Cooperative Vehicle-Signal Control Considering Energy and Mobility in Connected Environment

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COOPERATIVE VEHICLE-SIGNAL CONTROL CONSIDERING ENERGY AND MOBILITY IN CONNECTED ENVIRONMENT

COOPERATIVE VEHICLE-SIGNAL CONTROL CONSIDERING ENERGY AND MOBILITY IN CONNECTED ENVIRONMENT

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Abstract

The development of connected vehicle (CV) technologies enables advanced management of individual vehicles and traffic signals to improve urban mobility and energy efficiency. In this thesis, a cooperative vehicle-signal control system will be developed to integrate an Eco-driving system and a proactive signal control system under a mixed connected environment with both connected vehicles (CVs) and human-driven vehicles (HDVs). The system utilizes CVs to conduct an accurate prediction of queue length and delay at different approaches of intersections. Then, a queue-based optimal control strategy is established to minimize the fuel usage of individual CVs and the travel time delay of entire intersections. The system applies the model predictive control to search for the optimal signal timing plan for each intersection and the most-fuel efficient speed profiles for each CV to gain the global optimum of the intersection. In this thesis, a simulation platform is designed to verify the effectiveness of the proposed system under different traffic scenarios. The comparison with the eco-driving only and signal control only algorithms verifies that the cooperative system has a much more extensive reduction range of the trip delay in the case of medium and high saturation. At low saturation, the effect of the system is not much different from that of the eco-driving algorithm, but it is still better than the signal control. Results show that the benefits of CVs are significant at all different market penetration rates of CVs. It also demonstrates the drawback of the system at high congestion levels.

Keywords: intelligent network connection; proactive signal control; Eco-driving; trajectory optimization; cooperative control system

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Table of Contents

Abstract **2**

Acknowledgement **2**

Table of Contents **2**

List of Figures **4**

List of Tables **5**

Background **1**

1.1 Introduction 1

1.2 Objectives 4

Literature Review **6**

2.1 Research on Eco-driving system 6

2.2 Research on Signal cont rol 10

2.3 Research on integrated signal and trajectory optimization 17

2.4 Research gap 18

2.5 Arrangement of chapters 19

Methodology **21**

3.1 Eco-cooperative adaptive cruise control 21

3.2 A simple model to describe the traffic dynamics at signalized intersections 26

3.3 Proactive signal control at intersection with connected vehicles 29

3.4 Cooperative vehicle-signal control system 34

3.5 CVSC Model 36

Result and Discussion **39**

4.1 Case study real-world network 39

4.2 INTEGRATION microscopic traffic simulator 40

4.3 Benefit analysis of the CVSC system 43

4.3.1 The effect of MPR on fuel consumption and delay time 46

McMaster University

4.3.2 The effect of Demand Level on fuel consumption and delay time 49
4.3.3 The effect of Green Time Ratio on fuel consumption and delay time 50
4.3.4 The effect of Offset on fuel consumption and delay time 52
4.3.5 Validate the effectiveness of the cooperated optimization model 54

Conclusions 58

Citationsand References 61

List of Figures

Fig. 3.1.1: The detailed description of Eco-CACC system....22

Fig. 3.2.1: Demonstration of the proactive signal control system....26

Fig. 3.2.2: Cumulative flow rates and delays....27

Fig. 3.2.3: Phase diagram....28

Fig. 3.3.1: Proactive control at one signalized intersection....29

Fig. 3.3.2: Flow chart of the proactive signal control system....34

Fig. 3.4.1: Demonstration of the cooperative vehicle-signal control framework....35

Fig. 3.4.2: The framework of the CVSC system....36

Fig. 4.1.1: FM 528, tested road segment in Houston, TX....39

Fig 4.2.1: The Van Aerde Traffic Stream Model....41

Fig. 4.2.2: Screenshot of INTEGRATION Software Interface for FM528....42

Fig. 4.3.1: Individual vehicle dynamics at the first intersection....43

Fig. 4.3.1.1: Benefit comparison at different MPRs....47

Fig. 4.3.1.2: Boxplot of fuel consumption saving rate of different MPR....48

Fig. 4.3.2.1: Benefit comparison at different demand levels....50

Fig. 4.3.3.1: Benefit comparison at different green timing ratios 52

Fig. 4.3.4.1: Benefit comparison at different offsets....53

Fig. 4.3.5.1: Average delay and travel time as a function of MPR for saturation of 1.25....54

Fig. 4.3.5.2: Average delay and travel time as a function of MPR for saturation of 1.75....55

Fig. 4.3.5.2: Average delay and travel time as a function of MPR for saturation of 0.7....56

List of Tables

Tab. 4.3.1: Comparison of the overall network performance on FM528 at MPR = 5% 44
Tab. 4.3.2: Comparison of the overall network performance on FM528 at MPR = 60% 45
Tab. 4.3.5.1: Reduction Rate of Evaluation Indicators at Intersections with Demand Level 1.25....................55
Tab. 4.3.5.2: Reduction Rate of Evaluation Indicators at Intersections with Demand Level 0.7.................... 56

Background

1.1 Introduction

According to the International Energy Agency (IEA) [1], road transport is responsible for around 17% of global carbon dioxide emissions. Furthermore, the International Energy Agency reports that road transport emissions are growing faster than any other sector and could double by 2050 if no action is taken. As the number of cars worldwide continues to increase, the air pollution, energy consumption, and financial losses caused by motor vehicles will further exacerbate, which is a challenge for many cities around the world. According to the Canadian government website, every 3 minutes of vehicle delay will result in the waste of 3.6 liters of fuel and an increase of 0.216 kilograms of gas emissions, while 0.08 liters of fuel can drive an ordinary vehicle for one kilometer. Taking the 423.3 million vehicles in New York as an example, if each vehicle reduces congestion by 1 minute per day, the city will reduce greenhouse gas emissions by 19,267 tons. At present, all countries in the world are exploring countermeasures to improve fuel and traffic flow efficiency and have successively proposed to give priority to the development of public transportation [2], the development of clean energy [3] and power technology [4], the rational planning of road traffic environment [5] and the strengthening of traffic management. A series of methods, such as [6], are aimed at alleviating traffic congestion, reducing traffic delays, and reducing vehicle fuel consumption and pollutant gas emissions. Especially with the rapid development and widespread adoption of vehicle-to-everything (V2X) technology in recent years, traffic congestion management is seeking solutions in the direction of intelligent transportation technology.

Intersections are the junctions of traffic flows in the urban road network, and traffic signals are needed to achieve temporal and spatial separation of traffic flows in different directions. A large amount of research has found that poor intersection signal control has a significant truncation effect on traffic flow, leading to increased delay time, pollutant gas emissions, and fuel consumption. As a key node in urban traffic, the effectiveness of intersection control has a significant impact on the overall smoothness of urban traffic. Vehicles traveling on urban roads are affected by intersection control devices and exhibit the following challenges: 1) stop-and-go fluctuations, the frequent acceleration and deceleration process of the vehicle [7]; 2) the driving speed of a vehicle is too high, even exceeding the speed limit; 3) the extra idling time, these will all result in higher fuel consumption rate and pollutant emission rate [8]. Therefore, reasonable vehicle speed control and signal control to reduce traffic oscillation and avoid idling has become a new entry point and research direction for reducing traffic pollution.

Traditional speed-limiting measures (including traffic police law enforcement, speed reducing facilities and speed-limit signs, etc.) and traditional pre-time signal control have been widely used in the study of vehicle speeding control, smoothing traffic flow oscillations, and time-space traffic flow segmentation. However, with the continuous development of the transportation industry, road traffic conditions have become increasingly complex. Traditional macroscopic control methods cannot adapt to the rapidly changing traffic flow and actual traffic control needs, and the control effect gradually declines [9]. Therefore, how to start from a microscopic perspective, use existing technological means to real-time perceive the traffic conditions of roads and vehicles, and then real-time control vehicle driving speed and signal light duration, to achieve reasonable control of vehicle speed range and reduce speed fluctuations, reduce waiting time of vehicles before red lights, and ensure traffic safety while minimizing the energy consumed by vehicle operations, pollutants produced, and time wasted by drivers waiting on the road has important practical significance.

With the continuous development of intelligent transportation system (ITS) in recent years, the advancement of various advanced computer technologies, electronic communication technologies, and sensor technologies has provided a feasible way to achieve micro-control of road traffic [10, 11]. At present, some countries have developed a series of corresponding vehicle speed control systems, such as Intelligent Speed Adaptation System (ISA) [12] and Advanced Driver Assistant System (IDAS) [13]. Different from traditional road speed limiting devices, similar onboard speed control systems can output customized speed control solutions according to the traffic environment and travel needs of the vehicle. However, due to the use of distributed layout (vehicle), the vehicles are all pursuing the maximization of their own interests, which is likely to have a negative impact on the overall road traffic system, resulting in a decrease in road traffic mobility. They cannot well adapt to the urban road environment with high road traffic pressure [14].

The gradual maturity of the vehicle-to-everything (V2X) technology has promoted the development of adaptive cruise control technology, which achieves microscopic optimal speed control in traditional road traffic systems. It has gradually developed into an eco-driving control system aimed at energy saving and emission reduction. Eco-driving controls include two categories: highway eco-driving and intersection eco-driving [15]. Research on eco-friendly driving on highways started earlier, and relatively the results of many studies have been carried out based on Cooperative Adaptive Cruise Control (CACC) [16]. Because the vehicle is driving on the highway, there is almost no interference from traffic control equipment, such as signal lights. And there are relatively few junctions and lane changes on the highway. So, it is relatively simple to develop eco-driving strategies on highways. Research on environmentally friendly driving at intersections started late. And it often simplifies the complex road traffic environment and vehicle motion characteristics at intersections by using completely networked and fully automated driving environments. As a result, the research results cannot be applied to networked autonomous driving environments where autonomous vehicles and traditional human-driven vehicles are mixed. The recent feasibility and practical significance of such research are relatively low [17].

In order to enhance the adaptability of signalized intersections and environmentally friendly driving control to today's road traffic environment, this thesis conducts in-depth research on environmentally friendly driving control at signalized intersections based on mixed traffic of networked human-driven vehicles and traditional human-driven vehicles, with vehicle trajectories and traffic signals as the research objects. With the goals of ensuring traffic maneuverability, improving vehicle fuel efficiency, and reducing vehicle pollutant emissions, a cooperative optimization control method for signalized intersections and environmentally friendly driving is studied, with connected vehicles as the control objects, using optimal control theory. Real-time road traffic and vehicle status information is obtained through vehicle-to-everything (V2X) communication, and the indirect control of traditional human-driven vehicles by connected vehicles is achieved through car-following behaviors. In this study, the innovative integration of fuel consumption and delay time as two objective functions into a collaborative objective function is proposed, and the impact of fuel consumption and delay time on the collaborative objective function can be adjusted according to the degree of attention. The collaborative control system in this mixed traffic system is then extended to include multiple intersection segments with multiple lanes, and positive performance in fuel savings and delay time savings is achieved even in over-saturated test road sections. Based on these two innovations, a signal timing and vehicle speed control method that considers energy and maneuverability in a coordinated vehicle signal control environment is explored, with the aim of maximizing the overall system optimization. This approach can effectively improve the traffic efficiency of signalized intersections, enhance vehicle fuel efficiency, reduce vehicle pollutant emissions, improve road traffic operational efficiency, and reduce urban road traffic air pollution.

1.2 Objectives

Achieving energy savings and reducing emissions in urban road traffic requires a comprehensive approach that goes beyond macro-level control measures such as reducing travel demand, minimizing traffic delays, and optimizing road network structure. It also necessitates precise control of vehicles at a micro level within the traffic road network. During actual driving, signalized intersections stand out as areas of high fuel consumption and pollution for vehicles. When vehicles approach and traverse these intersections, frequent speed adjustments, excessive cruising speeds, stopping at red signals, queuing, and other movement behaviors can impose a heavy engine load and dissipate the vehicle's kinetic energy. This, in turn, leads to increased fuel consumption rates and pollutant emissions.

The exclusive implementation of intersection signal control or vehicle speed guidance alone falls short of achieving comprehensive and optimal management of all vehicles at intersections. As a result, researchers have recognized the potential for synergistic enhancement by integrating intersection signal control with speed guidance for approaching vehicles. This integration allows for the combined effects of control to be maximized, and it represents a prominent research direction in recent years. In view of this, this thesis conducts research on the collaborative optimization control of signalized intersections in the mixed environment of connected vehicles and traditional vehicles. The purpose of this thesis is to try to use the optimal control theory to achieve a win-win control effect in terms of intersection capacity and vehicle fuel efficiency from the perspective of optimal overall system revenue. The detailed objectives are shown below:

(1) Get a positive benefit from the mixed traffic environment with multiple intersections and oversaturated situations. We can only collect real-time traffic status data from connected vehicles and then predict the traffic parameters of traditional vehicles. With the aim of

achieving overall optimization, we can provide suggested speeds to connected vehicles to influence the driving behavior of regular vehicles. This can improve traffic efficiency and fuel utilization of vehicles when traveling across even high-volume multiple intersections.

(2) Coordinated control of vehicle trajectories and signal timing at intersections. To optimize individual vehicle trajectories and time-domain signal timing, which are two different objectives in traffic flow, they need to be coupled and co-optimized. Furthermore, the balance between these two objectives must be maintained, ensuring the enhancement of intersection capacity while simultaneously improving fuel utilization efficiency. This achieves the ultimate goal of achieving coordinated optimization.

Literature Review

2.1 Research on Eco-driving system

The concept of "eco-driving" was initially introduced as a means to decrease the fuel consumption and pollutant emissions produced by heavy-duty freight vehicles. Its main control method is driver training, which standardizes driving behavior during the driving process and reduces bad high-energy consumption habits [20].

Generally speaking, Eco-driving research can be divided into eco-driving based on urban road conditions [21] and eco-driving based on highway road conditions [22]. Under highway conditions, since the traffic flow is continuous and vehicles are rarely affected by traffic signals, vehicles can usually travel to specific destinations without any restrictions. In contrast to highway conditions, urban road conditions are more complex, and traffic control devices are usually installed, which frequently interrupt the flow of traffic. Influenced by traffic lights, eco-driving in urban road conditions mainly focuses on intersections. When driving through signal-controlled intersections, drivers often cause frequent acceleration, deceleration, and even stop and wait near intersections due to a lack of knowledge about the status of the signal lights and the complex road conditions ahead. This behavior not only leads to increased fuel consumption but also contributes to higher exhaust emissions.

Although vehicles are unrestricted continuous flows under highway conditions, their macroscopic and microscopic performances are the same as those of intersection environmental driving control. The main method is to reduce the duration and frequency of acceleration and deceleration during the approach to intersections, and avoid stopping and waiting behavior in front of intersections to reduce fuel consumption and pollutant emissions during vehicle operation.

Mandava et al. proposed a speed optimization method for a single vehicle at signalized intersections under low road traffic pressure by minimizing the sum of the absolute values of acceleration of the target vehicle during the driving process, reducing speed fluctuations of the vehicle when approaching the intersection, and thus reducing fuel consumption and pollutant emissions [23]. Li et al. further tested the optimization algorithm through detailed simulation. Since the optimization algorithm only focuses on minimizing acceleration without considering the impact of speed on fuel consumption, its effect on improving fuel efficiency is limited, only about 5% [24]. At the same time, Saboohi et al. analyzed the effect of engine load on fuel consumption. They constructed a vehicle speed optimization control method based on minimizing engine load as the objective function. Since the calculation of engine load fully considers the speed and acceleration of vehicle motion, the optimization output results are more adaptable to actual vehicle operation, and the simulation test showed a fuel saving of 1.5 liters per 100 kilometers and an improvement in fuel efficiency of about 10% [25]. Vreeswijk et al. proposed an eco-Adaptive Balancing and Control system, which is a two-layer optimization system with path optimization capability at the network layer and intersection speed optimization capability at the local layer. However, its speed optimization only relies on the definition of expected acceleration, so the overall control effect of the system has not achieved a breakthrough [26].

