 9th international conference on Mobile systems, applications, and services*, 2011, pp. 127-140.
- [49] B. Asadi and A. Vahidi, "Predictive cruise control: Utilizing upcoming traffic signal information for improving fuel economy and reducing trip time," *Control Systems Technology, IEEE Transactions on*, vol. 19, pp. 707-714, 2011.

- [50] G. Mahler and A. Vahidi, "An optimal velocity-planning scheme for vehicle energy efficiency through probabilistic prediction of traffic-signal timing," *IEEE Transactions on Intelligent Transportation Systems*, vol. 15, pp. 2516-2523, 2014.
- [51] B. HomChaudhuri, A. Vahidi, and P. Pisu, "A fuel economic model predictive control strategy for a group of connected vehicles in urban roads," in *2015 American Control Conference (ACC)*, 2015, pp. 2741-2746.
- [52] B. HomChaudhuri, A. Vahidi, and P. Pisu, "A fuel economic model predictive control strategy for a group of connected vehicles in urban roads," in *American Control Conference (ACC)*, 2015, 2015, pp. 2741-2746.
- [53] J. Argote, E. Christofa, Y. Xuan, and A. Skabardonis, "Estimation of measures of effectiveness based on connected vehicle data," in *2011 14th International IEEE Conference on Intelligent Transportation Systems (ITSC)*, 2011, pp. 1767-1772.
- [54] J. Argote-Cabañero, E. Christofa, and A. Skabardonis, "Connected vehicle penetration rate for estimation of arterial measures of effectiveness," *Transportation Research Part C: Emerging Technologies*, vol. 60, pp. 298-312, 2015.
- [55] D. Wang, M. Hu, Y. Wang, J. Wang, H. Qin, and Y. Bian, "Model predictive control-based cooperative lane change strategy for improving traffic flow," *Advances in Mechanical Engineering*, vol. 8, p. 1687814016632992, 2016.
- [56] L. Barr and W. Najm, "Crash problem characteristics for the intelligent vehicle initiative," in *Transportation Research Board 80th Annual Meeting*, 2001.
- [57] S. K. Young, C. A. Eberhard, and P. J. Moffa, "Development of performance specifications for collision avoidance systems for lane change, merging, and backing. Task 2 interim report: Functional goals establishment," *US Department of Transportation, National Highway Traffic Safety Administration*, 1995.
- [58] A. Sasoh and T. Ohara, "Shock wave relation containing lane change source term for two-lane traffic flow," *Journal of the Physical Society of Japan*, vol. 71, pp. 2339-2347, 2002.
- [59] J. Gonder, M. Earleywine, and W. Sparks, "Final report on the fuel saving effectiveness of various driver feedback approaches," National Renewable Energy Laboratory (NREL), Golden, CO.2011.
- [60] C. F. Choudhury, M. E. Ben-Akiva, T. Toledo, G. Lee, and A. Rao, "Modeling cooperative lane changing and forced merging behavior," in *86th Annual Meeting of the Transportation Research Board, Washington, DC*, 2007.
- [61] P. G. Gipps, "A model for the structure of lane-changing decisions," *Transportation Research Part B: Methodological*, vol. 20, pp. 403-414, 1986.
- [62] P. Hidas, "Modelling lane changing and merging in microscopic traffic simulation," *Transportation Research Part C: Emerging Technologies*, vol. 10, pp. 351-371, 2002.
- [63] P. Hidas, "Modelling vehicle interactions in microscopic simulation of merging and weaving," *Transportation Research Part C: Emerging Technologies*, vol. 13, pp. 37-62, 2005.

- [64] Q. Yang and H. N. Koutsopoulos, "A microscopic traffic simulator for evaluation of dynamic traffic management systems," *Transportation Research Part C: Emerging Technologies*, vol. 4, pp. 113-129, 1996.
- [65] A. Kesting, M. Treiber, and D. Helbing, "General lane-changing model MOBIL for car-following models," *Transportation Research Record: Journal of the Transportation Research Board*, 2007.
- [66] T. Toledo, H. Koutsopoulos, and M. Ben-Akiva, "Modeling integrated lane-changing behavior," *Transportation Research Record: Journal of the Transportation Research Board*, pp. 30-38, 2003.