Kamal introduced the model predictive control method into the intersection eco-driving control, which converts road speed limit constraints and safety distance constraints into cost form and integrates them with vehicle fuel consumption, acceleration, and braking costs to form a unified cost function. The optimal speed is obtained by solving the speed through the acceleration control process. This method can increase the single-vehicle fuel consumption reduction rate to 12.85% [27]. Based on previous research [23], Barth further proposed a dynamic eco-driving control system for signalized intersections and a corresponding speed optimization method. This method uses vehicle fuel consumption as the objective function and a trigonometric function curve as the spline curve for vehicle acceleration and deceleration. The two parameters of the trigonometric function period and amplitude are used to replace a large number of continuous speed values as control variables for optimization. The calculation speed is significantly improved. As the optimization problem's objective function uses a vehicle micro fuel consumption and pollutant emission model segmented by acceleration and deceleration, the speed trajectory function needs to be segmented in advance during the optimization process. Combining the simplified spline curve and the deviation between the actual vehicle speed trajectory, the optimized output speed solution is not a globally optimal solution, which limits the method's control effect. The vehicle fuel efficiency improvement is also at the level of 12.3% [28]. Xia et al. conducted simulation tests on the signalized intersection dynamic eco-driving control method proposed by Barth on a multi-vehicle road. Since the control target of this method is single-vehicle optimization, to achieve a stable control effect, rolling optimization control needs to be adopted to adapt to the changing road traffic status ahead, increasing the system's computational burden. If rolling optimization control is not adopted, the optimal speed plan will face the risk of failure under the interference of the leading driver's random driving behavior [29]. During this period, Rakha also conducted research on eco-driving control at signalized intersections. He compared the fuel consumption of speed trajectories of different line types in advance and selected the speed curve with the highest fuel efficiency as the spline curve. The overall speed trajectory optimization was completed by optimizing the characteristic points of the spline curve, which is similar to the speed optimization algorithm proposed by Barth [30]. Miyatake et al. also constructed the objective function of the speed optimization problem with vehicle fuel consumption and converted the optimization problem into a multi-level decision-making process, using the dynamic programming algorithm to solve it [31]. Mensing et al., based on the characteristics of the vehicle power system, constructed a vehicle fuel consumption model with vehicle speed and acceleration as independent variables, and constructed a speed optimization problem with vehicle acceleration as the control variable. The problem was also solved using the dynamic programming algorithm [32]. Both studies use dynamic programming algorithms to decompose the optimization problem to accelerate the solution process.

Boriboonsomsin et al. proposed an eco-driving speed optimization algorithm based on Vehicle-Specific Power (VSP). This algorithm relies on digital maps and data fusion technology to obtain road historical and real-time status information, which serves as a constraint in the optimization process for straight-ahead vehicle speeds [33]. Xia et al. conducted on-road tests of Barth's dynamic eco-driving system at a signalized intersection for a single vehicle, and the results showed a 14.06% improvement in vehicle fuel efficiency. The data refresh rate during the testing process was 1Hz, meaning that the duration for rolling optimization of speed plans needed to be less than 1 second. Due to the high cost of field testing in a multi-vehicle environment, testing the feasibility of only a single control method is currently not very practical given the incomplete state of the theoretical system [34].

While signalized intersection eco-driving control with the objective of optimizing single-vehicle fuel efficiency can effectively reduce vehicle fuel consumption and pollutant emissions, it can also result in increased travel time, particularly in high traffic environments where vehicle delays can rapidly accumulate. Therefore, Xia et al. improved the signalized intersection dynamic eco-driving control method proposed by Barth by adding the impact of controlled vehicles on the running of following vehicles as a constraint in the control algorithm to avoid adverse effects of single-vehicle optimal control on following vehicles [35]. Subsequently, Xia et al. continued to conduct simulation tests on the improved signalized intersection eco-driving control method in a multi-intersection and road network environment, and the test results showed that the control system could effectively improve vehicle fuel efficiency under both single-lane multi-intersection and multi-lane road network conditions while reducing the adverse effects on vehicle operational efficiency. At the same time, the test results also showed that the fuel consumption required for rapid acceleration or deceleration to a stable cruising speed was lower than that required for slow acceleration or deceleration to the same stable cruising speed, so in the eco-driving control process, each control system should adopt a fast vehicle speed adjustment strategy to obtain the optimal vehicle speed plan [36]. Nunzio proposed a multi-signal intersection eco-driving control method that converts the constraints on road traffic conditions between multiple signalized intersections and the feasible spatio-temporal paths within the vehicle dynamics constraint range into a weighted directed acyclic graph (WDAG). The directed graph has the spatio-temporal location of the vehicle when it enters the eco-driving control range as the root node and the spatio-temporal location when it leaves the eco-driving control range as the target node, constructing a feasible spatio-temporal path tree structure. The fuel consumption model of the vehicle is used to evaluate each feasible spatio-temporal path plan to find the optimal solution. This method only calculates and compares the predefined spatio-temporal paths, and there is no direct optimization process in the control process, so it has the advantage of fast computation speed, but there is a large error between the output optimal spatio-temporal path of the vehicle and the actual spatio-temporal path of the vehicle during operation [37].

Currently, the control of environmentally friendly driving at signalized intersections is gradually shifting from pursuing individual vehicle optimality to system optimality. Hao et al. designed a sensing control framework for environmentally friendly driving at signalized intersections in a connected and automated driving environment based on Barth's analysis [38]. Lee et al. proposed a vehicle control method for unsignalized intersections in a fully connected and automated driving environment, which minimizes the spatiotemporal overlap length of vehicle trajectories in different directions in the road crossing area to avoid collisions of autonomous vehicles [39]. The additional benefit of minimizing the spatiotemporal trajectory length is smooth trajectories, which resulted in good energy-saving and emission-reducing effects in subsequent testing and verification [40]. As research progresses, the pursuit of vehicle fuel efficiency alone in environmentally friendly driving control methods can easily lead to a decrease in intersection traffic mobility, i.e., a decrease in intersection throughput. To reduce the impact of environmentally friendly driving control on intersection mobility, subsequent research gradually begins to include intersection mobility preservation and vehicle fuel efficiency improvement as joint optimization control objectives. Zhou and Ma enforced the minimum headway between vehicles by controlling the terminal state of the vehicle at the intersection stop line during trajectory optimization in a fully connected and automated driving environment, thereby avoiding the negative impact of environmentally friendly driving control on intersection throughput. They used the Greedy Shooting algorithm to segmentally construct the spatiotemporal trajectory of the vehicle approaching the signalized intersection to avoid NP-Hard problems in spatiotemporal trajectory smoothness optimization [41, 42]. He et al. used similar methods to reduce the impact of environmentally friendly driving control on intersection mobility. They calculated the earliest arrival time of the controlled vehicle at the intersection stop line using the spatiotemporal position of the last vehicle in the queue near the intersection stop line as a terminal constraint in the optimization problem. Although this algorithm is for individual vehicle optimal control, it controls the terminal constraint of the optimization problem to make the controlled vehicle pass through the intersection as quickly as possible and minimize its impact on the following vehicles [43].

2.2 Research on Signal control

Although many valuable studies have been carried out in the field of eco-driving, the congested traffic network still causes continuous negative effects, such as increased delays and increased environmental pollution. Therefore, using optimized and advanced traffic signal control methods and technologies to improve the application level of traffic signal control has also become a crucial research direction.

Signal control systems that cannot predict traffic demand in real-time are called passive signal control. Timing control is the first passive signal control strategy [44-46]. Owing to its straightforwardness, the method that relies on the pre-established phase sequence and green light intervals is currently the most widespread approach for signal control in both singular and networked traffic systems. Allsop [47,48] by establishing a mathematical program to reduce waiting time and increase throughput optimization of single-point intersections; however, due to its inability to interact with traffic demand in real-time and the limitations of preset stages, which reduces the operating efficiency of the signal control to a certain extent.

Heydecker et al. [49] proposed a signal timing method based on signal groups with the aim of achieving a more flexible signal timing structure. It can better adapt to varying urban traffic conditions and road geometries. The method defines the signal setup by specifying the start and duration of the green light signal group, and even includes a simultaneous optimization procedure for the green light interval, period, and phase sequence. Silcock [50] developed a method for optimizing single-point signals based on signal groups and provided a detailed mathematical framework for the process. Wong et al. [51,52] extended the signal group-based area traffic control method by incorporating the derivative of the performance index [53-55] and designed a lane-based approach that integrates signal group-based optimization methods with lane marking geometric design. One significant advantage of the signal group-based approach lies in its flexibility to optimize signal timing and period without the use of predefined signal phases and phase sequences.

Traditional signal optimization usually assumes that the upstream traffic flow obeys a certain distribution (for example, Poisson distribution), and takes the sum of the different demands of the upstream flows as the downstream traffic arrival; Discrete arrival characteristics, there are differences in the distribution characteristics of vehicle arrivals in different periods; therefore, the random traffic demand description with a given distribution cannot really reflect the short-term traffic randomness; therefore, adaptive signal control based on traffic prediction has become a development Trend, that is, active signal control.

Dunne and Potts [56] and Green [57] proposed a two-stage heuristic signal control algorithm for adaptive control logic. This significant contribution to real-time response signal control systems represents one of the pioneering advancements in the field. The core tenet of the real-time response signal control system primarily entails induction control and adaptive signal control, also known as the Adaptive Traffic Signal Control System (ATCS).

Morris [58] and Gordon [59] proposed traffic-sensing control systems that employ a straightforward logic based on real-time traffic information obtained from detectors installed upstream or at stop lines. The objective is to extend or terminate signal controllers effectively. While these systems are straightforward and user-friendly, they exhibit some shortcomings in practical applications, including strict periodic structures, reaction logic limited to current traffic conditions, lack of optimal solutions for long-term or large-scale networks, and inadequate efficacy under oversaturated traffic conditions. To tackle these crucial challenges, the initial simple response signal control system has transformed into a comprehensive and intricate Adaptive Traffic Control System (ATCS). In this advanced system, both long-term and short-term control delays are utilized as performance indicators to enhance overall effectiveness. The binary selection algorithm proposed by Miller [60], based on the fundamental traffic-driven logic of vehicle delays, has been widely adopted in Adaptive Traffic Control Systems (ATCS) as a common concept. In recent decades, significant advancements in ATCS theory have been made by researchers such as Smith [61-63], Smith and Ghali [64], Smith and Van Vuren [65], and Smith and Mounce [66]. One of the most notable theoretical principles in ATCS is the P0 signal control strategy. Drawing upon Miller's algorithm and the P0 signal control strategy, the store-and-forward modeling approach has been extensively developed and implemented in various traffic scenarios. This approach forms the fundamental basis of a real-time optimized signal timing mathematical model, and its application has been demonstrated in numerous studies [67-76]. These methodologies establish periodic structures by taking into account different time and spatial scales of control delay. They have been successfully incorporated into multiple systems, including OPAC [77], PRODYN [78], ACS-Lite [79], and CRONOS [80]. These systems depend on the store-and-forward concept and leverage various rolling prediction models, including dynamic programming methods, to effectively control delays and manage diverted traffic flows. According to the adaptive control approach that was mentioned before, Varaiya [81] proposed a maximum-stress traffic signal control strategy for either individual intersections or road networks. This strategy emphasizes network performance optimization by considering three key variables: turning traffic at each intersection, adjacent intersections, and queue length, without requiring previous consideration of the overall traffic demand of the network. This technique has been widely adopted in adaptive control systems to reduce computation time. To further streamline real-time signal timing calculations and achieve a flexible and effective analysis period, Smith [82], Ge and Zhou [83], and Han et al. [84] have explored continuous signal models as approximations of traffic dynamics. These models enable the utilization of sensor technology within ATCS to continuously update traffic patterns in real time and adjust control strategies accordingly, based on real-time estimates of control delay. At present, the signal control structure design based on the signal group is the most flexible signal control structure, capable of responding to traffic demand in real time with the signal cycle (or smaller optimization step size) as the optimization unit. Therefore, this concept will be utilized to design the control system during signal structure optimization in this thesis.

The key to active traffic control is how to obtain the relevant parameters of traffic control in advance [85-90]. RHODES [85] is a typical signal control system based on traffic forecasting. This method is based on a mathematical model, ensuring system stability. Tests have shown that the system is more effective for semi-congested traffic networks. In addition, with the expansion of the traffic network, the complexity of the model will increase exponentially, and the computational complexity of the system will also increase accordingly increase, which is a disadvantage of this type of system. SCOOT [91] can detect the arrival of vehicles through the upstream detector to optimize the signal timing. However, the system adopts a centralized control structure, which is difficult to adapt to the real-time calculation of large-scale road networks, and the phase sequence cannot be automatically increased or decreased. And the change reduces the flexibility of the system; moreover, the system fails to correct the queuing prediction error well, which reduces the robustness of the system to a certain extent. Ding Heng [92] combined RBF neural network and Markov chain to predict short-term traffic flow, and established a predictive control method for polymorphic traffic characteristics. The signal phase is set, but the phase sequence cannot be dynamically adjusted according to traffic flow changes, and the selection of the control period is only suitable for the control interval in hours, and cannot reflect short-term (minutes, cycle intervals) random traffic demand. Variety. Jiang Hang [93] built a traffic flow prediction model under congestion based on cellular automata, and established an active signal method by embedding self-organizing control and macro basic graphs into the control system. Yin Junsong [94] built a regional active signal control strategy based on the prediction of traffic parameters such as queue length. However, the prediction model cannot clearly predict the parameter advance interval, which restricts the formulation of the active control strategy of the model. Coogan et al. [89] have presented a control methodology for adapting the time of day (ToD) signal plan using future traffic flow prediction. The predictive algorithm effectively identifies pertinent low-level structures in historical measurement data and forecasts forthcoming traffic flows by recognizing prominent structural trends in the data. Utilizing this prediction, the controller ascertains the optimal timing for implementing the updated signal plan. However, this method uses hours as the optimization interval, which is insufficient for predicting and dealing with short-term (signal period, 5 minutes, 10 minutes) sudden changes in traffic conditions. Its focus is on the longer forecast horizon of hourly sequences used in combination with conventional traffic signal timing techniques, such as pre-determined timing plans., proposing a control for adjusting the timing of period signals based on predictions of future traffic volumes method, but because the traffic with a long prediction interval cannot capture abnormal traffic conditions, it cannot reflect the real-time impact of random traffic demand on signal control.

To offer an enhanced control strategy for traffic in real-time, Lee et al. [95] established an IQA-based signal group predictive delay model for adaptive control, and based on this model, a single-point signal group-based classification model was established. The utilization of layer-adaptive signal control methods [96, 97] relies on the analysis of traffic flow predictions at the lane level. These methods facilitate the calculation of group-specific variables and parameters to support active global optimization techniques. The optimization procedures encompass the estimation of arrival and discharge rates, which are then represented as slopes within polygonal delay formulas. As a consequence, the strategic identification of the optimal signaling scheme exhibits a high level of versatility, relying on real-time projected traffic information. This information is effectively incorporated into the objective function of the polygonal delay formulation, as well as the direct differential equation of the adaptive group variable. By employing global optimization techniques that capitalize on signal grouping, the utilization of the most up-to-date information is enabled, facilitating the determination of the most suitable periodic structure for tactical-level control. However, the above-mentioned signal group-based signal control methods mostly target single-point intersections, ignoring the influence of surrounding intersection requirements, and this method needs to be installed at appropriate locations on the road. It is difficult to use vehicle detectors to obtain information about queuing and delays.

From the perspective of intersection correlation, signal control can be divided into two types: single point (single intersection) control and coordinated (multiple intersections) control. The previous studies are mostly described as single-point studies. In order to fully describe the impact of random arrival characteristics on signal control, the signal coordination research is reviewed next. Signal coordination control design refers to coordinating and optimizing the signal parameters (signal cycle, phase difference, green signal ratio, phase sequence) of multiple intersections to achieve the optimal signal control of the entire area (minimum delay, minimum the number of stops, minimum queue length, and maximum number of passes). Gazis et al. [67] first pointed out that it is more effective to optimize multiple intersections comprehensively than to optimize them individually. Many well-known signal control systems have developed coordinated signal control, such as SCATS (Sydney Coordinated Adaptive Traffic System) [98], SCOOT (Split, Cycle and Offset Optimization Technique) [99], TRANSYT [100] (Traffic Network Study Tool, Traffic Network Study Tool), a timing signal control system for offline operation.

The optimal suitable signal control scheme is generally decided based on the aim of minimizing the overall delay in the road network or maximizing the traffic capacity of the road network. A prevalent method to create an objective function for control optimization is to simulate the traffic control system as a D/D/1 queuing system and compute the total delay accordingly [101]. Alongside the signal cycle duration and green-to-red ratio, the phase difference is a key variable in signal coordination design. In the traditional coordinated control design, a series of intersections are usually designed with a common and fixed signal period [102], and then the green signal duration and phase differences are also calculated according to the change in traffic. Some early methods build the delay versus phase difference relationship from a queuing polygon map at downstream intersections and optimize it by performing an exhaustive search for all possible phase differences [103]. Abbas et al. [104] suggested a transition algorithm that fine-tunes the phase offset to enable maximum vehicle flow through the intersection during the green signal. Yafeng et al. [105] broke down and optimized the cycle duration, green signal duration and phase offset individually. They also created an offline phase offset refiner to tackle the challenge of an uncertain beginning or end of the green light. Most of the existing research are devoted to finding the phase difference that is obviously optimized for the coordinated control system. Because the quality of the phase difference design has a great influence on the delay variation, especially under the condition of oversaturation. The establishment of the traditional delay optimization function is usually a certain traffic arrival, which assumes that the traffic arrival is evenly distributed in the analysis period and takes it as a constant arrival rate. However, in general, the arrival of vehicles is uncertain due to the fluctuating traffic conditions (e.g., different days of the week, different hours of the day, different 10 minutes of the hour). Therefore, optimal control schemes designed for deterministic average conditions may not well match the actual stochastic traffic conditions. Compared with control schemes that introduce traffic randomness, control schemes that only consider the average flow rate may only lead to suboptimal solutions [106]. In addition, a random term that takes into account the effects of random arrivals is often added to the delay formula. Webster [45] introduced a formula for calculating delay time, called Webster delay formula, which is combined with a green time buffer to mitigate variability. Among them, the green light time buffer refers to a kind of compensation green light time, which is mainly calculated by using the determinism of the optimal control scheme through the delay formula. Heydecker [106] provided a comprehensive overview of this delay model, acknowledging a notable limitation: its inability to capture the instantaneous queuing process and accurately model overflow delays during oversaturated conditions. Moreover, the unresolved challenge of determining the optimal green-time buffer further complicates its practical implementation. To address these limitations, Lo [107] devised an overflow probability-based approach that enables analysis of the system state from one cycle to another, capturing transient phenomena. Additionally, Lo introduced the Phase Clearance Reliability (PCR) metric to test the benefit of the control system, which quantifies the probability that a vehicle will successfully pass through an intersection during the available green time in a particular phase.

2.3 Research on integrated signal and trajectory optimization

All the studies in the aforementioned two subsections demonstrated the advantages of CV-based applications in improving intersection mobility or energy efficiency. However, these studies only focused on achieving one objective (minimizing travel time delay of intersections or reducing fuel consumption of individual vehicles), and they were not designed to improve mobility and energy efficiency simultaneously. To overcome this challenge, numerous integrated signal and trajectory optimization systems have been developed in the literature.

Li et al. [108] proposed an algorithm that integrates vehicle path optimization with signal optimization based on the communication between the signal controller and the autonomous vehicle. They applied a rolling time-domain optimization strategy algorithm to a basic, single-lane intersection. Compared to traditional induction signal control with a series of flow requirements, simulation results demonstrate that the proposed algorithm can effectively decrease travel time and enhance traffic capacity.

Wang Yunpeng [109] et al. considered the interaction between ordinary vehicles, autonomous vehicles and signals in the traffic environment. In this traffic environment, traditional vehicles and automatic driving are mixed. So they combined speed planning and intersection signal control to propose a vehicle speed and traffic signal control method. A dual-objective collaborative optimization model to decrease fuel consumption and alleviate delays for vehicles at the same time and use genetic algorithm-particle swarm algorithm to solve. Finally, the SUMO simulation software is used for experimental verification. The results show that the model reduces the total fuel consumption of a single vehicle by more than 20.3% and the delay of a single vehicle by more than 4% when the vehicle speed is slightly reduced.

Feng [110] et al. proposed a two-stage optimal control framework including signal optimization and trajectory optimization for a simple intersection with only straight travel. Dynamic programming and optimal control theory are used to obtain minimum delay and minimum fuel consumption and emissions, respectively. Compared to pure fixed-signal control and adaptive control without trajectory optimization, the control framework can significantly reduce delays and emissions.

Wan [111] et al. proposed a pre-traffic signal suggestion system based on speed and a driving strategy to minimize fuel consumption. Using a suboptimal solution to the fuel minimization problem, the fuel economy is still significantly improved while maintaining comfortable driving performance. Experiments show that the connected vehicles with the speed suggestion system not only reduce their own fuel consumption, but also reduce the fuel consumption of the fleet with the increase of penetration rate.

Wang [112] et al. proposed a general framework for rolling temporal control for driver assistance systems. By predicting the behavior of other vehicles, the acceleration of the autonomous vehicle (AV) is regulated to optimize a cost function that accounts for various control objectives. The control framework is universal, with many optimized functions, which can be optimized for both individual vehicles and queues. Using the derived nonlinear model to predict the adaptive cruise control system (ACC), the results show that the vehicle behavior of the new system is smoother, and the fuel consumption is reduced by 18%.

In the context of a hybrid networked vehicle environment, Li et al. [113] tackled the challenge of accommodating the different steering requirements of a vast number of traditional vehicles and intelligent vehicles at intersections by proposing the Intersection Automatic Rule (IAP). To address the complex dynamic flow and right-of-way allocation issues, the authors formulated the IAP optimization problem as a special case of the machine scheduling problem, which captures heterogeneous vehicle motion and dynamic signal timing schedules. To find optimal solutions, they developed a sequential branch-and-bound method.

Yu and colleagues [114-116] explored the optimization of traffic signals and vehicle trajectories in a fully autonomous vehicle (CAV) environment, focusing on independent intersections with straight, left, and right turns. Using mixed integer linear programming, the team optimized the phase sequence, duration, and green light start time of signals in conjunction with vehicle trajectories to minimize delays and avoid stops. Simulation results demonstrated the effectiveness of the proposed approach, outperforming induction control in terms of capacity, delay, and emissions. Additionally, the team developed a predetermined trajectory control method to address the right-of-way problem at intersections for all CAV environments, eliminating the need for signal control. However, the analysis based on queuing theory showed that the reservation-based method might not be suitable for handling high-saturation traffic flows with multiple conflict points.

2.4 Research gap

According to the literature review of previous studies, it can be seen that scholars in the field of transportation have already had relatively rich research results in the research of signal control considering energy saving, vehicle trajectory optimization and fuel consumption calculation model. However, the following problems still exist in the existing research:

Most of the existing CAV vehicle trajectory optimization research is aimed at the fully autonomous driving environment, which requires the vehicle to be highly networked. Even considering the collaborative optimization method for hybrid driving of networked autonomous vehicles and traditional vehicles, most of the research is on a single intersection, and it has not been extended to multiple intersections in depth. In addition, the performance of the cooperative control system at oversaturated intersections is often negative.

Therefore, the collaborative optimization method of vehicle trajectory and signal control at multi-intersections under mixed traffic flow conditions needs to be further studied. At the same time, it is necessary to further improve the sensitivity analysis of different factors such as CAV market penetration rate, traffic demand level, green light rate, and signal offset to the collaborative optimization algorithm of vehicle trajectory and signal control, especially in the case of mixed traffic flow.

2.5 Arrangement of chapters

This thesis is oriented towards the optimization of cooperative vehicle signal control considering energy and mobility in a hybrid interconnected environment. The content of the full text is arranged as follows:

The first chapter is the introduction, which introduces the background of the current traffic development.

Then the second chapter reviews the relevant research literature and analyzes the purpose and significance of the research topic.

In Chapter 3, the kinematic wave model is presented as a means of depicting the generation and dispersal of vehicle queues, followed by a discussion on the development of the Eco-CACC algorithm. Then, we introduce a proactive signal control system based on connected vehicles.

The fourth chapter proposes the control algorithm of signal and trajectory synergy. By analyzing the objective function and constraint form of the model, the optimal green light signal timing and vehicle speed guidance scheme are obtained.

The fifth chapter conducts a simulation analysis for the proposed model algorithm design case. The simulation platform is built through integration. Different control methods are compared in it and the results are analyzed in different scenarios.

The sixth chapter summarizes and analyzes the full text, draws the conclusion of this paper, and determines the possible research direction in the future.

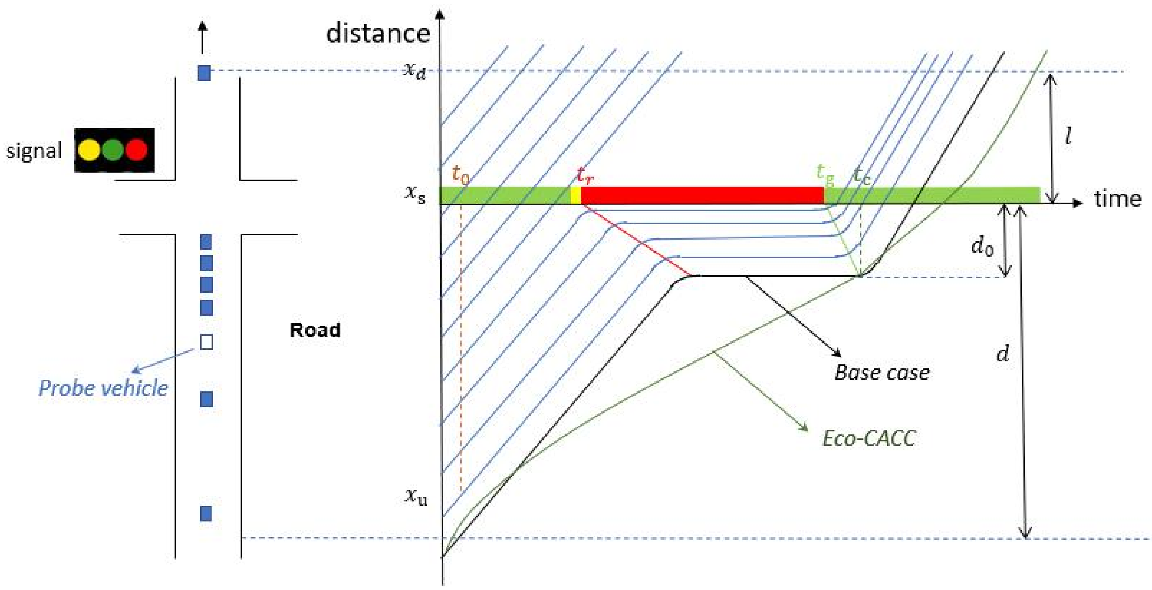
Methodology

3.1 Eco-cooperative adaptive cruise control

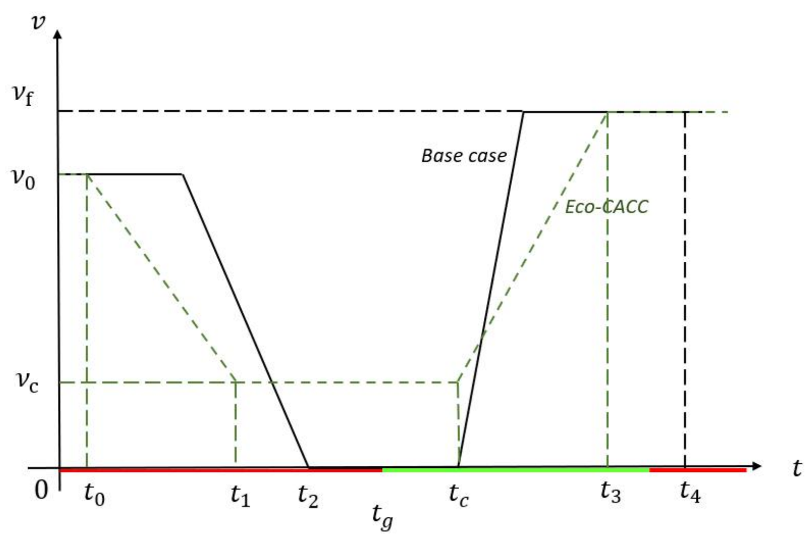
In this section, we use an algorithm named Eco-Cooperative Adaptive Cruise Control (ECACC) [117], which employs real-time data obtained through vehicle-infrastructure communication and vehicle platoon prediction in conjunction with traffic signal phase and published by Dr. Hao Yang in previous. The primary objective of this algorithm is to determine the vehicle trajectory that yields the lowest fuel consumption, which is subsequently updated in real-time to the vehicles entering the intersection. By doing so, the proposed eco-cooperative adaptive cruise control system aims to optimize fuel efficiency in urban traffic scenarios.

Since vehicles entering the intersection are considered to be influenced by vehicles queuing in front of the stop bar, the algorithm needs to estimate a suggested speed that varies over time instead of providing a constant speed. This suggested speed is to allow the rover to decelerate somewhat before reaching the stop line or the end of the queue. Thereby achieving the purpose of passing through the intersection smoothly without stopping. Once the queue is released, vehicles can accelerate to free-flow speeds. According to this purpose, the eco-driving algorithm is applied to obtain the appropriate acceleration and deceleration levels, so that the vehicle travels according to the recommended speed to minimize fuel consumption.

Fig. 3.1.1 is the description of the Eco-CACC system. The system leverages V2S communication to acquire signal phasing and timing information, as well as the dynamics of connected vehicles to estimate the queue length ahead of the intersection. This information is then utilized to estimate the queue length for all directions and derive the optimal speed profiles for connected vehicles. A detailed description of the system is provided below.



(a)



(b)

Fig. 3.1.1: The detailed description of Eco-CACC system

As shown in Fig. 3.1.1(a), the convoy is entering and passing through an intersection. There are two locations x_u and x_d, for the upstream and downstream respectively. And the position of the semaphore is x_s, set the control is [x_u, x_d]. When the vehicle reaches position x_u, the ECO-CACC system is activated until the vehicle moves out of position x_d.

On the upstream section of the intersection [x_u, x_s], when the detection vehicle detects a red light at the intersection or there are vehicles queuing up, the algorithm will calculate a suggested speed $v(t)$ with the minimum fuel consumption. Upon arrival at location x_u at t_0, the probe vehicle is initially traveling at a speed of v_0. Set the distance between the start point of the control area to the stop line as d and the distance between the stop bar and the location x_d as l.