- [67] T. Toledo, C. Choudhury, and M. Ben-Akiva, "Lane-changing model with explicit target lane choice," *Transportation Research Record: Journal of the Transportation Research Board*, pp. 157-165, 2005.
- [68] M. Kamal, S. Taguchi, and T. Yoshimura, "Efficient vehicle driving on multi-lane roads using model predictive control under a connected vehicle environment," in *Intelligent Vehicles Symposium (IV)*, 2015 IEEE, 2015, pp. 736-741.
- [69] M. Wang, S. P. Hoogendoorn, W. Daamen, B. van Arem, and R. Happee, "Game theoretic approach for predictive lane-changing and car-following control," *Transportation Research Part C: Emerging Technologies*, vol. 58, pp. 73-92, 2015.
- [70] Q. W. B. A. T. Weiskircher, "Optimal Assigner Decisions in A Hybrid Predictive Control of an Autonomous Vehicle in Public Traffic," in *The 2016 American Control Conference*, MA, USA, 2016.
- [71] B. De Schutter, "Optimizing acyclic traffic signal switching sequences through an extended linear complementarity problem formulation," *European Journal of Operational Research*, vol. 139, pp. 400-415, 2002.
- [72] C. Wuthishuwong and A. Traechtler, "Consensus coordination in the network of Autonomous Intersection Management," in *Informatics in Control, Automation and Robotics (ICINCO)*, 2014 11th International Conference on, 2014, pp. 794-801.
- [73] C. Wuthishuwong and A. Traechtler, "Coordination of multiple autonomous intersections by using local neighborhood information," in *2013 International Conference on Connected Vehicles and Expo (ICCVE)*, 2013, pp. 48-53.
- [74] M. Tlig, O. Buffet, and O. Simonin, "Stop-free strategies for traffic networks: Decentralized on-line optimization," in *ECAI 2014-21th European Conference on Artificial Intelligence. Including Prestigious Applications of Artificial Intelligence (PAIS-2014)*, 2014.
- [75] M. Hausknecht, T.-C. Au, and P. Stone, "Autonomous intersection management: Multi-intersection optimization," in *Intelligent Robots and Systems (IROS)*, 2011 IEEE/RSJ International Conference on, 2011, pp. 4581-4586.
- [76] K. Dresner and P. Stone, "A multiagent approach to autonomous intersection management," *Journal of artificial intelligence research*, pp. 591-656, 2008.
- [77] R. O. S. R. M. Murray, "Consensus protocols for networks of dynamic agents," in *Proceedings of the 2003 American Controls Conference*, 2003.

- [78] R. Olfati-Saber, J. A. Fax, and R. M. Murray, "Consensus and cooperation in networked multi-agent systems," *Proceedings of the IEEE*, vol. 95, pp. 215-233, 2007.
- [79] F. L. Hall, "Traffic stream characteristics," *Traffic Flow Theory. US Federal Highway Administration*, 1996.
- [80] E. Hellström, J. Åslund, and L. Nielsen, "Design of an efficient algorithm for fuel-optimal look-ahead control," *Control Engineering Practice*, vol. 18, pp. 1318-1327, 2010.
- [81] R. Olfati-Saber, A. Fax, and R. M. Murray, "Consensus and cooperation in networked multi-agent systems," *Proceedings of the IEEE*, vol. 95, pp. 215-233, 2007.
- [82] C. Wuthishuwong and A. Traechtler, "Coordination of multiple autonomous intersections by using local neighborhood information," in *Connected Vehicles and Expo (ICCVE), 2013 International Conference on*, 2013, pp. 48-53.
- [83] D. Q. Mayne, J. B. Rawlings, C. V. Rao, and P. O. Scokaert, "Constrained model predictive control: Stability and optimality," *Automatica*, vol. 36, pp. 789-814, 2000.
- [84] L. Grüne and J. Pannek, *Nonlinear model predictive control*: Springer, 2011.
- [85] M. Kamal, A. Samad, M. Mukai, J. Murata, and T. Kawabe, "Model predictive control of vehicles on urban roads for improved fuel economy," *Control Systems Technology, IEEE Transactions on*, vol. 21, pp. 831-841, 2013.