As we said before, we need provide a suggested speed to prohibit stopping of the vehicles in the intersection. In order to achieve this aim, the vehicle need to decelerate to a cruising speed v_c by a constant deceleration (a_-), so that the vehicle reaches the end of the queue at the time t_c precisely just when it disappears or reaches the stop line immediately after the time t_g that the light turns green. And then, when the vehicle passes through the intersection and enters the downstream of the intersection, the algorithm will calculate a constant acceleration a_+ to accelerate the vehicle to the road speed limit v_f.

As depicted in Fig. 3.1.1(b), application of the Eco-CACC algorithm results in a smoother vehicle trajectory and eliminates the need for the vehicle to stop at the intersection, thus achieving the goal of fuel consumption optimization. The objective is as follows.

$$min_{a_-,a_+} \int_{t_0}^{t_0+T} F\Big(v(t),\ a(t)\Big)\,\mathrm{d}t \tag{4}$$

$$s.t.,\ \int_{t_0}^{t_0+T} v(t)dt = d + l \tag{5}$$

$$0 \le a_- \le a_-^d \tag{6}$$

$$0 \le a_+ \le a_+^a \tag{7}$$

Here, T denotes the duration of time for which the probe vehicle traverses the control segments upstream and downstream. a_+^a and a_-^d is the constant acceleration and deceleration level at which the vehicle stops and reaches free stream speed without control. The fuel consumption which is related with acceleration in the equation (4) can be described by:

$$F\Big(v(t),\ a(t)\Big) = \begin{cases} \alpha_0 + \alpha_1 P(t) + \alpha_2 P^2(t), P(t) \ge 0 \\ \alpha_0,\ P(t) < 0 \end{cases} \tag{8}$$

Here $F(t)$ is the rate of fuel consumption (L/s) at time t as a function of the vehicle's speed $v(t)$ and acceleration $a(t)$, defined by the VT-CPFM model [118]. The constants α_0, α_1, α_2 are vehicle-specific model parameters that are precisely calibrated for each vehicle. $P(t)$ is the vehicle power at time t, and it is a function of speed and acceleration.

$$P(t) = \left(\frac{R(t) + m \cdot a(t)(1.04 + 0.0025\xi(t)^2)}{3600\eta_d} \cdot v(t) \right)$$

$\xi(t)$ is the gear ratio at time t, and η_d is the driveline efficiency. m stands for vehicle mass.

As for $R(t)$:

$$R(t) = \frac{\rho}{25.92} C_D C_h A_f v(t)^2 + 9.8066m \frac{C_r}{1000}(C_1 v(t) + C_2) + 9.8066mG(t)$$

$R(t)$ is the resistance force (N). So, all the parameters $C_{D,}\, C_h, A_f, C_r, C_1, C_2$ in the formula are the different drag coefficients of the vehicle.

Now, the goal becomes to find the proper speed and acceleration of the vehicle to minimize the amount of fuel consumption. According to the speed characteristic profile at time t showed in Fig. 3.1.1(b):

$$v(t) = \begin{cases} v_0 - a_-(t - t_0), t \in [t_0, t_1) \\ v_c, \in [t_1, t_c) \\ v_c + a_+(t - t_c), t \in [t_c, t_3) \\ v_f, \in [t_3, T] \end{cases} \tag{9}$$

$$t_1 = \frac{v_0 - v_c}{a_-} + t_0 \tag{10}$$

$$t_c = t_g + \frac{d_0}{v_{BC}} \tag{11}$$

$$t_3 = \frac{v_f - v_c}{a_+} - t_c \tag{12}$$

$$d_0 = \begin{cases} \frac{v_{AB}}{v_0 + v_{AB}}[d - v_0(t_r - t_0)], \forall t \in \left[t_r - \frac{d}{v_0}, t_g + \frac{v_{AB}(t_g - t_r)}{v_{AB} + v_{BC}}\right] \\ 0, otherwise \end{cases} \tag{13}$$

$$v_0 \cdot (t_1 - t_0) - \frac{1}{2}a_- \cdot (t_1 - t_0)^2 + v_c \cdot (t_c - t_1) = x_u - x_d - d_0 \tag{14}$$

$$v_c \cdot (t_3 - t_c) - \frac{1}{2}a_+ \cdot (t_3 - t_c)^2 + v_f \cdot (t_4 - t_3) = x_d - x_0 + d_0 \tag{15}$$

According to the LWR model, v_{AB} is the speed of the shock wave from state A (the entrance of an intersection) to state B (the signal light changes from green to red, and traffic flow comes to a stop) is:

$$\nu_{AB} = \frac{q_0}{\rho_0 - \rho_m} \tag{2}$$

Once the red light turns green, the queued vehicles are gradually released, and the state downstream of the intersection is denoted as C, and the expression of the rarefaction wave formed at this time is:

$$v_{BC} = \frac{q_B}{\rho_B - \rho_m} \tag{3}$$

At state A, the traffic flow is q_0, and the density is ρ_0. As time passes, the signal light changes from green to red, and traffic flow comes to a stop. At state B, and the traffic density reaches the maximum value ρ_m, but the traffic flow is 0.

Equations (4) and (5) specify the acceleration and speed profiles to be used for the connected vehicle (CV). Equations (9) and (10) set the constraints for the CV's movement upstream and downstream of the intersection, respectively, where d_0 represents the queue length waiting behind the stop line. Equations (10), (11), and (12) describe the deceleration and acceleration of the CV. Additionally, the vehicle is subject to maximum deceleration (a_-^d) and maximum acceleration (a_+^a) in the vicinity of the intersection. After applying Eco-CACC, the trajectory of the controlled vehicle appears smoother compared to the basic scenario (indicated by Fig. 3.2.1(b) the black line). This approach of avoiding vehicle stops at intersections can significantly reduce fuel consumption.

The Eco-CACC algorithm is engaged upon the entry of the probe vehicle into the segment located upstream of the intersection, delimited by the x_u and x_s points. This algorithm suggests speed limits in two distinct scenarios, whilst in the absence of these, the road speed limit is proposed.

Firstly, when the traffic signal light is green, yet it is projected to turn red before the vehicle reaches the stop line, a speed recommendation lower than the current driving speed is presented. Secondly, when the traffic signal light is already red, and it is expected to remain so upon the vehicle's arrival at the stop line, a similar recommendation is issued. Additionally, the road speed limit is suggested in all other instances.

Upon the occurrence of either of the first two scenarios, the algorithm predicts the queue length at the intersection and computes the queue release time t_c, utilizing the sparse wave calculation formula in the LWR model (refer to formula (2)). Moreover, utilizing Equation (5) and Equation (9), the algorithm effectively calculates the optimal deceleration and acceleration values, with the aim of minimizing fuel consumption for vehicles. Subsequently, it provides speed guidance to the probe vehicle n in the following time step $t + \Delta t$, where Δt represents the interval for updating the speed advice. Upon the probe vehicle reaching the x_d point located downstream of the intersection, the Eco-CACC algorithm is disengaged.

3.2 A simple model to describe the traffic dynamics at signalized intersections

The objective of the next section is to formulate a proactive signal control system that effectively reduces vehicle delays at signalized intersections. So, in this section, a straightforward traffic signal model is introduced to capture the traffic flow of signalized intersections and devise signal control mechanisms that enhance intersection performance. Subsequently, this model can be utilized to expand on the development of proactive signal control systems. In [119], a proactive signal control system was constructed, utilizing Connected Vehicles (CVs) to search for optimal signal timing plans for intersections that minimize travel time delays for all vehicles.

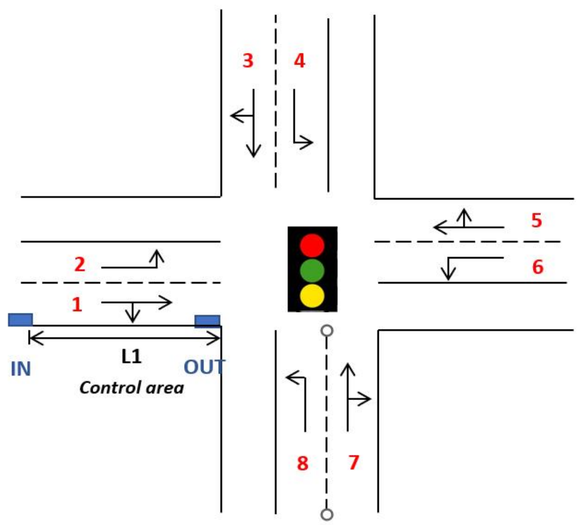


Fig. 3.2.1 Sample signalized intersection

Fig. 3.2.1 shows an example of a simple 4-leg intersection with 3 lanes, and all vehicle movements are categorized into M=8 groups. To get the data in the control area, we can set two loop detectors 'IN' and 'OUT', so the information of connected vehicles when passing these two detectors can be sensed.

Also the difference between the two cumulative flow rates is applied to estimate the time-dependent delay for each movement like Fig. 3.2.2.

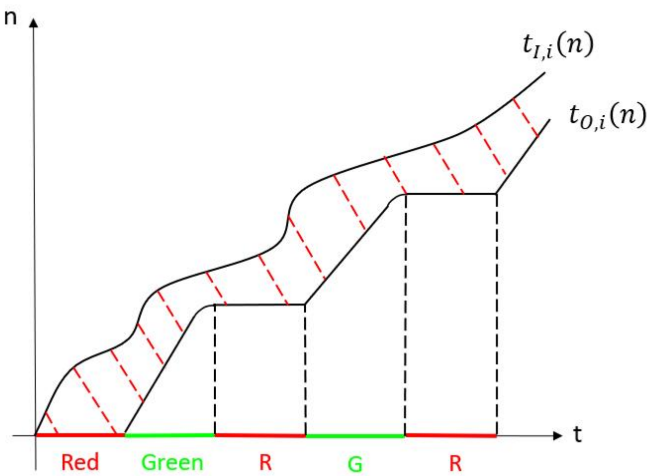


Fig. 3.2.2: Cumulative flow rates and delays

The distance between these two detectors and the road speed limit in movement 1 is L_1 and v_{f_1}, respectively. When the n-th vehicle travel through the location 'IN' and 'OUT', the time is recorded by $t_{I,i}(t)$ and $t_{O,i}(t)$ at time t. It's simple to get the total delay time in movement 1:

$$D_1 = \sum_{n=0}^{N_1} \left(t_{O,1}(n) - t_{I,1}(n) - \frac{L_1}{v_{f_1}} \right)$$

Here, N_1 represents the total number of vehicles in movement 1.

According to this logic, we can get the general discipline of the total delay time happened in the control area.

$$D_i = \sum_{n=0}^{N_i} \left(t_{O,i}(n) - t_{I,i}(n) - \frac{L_i}{v_{f_i}} \right) \quad (14)$$

Here, all the variables are defined for movement $i(i = 1, 2, 3, \ \ , M)$. N_i is the total number of vehicles. D_i represents total delay time of all vehicles in the control area. L_i represents the length of the control region. v_{f_i} is defined by the free flow speed in movement i.

Now our aim is to find the optimal SPaT schedule and minimize vehicle delays. As we can see in Fig. 3.2.1, the flow of traffic entering the intersection is determined by traffic demand, while the flow out of the intersection is determined by the SPaT plan. The objective for the optimal delay time is as follows:

$$\min_{p_j(t),\forall j=1,2,3,\cdots P} \sum_{i=1}^{M} D_i \tag{13}$$

Set P as the number of green phases in an intersection, and $p_j(t)$ represents the status of the green phase j at the time t. When phase j is activated, $p_j(t) = 1$. At the same time, $p_l(t) = 0, \forall l \neq j, l = 1, 2, \cdots P$. Apart from this, we also define the set of movements associated with phase j as S_j, and the permission of the movement i at time t is denoted as $m_i(t)$, $\forall i = 1,2,\cdots,M$.

$$m_i(t) = \begin{cases} 1, i\epsilon S_j, p_j(t) = 1, \forall j = 1,2,\cdots,P \\ \quad 0, \ otherwise \end{cases}$$

Usually, the variables within set S_j are typically predetermined by the traffic signal duration designer, and it becomes imperative to develop a suitable signal control system to determine the optimal value within a predefined cycle.

For example, in the intersection of Fig. 3.2.1, we can see P = 4,

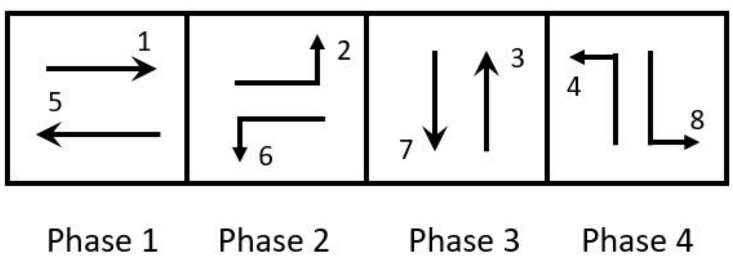


Fig. 3.2.3: Phase diagram

4 phases including 8 movements M_i, i=1, 2…8. Assume that the cycle length is denoted as C, and the green time and lost time (yellow and all-red times) of the phase j is g_j and l_j . So we can get $\Sigma_{j=1}^{4}(g_j + l_j) = C$. When $\sum_{z=1}^{j-1}(g_z + l_z) \leq mod\left(t - t_{off}, C\right) < \sum_{z=1}^{j-1}(g_z + l_z) - l_j$, the green light is assigned to phase j, $p_j(t) = 1$; otherwise, $p_j(t) = 0$; $mod\ (\cdot\ ,\ \cdot)$ is modulo operation, and t_{off} is the offset of the signal.

In practical applications, the majority of intersections adopt a pre-timed and actuated signal control system. The traffic signal designer pre-determines the phase sequence and duration of each phase and seeks to ease traffic congestion and minimize traffic delays based on historical data. However, this approach is incapable of adjusting the signal cycle and the duration of green lights in each phase based on the actual traffic volume in real time. For example, at an intersection in a certain city, the peak traffic flow is usually from 8 am to 10 am. However, on a certain day, due to some unexpected events, such as accidents, road reconstruction, and so on, many vehicles are forced to travel earlier or later. The signal design at the scheduled time cannot adjust the green light time in time according to the real-time traffic conditions, resulting in vehicle congestion. So, it is necessary to utilize a proactive signal control system to make the green time g_j and loss time l_j of each phase and the cycle length C changed with time by predicting the delay time. In addition, the model in this section relies heavily on the data of the loop detector, which will lead to low data accuracy and the disadvantages of requiring a lot of manpower and material resources for maintenance. So, we propose to further explore the proactive signal control system to overcome these shortcomings.

3.3 Proactive signal control at intersections with connected vehicles

In this section, we introduce a proactive control system that leverages connected vehicles to optimize Signal Phase and Timing (SPaT) plans. The primary objective is to minimize vehicle delays at a series of consecutive intersections. Utilizing the connected vehicle environment enables connected vehicles to establish communication between vehicles and traffic signals, enabling the signals to collect vehicle information and more accurately predict vehicle delays. It is important to note that this study assumes that not all vehicles on the road are connected and that only connected vehicles are able to transmit real-time traffic information to the signals.