- [86] U. S. D. o. Transportation, "The intelligent transportation systems for traffic signal control deployment benefits and lessons learned," 2007.
- [87] E. Brockfeld, R. Barlovic, A. Schadschneider, and M. Schreckenberg, "Optimizing traffic lights in a cellular automaton model for city traffic," *Physical Review E*, vol. 64, p. 056132, 2001.
- [88] P. Michalopoulos and G. Stephanopoulos, "Optimal control of oversaturated intersections: theoretical and practical considerations," *Traffic Engineering & Control*, vol. 19, 1978.
- [89] K. S. Nayaki, N. N. Krishnan, V. Joby, and R. Sreelakshmi, "Traffic Light Synchronization," in *Advances in Computing and Information Technology*, ed: Springer, 2013, pp. 97-106.
- [90] S.-B. Cools, C. Gershenson, and B. D'Hooghe, "Self-organizing traffic lights: A realistic simulation," in *Advances in applied self-organizing systems*, ed: Springer, 2013, pp. 45-55.
- [91] B. Asadi, "Predictive energy management in smart vehicles: Exploiting traffic and traffic signal preview for fuel saving," 2009.
- [92] A. Brahma, Y. Guezennec, and G. Rizzoni, "Optimal energy management in series hybrid electric vehicles," in *American Control Conference, 2000. Proceedings of the 2000*, 2000, pp. 60-64.
- [93] A. Vogel, D. Ramachandran, R. Gupta, and A. Raux, "Improving Hybrid Vehicle Fuel Efficiency Using Inverse Reinforcement Learning," in *AAAI*, 2012.

- [94] C. Zhang and A. Vahidi, "Predictive cruise control with probabilistic constraints for eco driving," in *ASME 2011 Dynamic Systems and Control Conference and Bath/ASME Symposium on Fluid Power and Motion Control*, 2011, pp. 233-238.
- [95] C. Zhang, A. Vahidi, X. Li, and D. Essenmacher, "Role of trip information preview in fuel economy of plug-in hybrid vehicles," in *ASME 2009 dynamic systems and control conference*, 2009, pp. 253-258.
- [96] C. Zhang, A. Vahidi, P. Pisu, X. Li, and K. Tennant, "Role of terrain preview in energy management of hybrid electric vehicles," *Vehicular Technology, IEEE Transactions on*, vol. 59, pp. 1139-1147, 2010.
- [97] Q. Gong, Y. Li, and Z.-R. Peng, "Trip-based optimal power management of plug-in hybrid electric vehicles," *Vehicular Technology, IEEE Transactions on*, vol. 57, pp. 3393-3401, 2008.
- [98] C. Sun, S. J. Moura, X. Hu, J. K. Hedrick, and F. Sun, "Dynamic traffic feedback data enabled energy management in plug-in hybrid electric vehicles," *Control Systems Technology, IEEE Transactions on*, vol. 23, pp. 1075-1086, 2015.
- [99] L. Guzzella and A. Sciarretta, *Vehicle propulsion systems* vol. 1: Springer, 2007.
- [100] X. Zhang and C. Mi, *Vehicle power management: modeling, control and optimization*: Springer Science & Business Media, 2011.
- [101] S. Onori, L. Serrao, and G. Rizzoni, "Adaptive equivalent consumption minimization strategy for hybrid electric vehicles," in *ASME 2010 Dynamic Systems and Control Conference*, 2010, pp. 499-505.
- [102] P. G. Gipps, "A behavioural car-following model for computer simulation," *Transportation Research Part B: Methodological*, vol. 15, pp. 105-111, 1981.
- [103] K. I. Ahmed, "Modeling drivers' acceleration and lane changing behavior," Massachusetts Institute of Technology, 1999.
- [104] D. Zhiyuan, B. HomChaudhuri, and P. Pisu, "Hierarchical Energy Management Control of Connected Hybrid Electric Vehicles on Urban Roads with Efficiencies Feedback," in *ASME 2016 Dynamic Systems and Control Conference*, 2016.