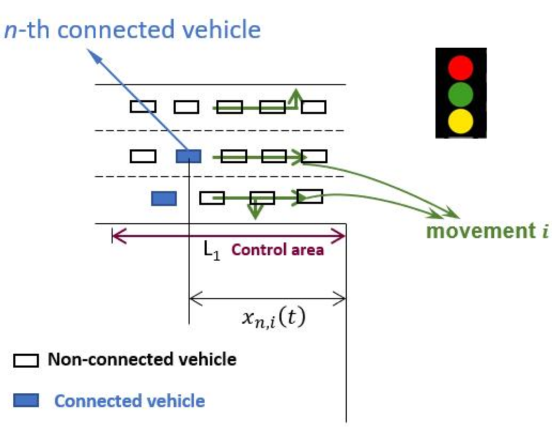


Fig. 3.3.1: Proactive control at one signalized intersection

As is shown in Fig. 3.3.1, we set the length of the control area in upstream is L_i. At time t,

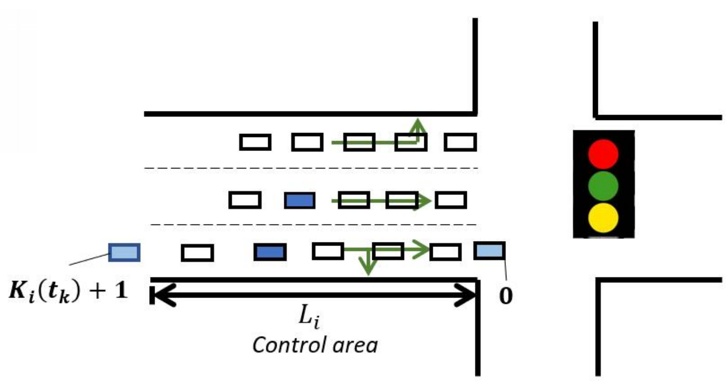
$K_i(t)$ ($\forall n = 1, 2, \cdots, K_i(t), i = 1, 2, \cdots, M$) represents the total number of vehicles traveling in movement i within the control area. When a connected vehicle passing through the control region, we can get its information, including the time it enters the control area ($\tau_{n,i}(t)$), the speed when it enters the control area $v'_{n,i}(t)$, current speed $v_{n,i}(t)$ and the distance from it to the signal in this intersection $x_{n,i}(t)$.

For now, the original data of the connected vehicles in the control region can be got. But as for the delay time of the unconnected vehicles without sensors on the road, we still need to do some other calculations. Then, the proactive signal control systems will use this information to make short-term predictions of the total delay at intersections for all vehicles, both connected and non-connected, by activating different green light phases. The following is how we employ an algorithm to select the most optimal green phase for the upcoming time interval, with the aim of minimizing delay.

First, the total duration of control is initially discretized into discrete time intervals of Δt, allowing for more precise and efficient analysis and modeling of the system. k represents the number of time steps. At the first-time step, k = 1, t ∈ $[t_0, t_{k=1})$, the controlled intersection implements its default phase to facilitate vehicle passage.

After traveling a time step, at the time $t_{k=1}$, we can det the data in the first-time step.

Suppose there are two connected vehicles ($n = 0$ and $n = K_i(t_k) + 1$)at the start and end of control area. cars at the intersection. Their location is set as $x_{0,i}(t_k) = 0$ and $x_{K_i(t_k)+1,i}(t_k) = L_i$.



According to the characteristics of the second virtual connected vehicle, the speed level at which it enters the intersection control area, and its current speed can be expressed as $v_{K_i(tk)+1,i}(t_k) = v'_{K_i(tk)+1,i}(t_k) = v_{K_i(tk),i}(t_k)$. (15)

It is known that the fundamental relationship between vehicle speed and density is $\rho_{n,i}(t_k) = V_i^{-1}(v_{n,i}(t_k))$. This relationship is subsequently employed to compute the density between two successive connected vehicles at movement i. Using the density, we can determine the number of non-connected vehicles between two consecutive connected vehicles as $N_{n,i}(t_k)$, where n is between 1 and $K_i(t_k) + 1$. The value of $N_{n,i}(t_k)$ is calculated as the minimum of $N_{n,i}(t_k) = min\{\rho_{n,i}(t_k)(x_{n,i}(t_k) - x_{n-1,i}(t_k)) - 1, 0\}$.(16)

For other information of non-connected vehicles $a_n = 1, 2, \dots, N_{n,i}(t_k)$ in the control region can be calculated as follows:

$$\tau'_{n,i,a_n}(t_k) = \tau_{n,i}(t_k) - a_n \cdot \frac{1}{v'_{n,i}(t_k)\cdot V_i^{-1}(v'_{n,i}(t_k))} \tag{17}$$

$$x'_{n,i,a_n}(t_k) = x_{n,i}(t_k) - a_n \cdot \frac{1}{V_i^{-1}(v_{n,i}(t_k)} \tag{18}$$

Here, $\tau'_{n,i,a_n}(t_k)$ represents their time when entering the control area and $x'_{n,i,a_n}(t_k)$ represents their distance to intersection.

Now, we got all the information of the vehicles on the control area. To simplify calculations, we have re-ordered the number of vehicles in the control region is $n, n = 1, 2, \dots, N_{n,i}(t_k)$, and $N_{n,i}(t_k) = K_i(t_k) + \sum_{u=1}^{K_i(t_k)+1} N_{u,i}(t_k)$. Also the variables related to the vehicles that pass the control area need to be updated accordingly a set $\{\tau''_{n,i}(t_k), x''_{n,i}(t_k), v''_{n,i}(t_k)\}$. These three variables represents the time entering the control region, the distance from current locations to the signal light and the speed entering the control area. These updates will then be used to estimate the total vehicle delay at the intersection.

Go on to the next time step k + 1, where t $\in (t_k, t_{k+1}]$, the total delay at the end of the step can be expressed by $D^j(t_{k+1})$, which is predicted by activating the green phase $j, j = 1, 2, \cdots, P$. When the light is green, $p_j\,(t_{k+1}) = 1$. Otherwise $p_j\,(t_{k+1}) = 0$. Now the objective of delay time can be written by:

$$D^j(t_{k+1}) = \sum_{i=1}^{M} \sum_{n=0}^{N_i(t_k)} \left(t_{O,i}(n) - t_{I,i}(n) - \frac{L_i}{v_{f_i}} \right) \tag{19}$$

The time of n-th vehicle entering the control area at the movement i can be shown directly：

$$t_{I,i}(n) = \tau''_{n,i}(t_k) \tag{20}$$

If the time that vehicle leave from the control area can be got, the delay time can be calculated. So now our problem is changed from delay time to the time leaving from the control area. According to the traffic light status at the previous time step, the time to leave the upstream of the intersection can be divided into the following cases:

(1) At time step k+1, where t $\in (t_k, t_{k+1}]$, movement i is not a green light, so $m_i(t_{k+1}) = 0$, then in the period of Δt, the vehicle needs to stop and wait in front of the stop line, so the queue is generated.

At this time, the quantity of vehicles preceding the nth vehicle is n-1. If the current delay time is to be minimized, the next step k+2 must be green. So the queue will not increase during the next red interval. According to the relationship between the nth car and the queued vehicles, it can be divided into two situations:

① If vehicle n enters the queue prior to its release, as indicated by $v_{f_i}(\Delta t + \Delta t^{'}) > x^{''}_{n,i}(t_k)$, the n-th vehicle is obliged to wait until $t_{k+1} + l_z + \delta^{'}$ to commence travel on the road. Here, $\delta^{'} = \frac{(n-1)\cdot \overline{s_i}}{w_i}$. Upon the liberation of the queue, the vehicle necessitates an extended duration, denoted as $\delta^{''} = \frac{(n-1)\cdot \overline{s_i}}{v_{f_i}}$, to reach the stop bar of the signal and successfully pass the intersection. Consequently, the departure time for the n-th vehicle is given by $t_{0,i}(n) = t_{k+1} + l_z + \delta^{''} = t_k + \Delta t^{'}$.

② If a vehicle does not enter the queue, it can continue to move toward the intersection at the speed limit of the road. Therefore, the departure time for such a vehicle is given by $t_{0,i}(n)$=$t_k + \frac{x^{''}_{n,i}(t_k)}{v_{f_i}}$.

In summary, when $m_i(t_{k+1}) = 0$

$$t_{0,i}(n) = \begin{cases} t_{k+1} + \Delta t^{'}, v_{f_i}(\Delta t + \Delta t^{'}) > x^{''}_{n,i}(t_k) \\ t_k + \frac{x^{''}_{n,i}(t_k)}{v_{f_i}},\ otherwise \end{cases} \tag{21}$$

Where $\Delta t^{'} = l_z + \frac{(n-1)\cdot \overline{s_i}}{w_i} + \frac{(n-1)\cdot \overline{s_i}}{v_{f_i}}$. Here, z is the phase number for the movement i, $\overline{s_i}$ is the jam spacing on the movement i, and ω_i is the vehicle queue releasing speed.

(2) In the scenario where the present traffic signal for movement i is red, but a green signal is anticipated to be allocated to it in the subsequent time step k + 1, denoted as $m_i(t_k) = 0$ and $m_i(t_{k+1}) = 1$, an immediate release of the queue preceding the n-th vehicle may happened. However, the vehicle must wait for Δt' to pass before it can be released and proceed to the stop bar. This scenario yields the departure time of the nth vehicle. The function of existing time can be expressed as：

If $m_i(t_k) = 0$ and $m_i(t_{k+1}) = 1$,

$$t_{0,i}(n) = \begin{cases} t_k + \Delta t', v_{f_i}\Delta t' > x''_{n,i}(t_k) \\ t_k + \frac{x''_{n,i}(t_k)}{v_{f_i}}, \ otherwise \end{cases} \tag{22}$$

(3) If it's green traffic signal at movement i currently, also it is scheduled to have a green signal in the next time step, then the delay will not be experienced by the nth vehicle entirely.. Consequently, the vehicle can proceed at the designated road speed limit v_{f_i} and traverse the remaining section of the link unimpeded. This scenario leads to the departure time of the nth vehicle given by $t_{0,i}(n)$=$t_k + \frac{x''_{n,i}(t_k)}{v_{f_i}}$.

When $m_i(t_k) = 1$ and $m_i(t_{k+1}) = 1$,

$$t_{0,i}(n) = t_k + \frac{x''_{n,i}(t_k)}{v_{f_i}} \tag{23}$$

The buffer, known as lost time l_z, is implemented to ensure that the system does not undergo phase changes frequently.

In addition,

$$m_i(t_{k+1}) = \begin{cases} 1, i\epsilon M_z, p_z(t_{k+1}) = 1 \\ 0, \ otherwise \end{cases} \tag{24}$$

$$p_z(t_{k+1}) = \begin{cases} 1, z = j \\ 0, otherwise \end{cases} \tag{25}$$

The above two formulas: Formula (24) identifies the permission of movements associated with the green phase j. Formula (25) means that the stage j is activated to release vehicles, and other stages assign red lights.

Then, the key part of the system is to optimize phase selection, as the main objective is to minimize the total delay experienced by all vehicles at the intersection. To achieve this objective, the phase is selected as j^*=arg$\underset{j,j=1,2,\ldots,P}{min} D^j(t_{k+1})$, which minimizes the time delay at time step k + 1.

To activate the selected phase and achieve the desired objective, the system applies green lights to phase j^* and red lights to all other phases of the intersection at time step k + 1. The value of k is then incremented by one. If k is less than T, the system returns to the information collection step to continue the process. If k is equal to or greater than T, the cycle of the algorithm is terminated. In Fig. 3.4.2, T means the total number of time steps.

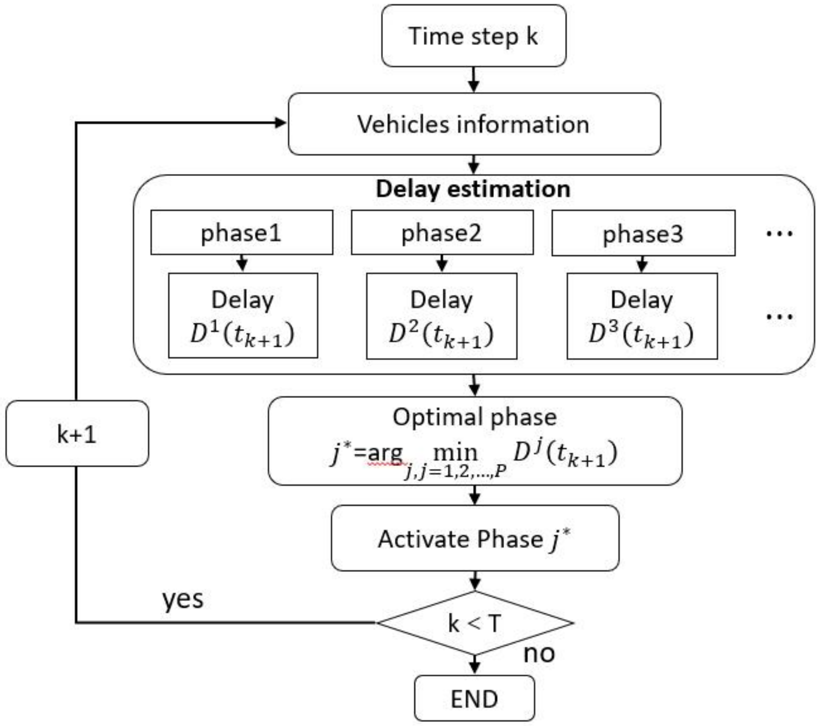


Fig. 3.3.2: Flow chart of the proactive signal control system

The proactive signal control system mentioned above can also optimize the signal plan of a particular intersection while considering multiple intersections. Additionally, the optimization process can take into account surrounding intersections and traffic conditions. In the scenario of multiple consecutive intersections, the inflow of traffic is contingent upon the outflow of the previous intersection. As a result, a phase change at the upstream intersection will inevitably affect the incoming traffic flow at the current intersection. Vehicle delays are predicted by information about vehicles entering the control area and then we can find out the optimal SPaT.

In addition, from the perspective of computational cost, the number of phases at each intersection generally does not exceed 8, which is completely coverable for this algorithm.

3.4 Cooperative vehicle-signal control system

This subsection presents the development of a Cooperative Vehicle-Signal Control (CVSC) system that merges the Proactive Signal Control System and the Eco-CACC system, resulting in the simultaneous optimization of signal timing plans and speed profiles of Connected Vehicles (CVs).

Fig. 3.4.1 demonstrates the framework of the CVSC system with CVs. When a CV approaches the intersection signal control area, the CV transmits its driving status (coordinates, speed, acceleration, destination, etc.) to traffic signals through V2S communication. With the information of all CVs and other traffic environment information, the CVSC system analyzes and predicts the current traffic conditions, calculates the optimal signal timing plan at the intersection, and the driving guidance information for different vehicles. The information is then sent back to each vehicle again through the roadside communication device and the smart in-vehicle device. Drivers follow the latest speed guidelines to reduce vehicle stops, delays and fuel consumption.

Fig. 3.4.1 Demonstration of the cooperative vehicle-signal control framework

The development of the CVSC system is structured into two steps, as illustrated in Fig. 3.4.2. In the first step, the Proactive Signal Control System is implemented, leveraging data collected by Connected Vehicles to identify the optimal signal timing plan for a full cycle. This system utilizes individual vehicle dynamics to estimate the optimal sequence and duration of all phases, with the aim of minimizing travel time delay for all vehicles traversing the intersection. Moving on to the second step, the Eco-CACC system is activated once the optimal phases are determined. For every Connected Vehicle in each direction, the system utilizes CV data and the assigned signal timing plan to estimate the queue length ahead. Based on the start and end times of the green light at each phase, the system further determines the optimal advisory speed profile to minimize fuel consumption. The smoothed vehicle behaviors, such as constant speed and traffic volumes, are also beneficial for the CVs to make a more accurate estimation of the inflow rate of each movement. The proactive signal control system can further reduce the overall intersection delay, resulting in improved intersection utilization efficiency, i.e., maximum volume and minimum fuel usage. The cooperative control system optimizes both the signal and vehicle trajectories simultaneously, leading to better intersection management in a mixed traffic conditions.

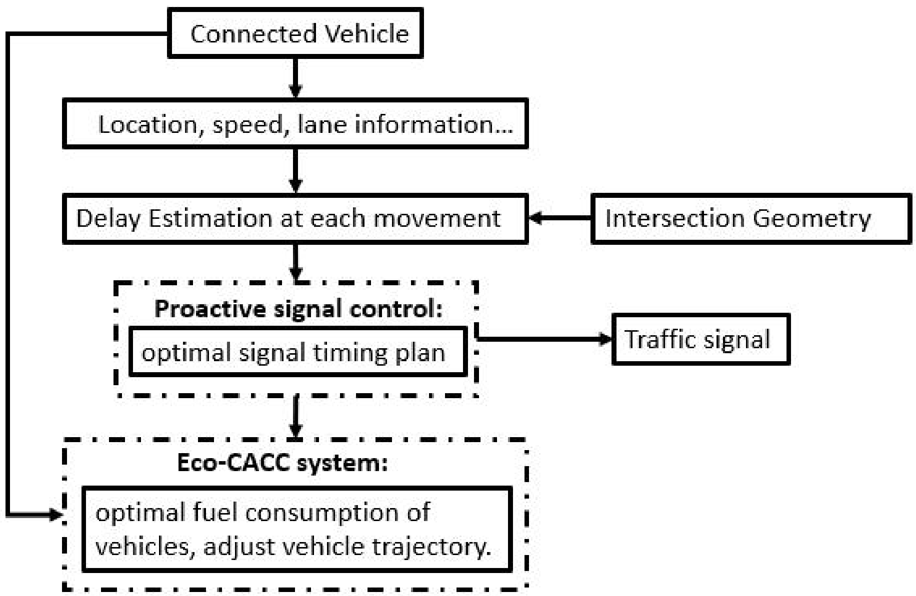


Fig. 3.4.2 The framework of the CVSC system

With the cooperative control, both signal and vehicle trajectories are optimized simultaneously to improve the intersection utilization efficiency of the entire intersection, i.e., minimum vehicle delay time and minimum fuel usage.

3.5 CVSC Model

The dual-objective collaborative optimization model of vehicle trajectory and intersection traffic signal timing scheme is as follows.

$$min\left\{\sum_{p_j,\forall j=1,2,3,\cdots P} F^*, D^*\right\} \tag{25}$$

$$\min_{p_j(t),\forall j=1,2,3,\cdots P} \sum_{i=1}^{M} D_i = \min_{p_j(t),\forall j=1,2,3,\cdots P} D^* \tag{26}$$

$$min_{a_-,a_+} \int_{t_0}^{t_0+T} F\left(v(t),\ a(t)\right) \mathrm{d}t = min\ F^* \tag{27}$$

In both the Eco-CACC and cooperative control systems, no constraints regarding minimum speed were implemented. Such constraints would prevent individual vehicles from attaining optimal speed profiles and hinder the attainment of minimal fuel consumption. Introducing a minimum speed restriction would significantly diminish the benefits of our proposed system.

To address the complexity and non-convexity of the bi-objective cooperative optimization problem, as well as the characteristics of the variables to be optimized, a heuristic algorithm, namely the hybrid genetic algorithm and particle swarm optimization (GA-PSO), is adopted in this chapter. To better coordinate the two optimization objectives, we non-dimensionalize the two objectives using weight factors, μ_1 and μ_2. μ_1 and μ_2 are used by the monetary factory. For example, when consuming one liter of the gasoline, the money lost will be \$1.5 based on the current gas price, and we can set μ_2 is \$4/L. If there is a delay for 1 hour, the financial loss is \$20. Based on the average salary in Toronto, we can set μ_2 is \$20/hr. And if we pay more attention to the fuel consumption, we can make μ_2 larger. We can increase the value of μ_1 when we pay attention to delay time more. Consequently, the original objective function (3.31) can be represented in the following form:

$$min\, M = \mu_1 \sum_{p_j, \forall j=1,2,3,\cdots P} F^* + \mu_2 D^* \tag{28}$$

The two independent tasks of vehicle trajectory estimation based on the vehicle motion model and optimization calculation based on the heuristic algorithm are coordinated and nested with each other to achieve better results.

After receiving a new genetic individual (i.e., a new phase activation plan in a 4-leg 8-phase intersection: at time step 2, movement 1 is activated in green light and other phases are red), the algorithm first uses the vehicle motion model to estimate the trajectories of all individual driving vehicles on all movements in this phase according to the signal timing. Subsequently, the optimal suggested speed trajectory and fuel consumption of each vehicle under the mixed traffic environment in the control area are obtained by using the queue length characteristics of the individual driving vehicles and the speed guidance function for crossing the intersection. After that, use the delay calculation formula to calculate the total delay of vehicles at the intersection, and select the next phase that needs to be activated. The complete solution process is as follows:

Step 1: Specify the total number of genetic iterations k_m, population size T, optimization model constraints Eq (5)-(7) and Eq (14);

Step 2: According to the constraints Eq (14), randomly generate the first group of genetic individuals (light status) to form the initial population;

Step 3: According to the vehicle motion model in Section 3.1, obtain the trajectories of all individual driving vehicles under each genetic individual;

Step 4: Use the PSO algorithm to solve the speed guidance problem under each genetic individual (Eq 9), extract the optimal reference speed trajectory and total fuel consumption of each mixed vehicle group, and use the delay Eq (19) to calculate the total delay;

Step 5: Evaluate and mark each genetic individual according to the fitness Eq (28);

Step 6: Evaluate all genetic individuals. If the maximum total number of iterations T is reached, the optimal individual and the optimal solution represented by it are output, and the calculation is stopped. Otherwise, go to step 7;

Step 7: Select regenerated individuals according to the fitness value, perform cross mutation to generate the next generation of new individuals, and aggregate to obtain a new generation of population. Increment the iteration count by 1 and return to step 3.

Result and Discussion

This section aims to evaluate the effectiveness of the proposed Coordinated Vehicle-Signal Control system in enhancing mobility and energy efficiency by simulating a real-world network.

4.1 Case study---- real-world network

This section will present a case study designed to assess the performance of the Coordinated Control System at multiple intersections. Four different scenarios, 1) base case without control, 2) eco-driving only, 3) proactive signal control only, and 4) cooperative control, will be simulated separately for three intersections at FM 528, in the Greater Houston Area, Texas to illustrate the effectiveness on mitigating traffic congestions. To simulate traffic conditions on the roads, the INTEGRATION microscopic traffic simulator developed by Virginia Tech [120, 121] is utilized.

Fig. 4.1.1 FM 528, tested road segment in Houston, TX

Fig. 4.1.1 shows the geometry of the FM 528 network with three intersections. The details of the network are described below.

1) The total length of the major through road, FM 528, is approximately 2.5 km. There are three intersections along the road: (A) Desota St., (B) Friendswood Lake Blvd., (C) Falcon Ridge Blvd./Briar Creek Dr.

2) There are two lanes on each approach of FM 528, and the maximum speed is 72 km/hr. An additional central left turn lane has been implemented in the intersection to facilitate exclusive left turns for vehicles traveling in both directions. Meanwhile, the right-most lanes of both directions accommodate both through and right-turn movements.

3) Speed limit on minor roads varies from 48 km/h to 64 km/h (i.e., 30 mph to 40 mph).

4) Currently, all intersections apply a well-tuned actuated signal control system implemented by TxDOT. Traffic signal phasing and timing data, as well as approach volumes, are provided by the TxDOT Houston District Office. The signals at the intersection are managed by Econolite ASC/3 controllers. Typically, the green extension for the major road through traffic, FM 528, ranges from 1.5 to 2 seconds, while it varies from 2 to 4 seconds for other approaches. Moreover, the green split of the major road through traffic is seen to fluctuate from 0.48 to 0.64.

5) There is at least one loop detector installed on each lane of the roads at all directions of the three intersections. Traffic volumes and occupancies are collected by the detectors to analyze traffic conditions. And the Queens OD estimator is applied to estimate the dynamic OD matrix for the network.

Under the base case without control, the analysis of loop detector data on the test road indicates that the total number of average daily trips (ADT) is over 45,000 on weekdays. The average travel time for vehicles on the test bed is approximately 4.5 minutes, corresponding to an average speed of 18 km/h or 11 mph, given the length of the test bed. This indicates that vehicles are significantly delayed in the test bed. The average stop delay caused by red lights is about 51.7 seconds.

4.2 INTEGRATION microscopic traffic simulator

In this subsection, we commence with a concise overview of INTEGRATION, followed by an elucidation of the integration of the CVSC algorithm into the INTEGRATION framework. The reasons for selecting the INTEGRATION, the microscopic traffic simulator developed by Virginia Tech, are as follows:

1. Open source:

The model is provided as an open-source platform, facilitating the seamless integration of vehicle or traffic control strategies into existing traffic systems. As an illustration, we have seamlessly integrated the INTEGRATION model with a CVSC algorithm, enabling effective vehicle-to-signal communication and accurate estimation of suggested speed limits and delay times. Then, we conduct a comprehensive analysis of the changes in the market penetration rate, demand level, green time ratio, and offset of the probe vehicle. Moreover, the algorithm's efficacy in real-world urban intersection configurations is thoroughly evaluated, encompassing various operational scenarios. Additionally, we meticulously analyze the algorithm's limitations under extreme road conditions, providing valuable insights into its applicability.

2. Has well-calibrated models:

It is conceptualized as a unified simulation and traffic distribution model that conducts traffic simulations by tracking the movement of individual vehicles at a resolution of 1/10 of a second. This level of granularity facilitates a meticulous examination of lane change behaviors and the propagation of shock waves. Not only can stops and delays be estimated, but also fuel consumed by vehicles and emissions from each vehicle's origin until it exits the network at its destination. The model in Integration is mainly based on Van Aerde's basic diagram to analyze the macroscopic traffic dynamics on the road. In the fundamental diagram, the relationship between traffic flow density, flow rate and speed is shown in Fig. 4.2.1.

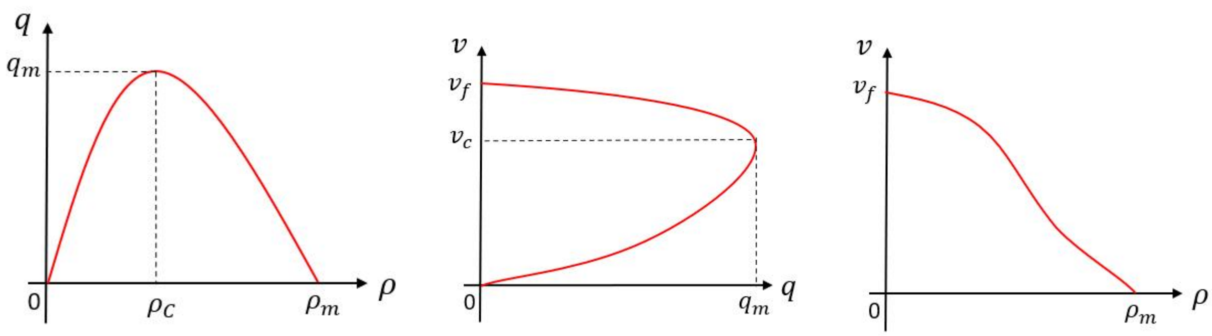


Fig 4.2.1: The Van Aerde Traffic Stream Model

Car following model: Integration utilizes Van Aerde's car-following model, which integrates the Greenshields car-following model and the Pipes car-following model into a unified regime model, effectively addressing the limitations of these two models.

Lane change model: The lane change model in integration is developed from Gipps's lane change model, which can be divided into autonomous lane change and forced lane change according to the desirability and necessity of lane change. It depends on whether there are better traffic conditions or if drivers have to change lanes.

The fuel consumption model: INTEGRATION applies a VT-Micro model, which effectively captures the transient vehicle influences on fuel consumption and emission rates, similar to the emission models employed. Thus, the emission of compounds, such as HC, CO, CO2, NOx, and PM, can be directly obtained from the output file.

Within the INTEGRATION software, we have integrated vehicle-to-signal communications to facilitate the transmission of two types of information to probe vehicles: (1) the information of the signal from the intersection, including phase time, cycle length, and so on, and (2) the information of the waiting vehicles, comprising the queue length and estimated dissipation time, derived from loop detectors positioned at the entry and exit points of the control segment. As outlined in Section 3.4, the CVSC algorithm employs this data to estimate the recommended speed limit. Consequently, at each Deci second, the probe vehicle can get the updated recommended speed limit, enabling it to optimize its trajectory for intersection passage. Then, the delay estimation in the intersection is made by the proactive signal control to find the optimal phasing and timing plan. Therefore, INTEGRATION offers a thorough analysis of the influence exerted by the CVSC algorithm on the driving behaviors of connected vehicles, as well as its environmental advantages in enhancing road network performance.

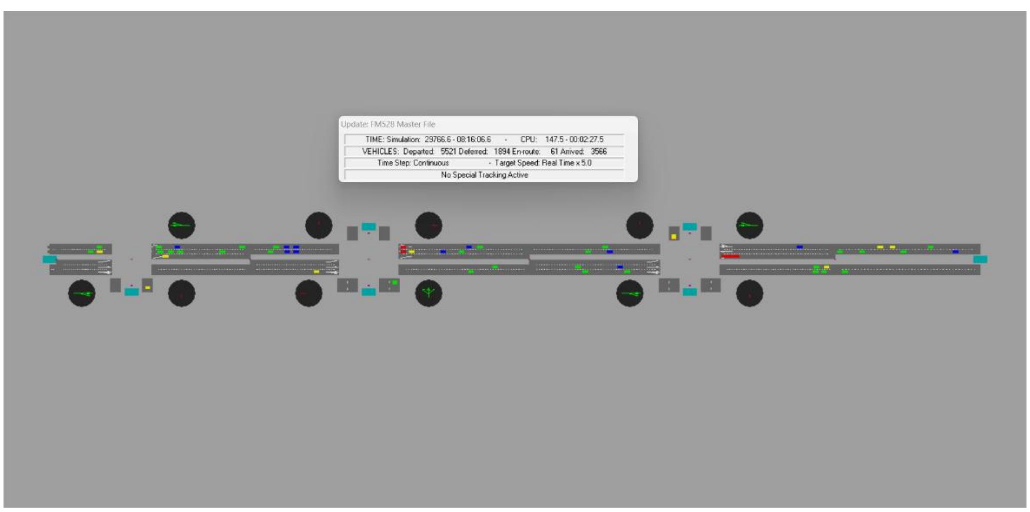


Fig. 4.2.2. Screenshot of INTEGRATION Software Interface for FM528

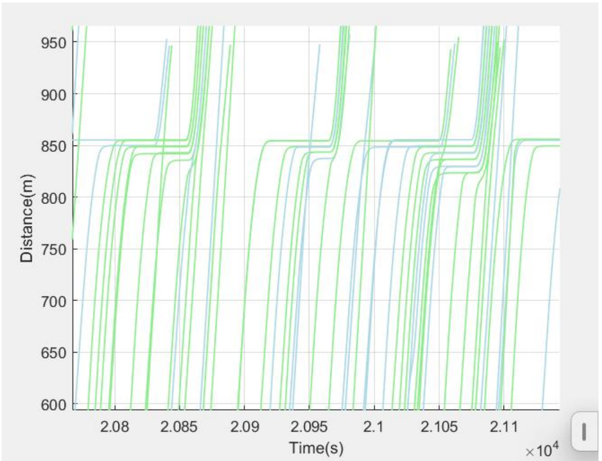
3. Computational efficiency:

Integration is known for its high computational efficiency. Compared to existing commercial simulators, it can run simulations much faster, making it easier to conduct a large number of simulations in a shorter amount of time. This is important for evaluating the effectiveness of different traffic management strategies and for making informed decisions about traffic infrastructure improvements. For instance, the lane change model within INTEGRATION internally calculates the lane connectivity during diverge or merge scenarios, thereby significantly reducing the coding time for model users in establishing link connectivity.