- [105] P. Belotti, C. Kirches, S. Leyffer, J. Linderoth, J. Luedtke, and A. Mahajan, "Mixed-integer nonlinear optimization," *Acta Numerica*, vol. 22, pp. 1-131, 2013.
- [106] R. Yi and H. School, "A Probability-Based Model of Traffic Flow," 2016.
- [107] B. HomChaudhuri, R. Lin, and P. Pisu, "Hierarchical control strategies for energy management of connected hybrid electric vehicles in urban roads," *Transportation Research Part C: Emerging Technologies*, vol. 62, pp. 70-86, 2016.
- [108] Z. Du, L. Qiu, and P. Pierluigi, "Hierarchical Energy Management Control of Connected Hybrid Electric Vehicles on Urban Roads with Efficiencies Feedback," presented at the the ASME 2016 Dynamic Systems and Control Conference Minneapolis, Minnesota, USA, 2016.
- [109] Z. Du and P. Pisu, "A fuel efficient control strategy for connected vehicles in multiple-lane urban roads," in *Decision and Control (CDC), 2016 IEEE 55th Conference on*, 2016, pp. 715-720.

- [110] F. Bai and H. Krishnan, "Reliability analysis of DSRC wireless communication for vehicle safety applications," in *Intelligent Transportation Systems Conference, 2006. ITSC'06. IEEE*, 2006, pp. 355-362.
- [111] G. Orosz, J. Moehlis, and F. Bullo, "Robotic reactions: Delay-induced patterns in autonomous vehicle systems," *Physical Review E*, vol. 81, p. 025204, 2010.
- [112] R. Szalai and G. Orosz, "Decomposing the dynamics of heterogeneous delayed networks with applications to connected vehicle systems," *Physical Review E*, vol. 88, p. 040902, 2013.
- [113] A. C. Bajpai, L. R. Mustoe, and D. Walker, "Advanced engineering mathematics," 1977.
- [114] J. Kurzweil, "Small delays don't matter," in *Proceedings of the Symposium on Differential Equations and Dynamical Systems*, 1971, pp. 47-49.
- [115] R. Driver, D. Sasser, and M. Slater, "The Equation $\dot{x} = \frac{1}{4}ax + b$ With," *Small" Delay*, " *Am. Math. Mon.*, vol. 80, pp. 990-995, 1973.
- [116] S. Guillouez, I. L'Heureux, and A. Longtin, "Small delay approximation of stochastic delay differential equations," *Physical Review E*, vol. 59, p. 3970, 1999.
- [117] Y. Asai, Y. Tasaka, K. Nomura, T. Nomura, M. Casadio, and P. Morasso, "A model of postural control in quiet standing: robust compensation of delay-induced instability using intermittent activation of feedback control," *PLoS One*, vol. 4, p. e6169, 2009.
- [118] X. Qu, M. A. Nussbaum, and M. L. Madigan, "A balance control model of quiet upright stance based on an optimal control strategy," *Journal of biomechanics*, vol. 40, pp. 3590-3597, 2007.
- [119] P. Paoletti and L. Mahadevan, "Balancing on tightropes and slacklines," *Journal of The Royal Society Interface*, vol. 9, pp. 2097-2108, 2012.
- [120] T. Insperger, "On the approximation of delayed systems by taylor series expansion," *Journal of Computational and Nonlinear Dynamics*, vol. 10, p. 024503, 2015.
- [121] A. Domahidi, A. U. Zgraggen, M. N. Zeilinger, M. Morari, and C. N. Jones, "Efficient interior point methods for multistage problems arising in receding horizon control," in *Decision and Control (CDC), 2012 IEEE 51st Annual Conference on*, 2012, pp. 668-674.
- [122] Y. Wang and S. Boyd, "Fast model predictive control using online optimization," *IEEE Transactions on Control Systems Technology*, vol. 18, pp. 267-278, 2010.
- [123] B. HomChaudhuri, A. Vahidi, and P. Pisu, "Fast Model Predictive Control-Based Fuel Efficient Control Strategy for a Group of Connected Vehicles in Urban Road Conditions," *IEEE Transactions on Control Systems Technology*, vol. 25, pp. 760-767, 2017.