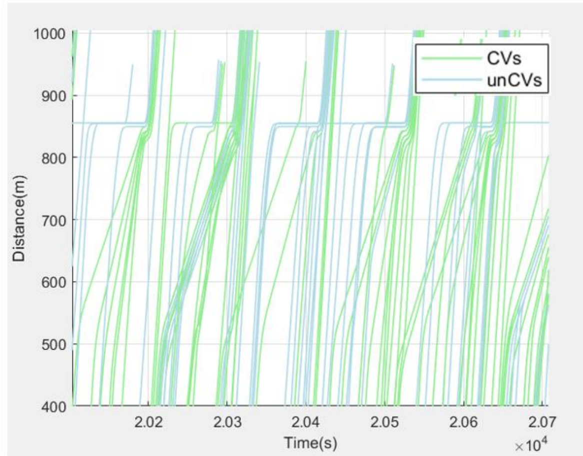
4.3 Benefit analysis of the CVSC system

In this subsection, the proposed CVSC system is deployed in the aforementioned simulation environment. To assess the traffic conditions of the test network before and after implementing the control system, the simulation incorporates four detectors at each intersection. These detectors are responsible for monitoring vehicles entering the intersection across all lanes. Furthermore, to enable short-term traffic flow predictions, Connected Vehicles (CVs) are utilized to gather crucial information, including the vehicle's current position, speed, time of entry into the control area, and speed data. This collected data is then utilized by the proactive signal control system to optimize signal timings and make informed decisions. The update interval Δt of all movements of the proactive signal control system is set as 10s and the length of the control area for the eco-driving system is set as 200 m.

Fig. 4.3.1 summarizes the trajectories and velocity distributions of individual vehicles passing through the intersection when the CV's market penetration rate (MPR) is 60%. Compared with the trajectories under the predetermined conditions in Fig. 4.2.1(a), the CVSC system can make the trajectories of the vehicles driving through the intersections smoother, so as to obtain the effect of passing through the intersections controlled by the Eco-CACC system without stopping. Meanwhile, through proactive signal control, both CV and non-CV can be released with more intelligent settings of traffic lights, so this will allow vehicles to traverse the intersection with smaller possibilities to meet red lights and reduce delay.



(a)



(b)

Fig. 4.3.1: Individual vehicle dynamics at the first intersection: (a) trajectories with the pre-time signal, (b) trajectories with the CVSC system

At the same time, using a CVSC system smooths not only the behavior of individual vehicles, but also the behavior of other vehicles. Therefore, the speed distribution of all vehicles is not extreme. Instead, many vehicles travel at speeds between 0 and 20 m/s, i.e., they can move smoothly through the intersection. By comparing these two scenarios, the CVSC system can reduce the average fuel consumption of CV and non-CV by about 33%. On the other hand, by deploying active signal control, the delay in travel time for all vehicles can be further reduced by optimal signal timing planning. Average delays across intersections were reduced by 66.6%.

Measurement (per trip)	Before	After	Diff
Travel Distance (km)	2.0986	2.093	0.27%
Travel Time (second)	249.7893	169.232	32.25%
Delay (second)	144.3615	64.4893	55.33%
Stop Delay (second)	77.3176	45.0591	41.72%
Vehicle Stops	2.1601	1.7976	16.78%
Fuel Usage (liter)	0.2997	0.2446	18.39%
HC (gram)	0.9026	0.8321	7.81%
CO (gram)	22.1195	21.4942	2.83%
NOx (gram)	0.729	0.6188	15.12%
CO2 (gram)	665.2229	540.1666	18.80%

Tab. 4.3.1: Comparison of the overall network performance on FM528 at MPR = 5%

Measurement (per trip)	Before	After	Diff
Travel Distance (km)	2.0902	2.0903	0.00%
Travel Time (second)	256.6291	155.7612	39.30%
Delay (second)	151.098	50.4748	66.59%
Stop Delay (second)	80.9182	28.0999	65.27%
Vehicle Stops	2.1185	1.3597	35.82%
Fuel Usage (liter)	0.3026	0.2038236	32.64%
HC (gram)	0.9967	0.8536	14.36%
CO (gram)	22.9188	21.6526	5.52%
NOx (gram)	0.7302	0.6122	16.16%
CO2 (gram)	672.4247	532.9706	20.74%

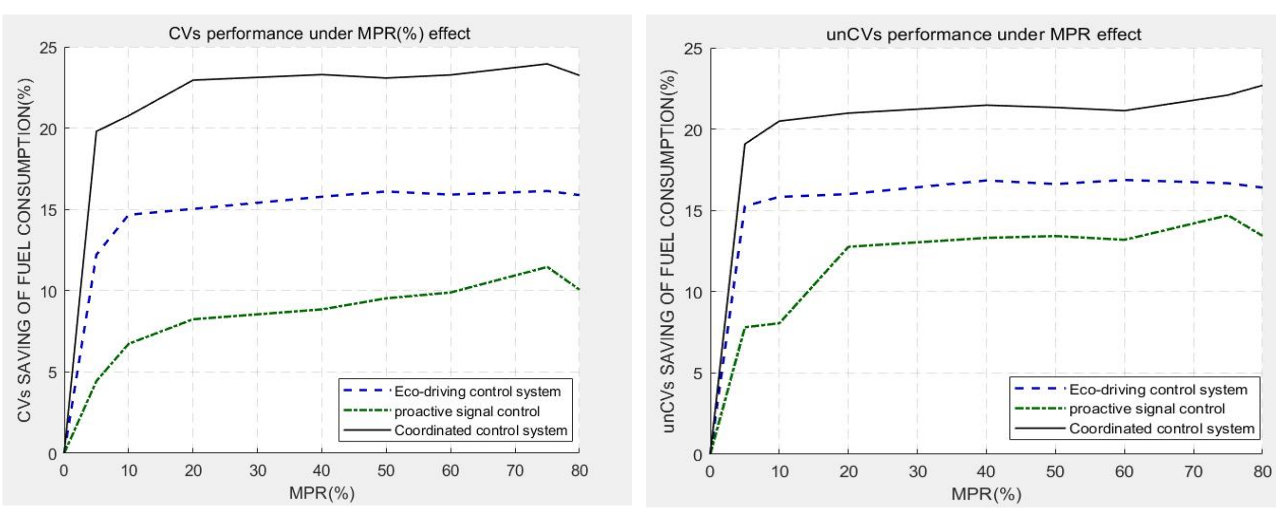
Tab. 4.3.2: Comparison of the overall network performance on FM528 at MPR = 60%

Tables 4.3.2 and 4.3.3 provide a comparative analysis of the network's overall performance prior to and subsequent to the implementation of the proposed system under two different MPR values: 5% and 60%. At an MPR of 5%, the average trip distance remained constant at 2.1 km before and after deploying the cooperative control system. However, the traffic congestion at the intersection experienced a significant reduction after the implementation of the proposed system. The average travel time exhibited a reduction of approximately 32%, while the delays were curtailed by 55%. Additionally, the stop delays incurred by individual vehicles were mitigated as well. The average number of stops per vehicle decreased from 2.16 to 1.8, indicating that after control, the probability of vehicles waiting for a red light becomes smaller. Moreover, even for vehicles halted at intersections, the stop delays were reduced considerably, achieving a 42% reduction. The system's efficacy in curbing intersection congestion translated into enhanced fuel efficiency and reduced vehicle emissions, with an 18.4% and 18.8% reduction in fuel consumption and CO_2 emissions, respectively. The coordinated control system also positively impacted the emission of other polluting gases, such as CO and NOx, which recorded a decrease as the MPR value increased.

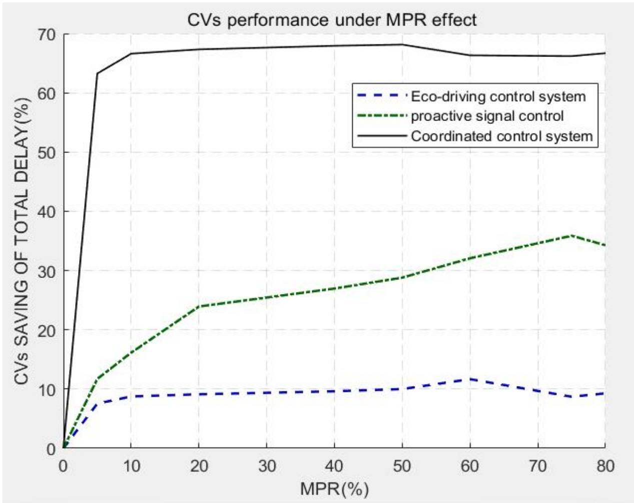
In addition, with an MPR of 60%, the total number of vehicle trips amounted to 45,000, with the average distance per trip unchanged at 2.1 kilometers, both before and after the implementation of the cooperative control system. The system delivered significant congestion reduction at the intersection. The average travel time decreased by 39.3%, and the delays were reduced by 65%. Also, stop delays experienced by individual vehicles were markedly reduced, with the average number of stops per vehicle declining from 2.11 to 1.35. Even for vehicles stationary at intersections, stop delays experienced a 66% reduction. Less congested intersections also improve fuel efficiency and reduce vehicle emissions. The coordinated control system reduced overall fuel consumption and CO_2 emissions by 32.64% and 20.74%, equivalent to $1,341 in fuel savings per day (assuming gasoline prices are $4 per gallon).

4.3.1 The effect of MPR on fuel consumption and delay time

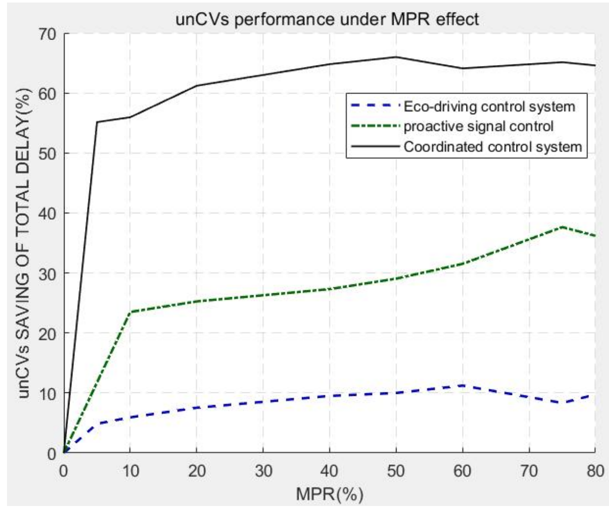
Additionally, Fig. 4.3.1.1 compares the mobility and energy benefits of CVs and non-CVs in the network using different control strategies, including Eco-CACC, proactive signal control, and CVSC, under various MPRs of CVs. The results indicate that all three systems can improve network performance compared to the base case. The CVSC system achieves the highest savings in both travel time delay and fuel consumption for both CVs and non-CVs at all MPRs, with larger savings at higher MPRs. This is because the CVSC system optimizes signal timing plans and smooths CV trajectories simultaneously, resulting in more efficient signal control with more accurate road condition estimations and more vehicles smoothed for higher energy efficiency. The Eco-CACC system mainly reduces acceleration delays at intersections to smooth CV trajectories, with only a marginal impact on improving mobility. The proactive signal control minimizes travel time delay with the optimal timing plan, allowing both CVs and non-CVs to move faster and consume less fuel. These findings confirm the significant advantages of the CVSC system in improving the performance of the entire network.



(a) (b)



(c)



(d)

Fig. 4.3.1.1: Benefit comparison at different MPRs: (a) savings in fuel consumption for CVs, (b) savings in fuel consumption for non-CVs, (c) savings in travel time delay for CVs, and (d) savings in travel time delay for non-CVs

From Fig. 4.3.1.1(a) and (b), we can observe that when only the Eco-CACC algorithm is applied, and MPR=5%, compared with the basic scenario, the fuel saving rate of the vehicle is significantly improved. But with the increase of MPR, the savings rate did not continue to maintain a linear growth trend. This is because, in the case of normal traffic demand level, only the application of Eco-CACC system control can already effectively smooth the trajectory of vehicles on the control section, even if the MPR is only 5%. The traffic flow can be affected by the connected vehicles smoothly going through the intersection, so as to reduce fuel consumption and improve fuel utilization. So as the MPR continues to increase, the savings in fuel consumption do not show a significant increase.

Then, to analyze the data of the control system mentioned in this thesis. Since the proportion of networked vehicles is considered to be a key factor affecting the fuel consumption rate, the data (MPR, Fuel Consumption) is analyzed according to the value of MPR and the type of control system Group and draw a boxplot. In this section, these two variables will be analyzed to determine whether there is a significant relationship between them. The analysis is based on boxplots generated from the available data.

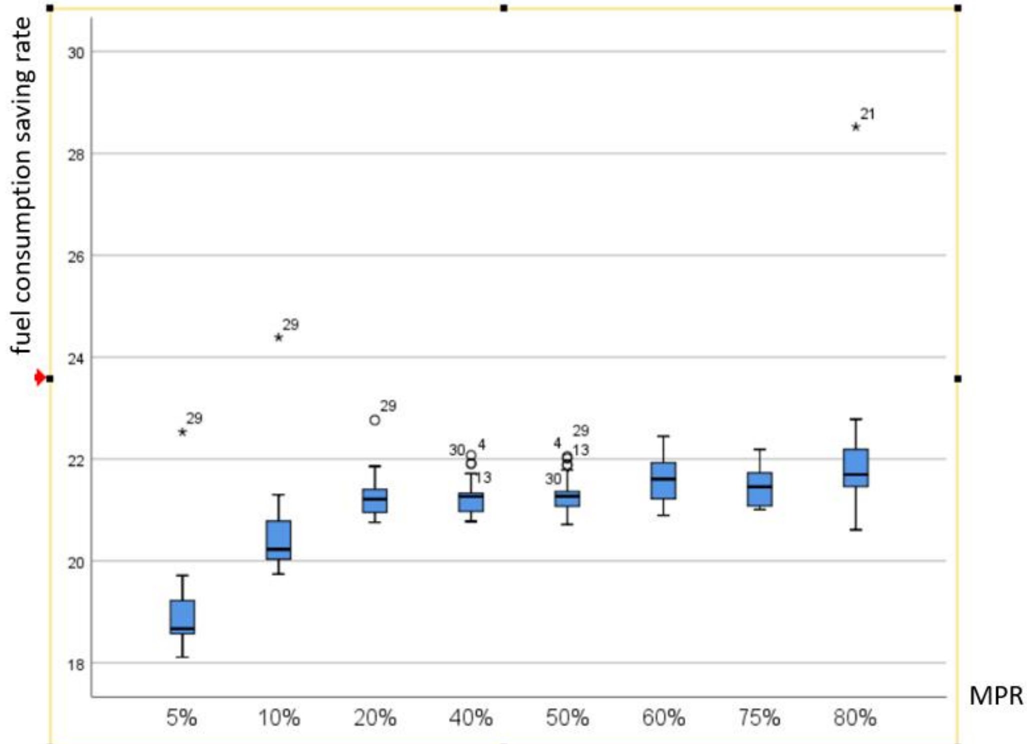


Fig. 4.3.1.2 Boxplot of fuel consumption saving rate of different MPR

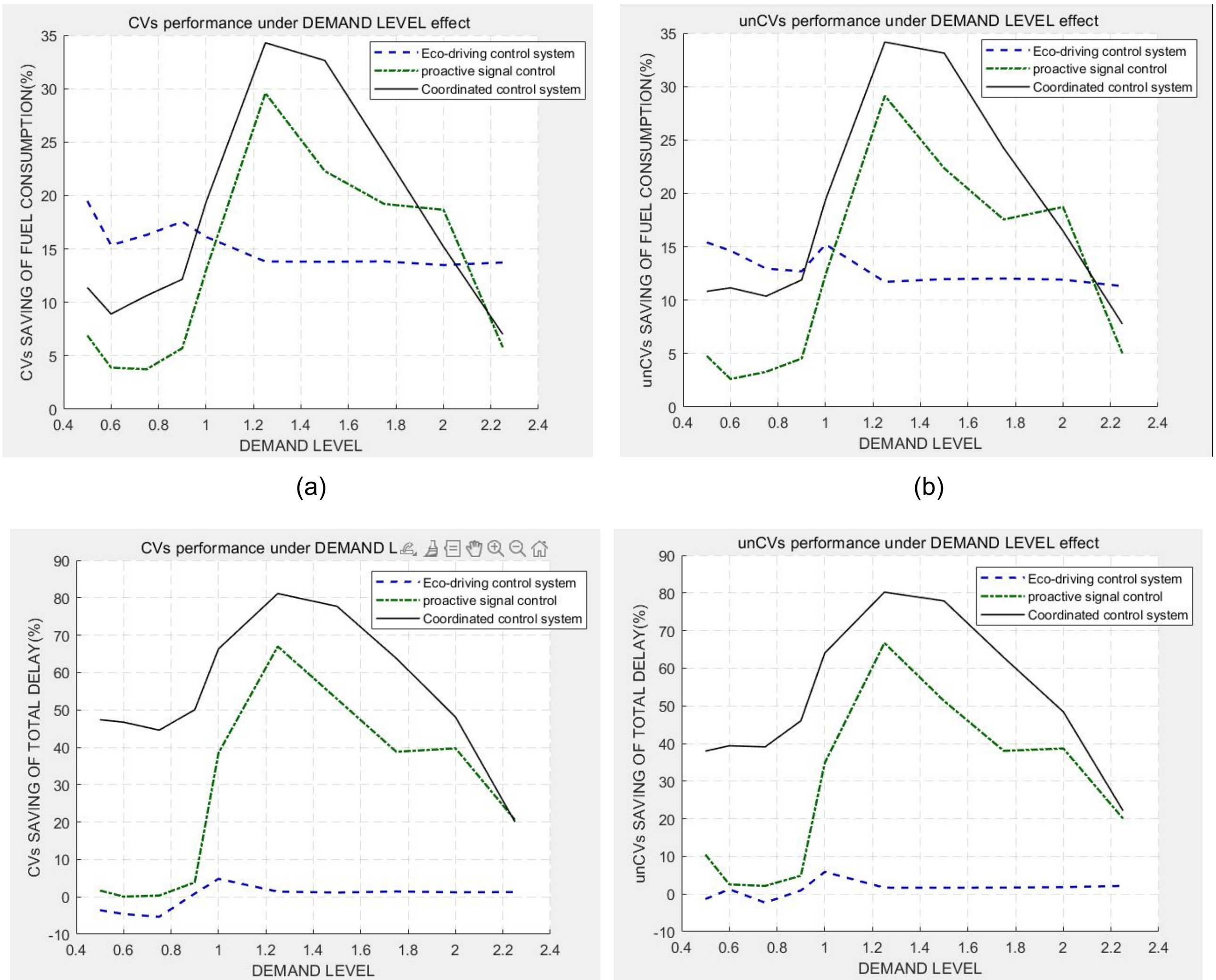
The height of the boxes represents the interquartile range (IQR), which represents the spread of the data. The flatter the box, the smaller the spread and the more consistent the data. The predictions are also more reliable currently.

The distance between the upper and lower quartiles represents the range of the middle 50% of the data. Smaller distances indicate that the data are more clustered around the median, which is the case in this analysis. The closeness of the upper and lower quartiles indicates a strong relationship between the proportion of connected vehicles on the road and fuel consumption rates. There are some outliers in the data, but they are not important enough to affect the overall relationship between the two variables.

As shown in Fig. 4.3.1.2, when MPR=20%-50%, the data is relatively concentrated, and when MPR is other values, the data is relatively dispersed. This boxplot analysis revealed a significant relationship between the proportion of connected vehicles on the road and the fuel consumption rate, so this relationship can then be used to make an approximate prediction of fuel consumption given the MPR. The trends in the boxplots are consistent with the expectation that fuel consumption rates decrease as the proportion of connected vehicles on the road increases. Overall, the data analysis shows that systems in connected vehicles on the road can significantly reduce fuel consumption rates.

4.3.2 The effect of Demand Level on fuel consumption and delay time

In addition to examining the MPRs of CVs, a test was performed to evaluate the benefits of the CVSC system under different levels of demand. The demand levels were calibrated from real-world data and ranged from 50% to 225%. The results, summarized in Fig. 4.3.2.1 at MPR=60%, indicate that the CVSC system yields the shortest travel time delay compared to the Eco-CACC and proactive signal control systems. There exists a concave relationship between the savings in fuel consumption and travel time and demand levels. At lower demand levels, due to the smooth trajectories generated by the Eco-CACC system and the reduced congestion from the proactive signal control, larger savings in fuel consumption and travel time delay are observed from the CVSC system. As the roads become more congested, the benefits of the CVSC control become more significant due to the improved intersection capacities from the proactive signal control. However, when the roads are too congested and multiple rolling queues occur, resulting in more stop-and-go behaviors, the savings in fuel consumption become smaller. For the Eco-CACC system only, it is also able to gain significant savings in fuel consumption. While it does not affect the signal timing plan, it will rarely change the travel time delay of both CVs and non-CVs. For the proactive control only, at low demand levels, as the signal timing set in the real-world has already been tuned to optimize the entire network mobility, the proactive signal control cannot further improve the network mobility a lot, i.e., the travel time delay reduction is marginal. Once the road becomes more congested, the advantages of the proactive signal control can be more significant. However, if the road is too congested, the performance of the proactive control will be similar to the CVSC system as the demand exceeds the capacity of the intersections even after the control. By comparing the performance under different demand levels, we can conclude that the benefits of the CVSC system are maximized at saturated demand levels.



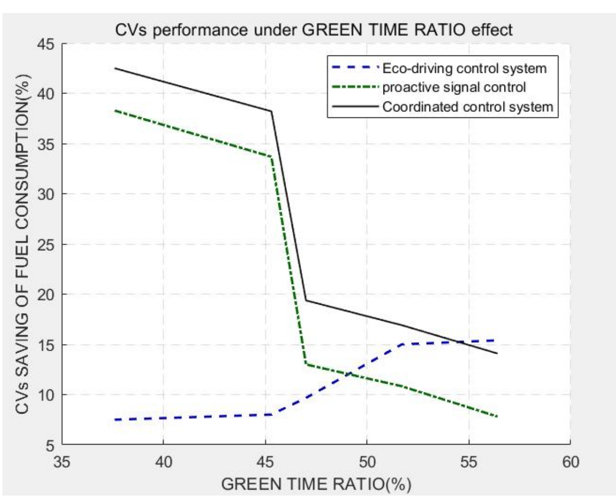
(a) (b)

(c) (d)

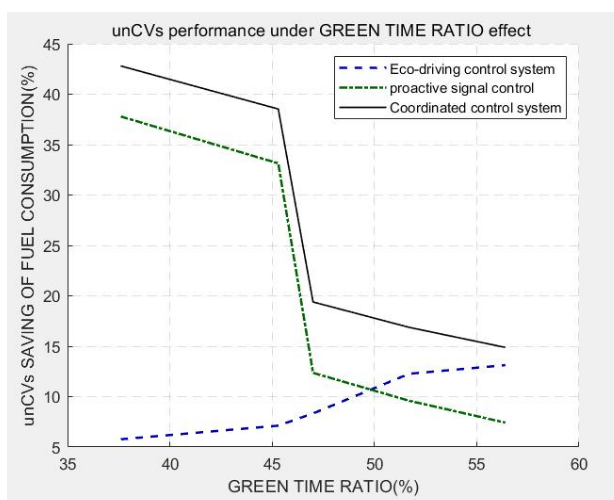
Fig. 4.3.2.1: Benefit comparison at different demand levels: (a) savings in fuel consumption for CVs, (b) savings in fuel consumption for non-CVs, (c) savings in travel time delay for CVs, and (d) savings in travel time delay for non-CVs

4.3.3 The effect of Green Time Ratio on fuel consumption and delay time

Aiming at the influence of the parameter green time ratio on the control system, we use the scheduled control system as a reference. In the case of keeping the length of the signal cycle unchanged and changing the green light signal duration of the main road, the performance of each control system ranges from 37.6% to 56.4%. This range is selected because under the predetermined signal light control system, the proportion of green light signals on the main road is set to 47%, and the remaining 53% are lost time (including yellow + red lights). Since the fuel saving of the Eco-CACC system is to ensure that the vehicle just meets the release of the vehicle when it reaches the end of the waiting queue, the fuel consumption rate of the vehicle on the main road will change with the change of the green signal ratio. Under the scheduled signal control system, the fuel consumption rate and delay of vehicles on the main road will decrease with the increase of the green letter ratio. According to the algorithm of the Eco-CACC system, fuel consumption and delay are also reduced, and the reduction rate is greater than that of the scheduled control system. As shown in Fig. 4.3.3.1 below, under the Eco-CACC control system, the fuel saving rate and delay saving rate are on the rise. However, for the proactive signal control system and the cooperative control system, the change in the green signal ratio does not reduce the total delay and the fuel consumption. So the observed delay time and fuel consumption results remain the same under different green signal ratios. Therefore, the optimization of fuel and delay by the cooperative control system is the result of applying the ECO-CACC system. It can be seen from Fig. 4.3.3.1 that compared with the optimal pre-time control system, the trend presented under the proactive signal control system or the cooperative control system is that the amount of delay savings decreases with the increase of the green word rate. By comparing the performance under different green signal ratios, we can conclude that the benefit of the CVSC system decreases as the main road green signal ratio of the intersection increases (when fuel and delay only on the main road are calculated).



(a)



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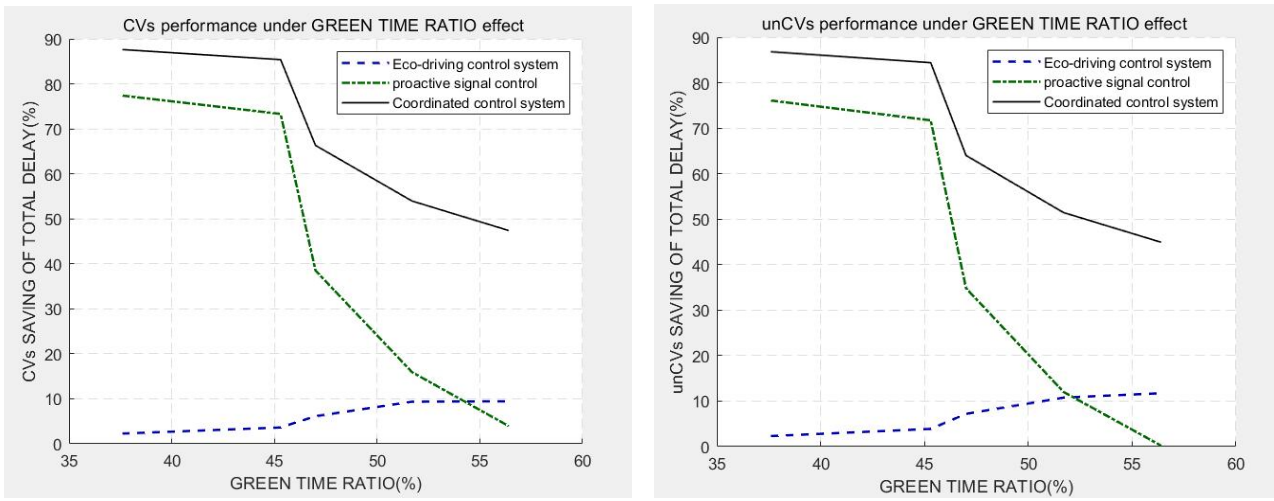
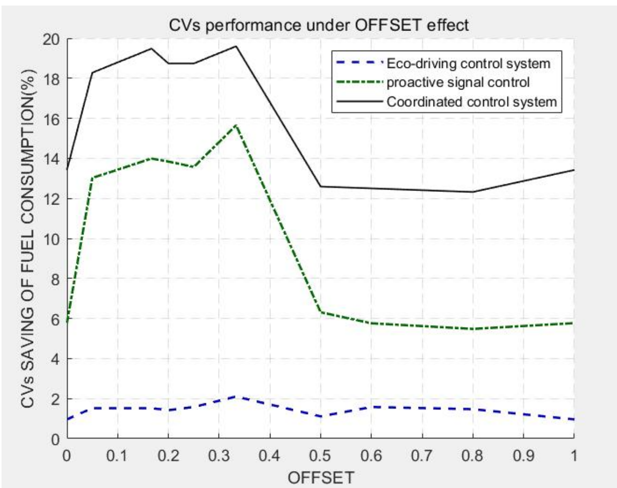


(c) (d)

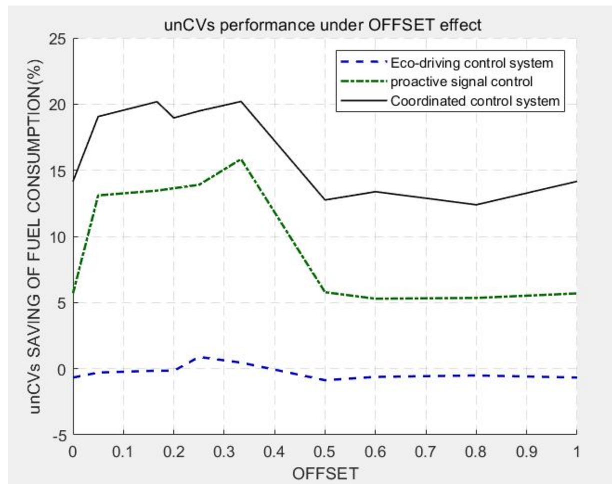
Fig. 4.3.3.1: Benefit comparison at different green timing ratios: (a) savings in fuel consumption for CVs, (b) savings in fuel consumption for non-CVs, (c) savings in travel time delay for CVs, and (d) savings in travel time delay for non-CVs

4.3.4 The effect of Offset on fuel consumption and delay time

Similarly, for the influence of the parameter offset on the control system, the parameter green signal ratio also acts on the control of the signal light. We use the scheduled time control system as a reference. The ratio of offset is also the ratio of the signal cycle in the predetermined timing system, ranging from 0 to one signal cycle of a signalized intersection. According to the maximum driving speed of this road section 72km/h and the distance between these three intersections, when considering the forward green wave belt and the reverse green wave belt at the same time, if the offset value is between 0.5-1, it can enjoy the benefits of the green wave belt, and pass through the continuous intersections in this road section without encountering red lights. Since the fuel saving of the Eco-CACC system rely on ensuring that the vehicle just meets the release of the vehicle when it reaches the end of the waiting queue, changes in the offset will reduce the number of queuing vehicles. As a result, fuel consumption exhibits a similar trend to that of the scheduled system. At the same time, the total delay of vehicles under the ECO-CACC control system will be reduced due to the greatly reduced stop delay. For the proactive signal control system, the change of offset is independent of the delay and fuel consumption under the proactive signal control. Therefore, the fuel saving rate and delay saving rate under the proactive signal control and cooperative control systems are entirely due to the optimization of the signal. And because the cooperative control system simultaneously optimizes vehicle trajectories, the CVSC system can observe more fuel consumption savings and travel time delays. By comparing the performance at different offsets and the results shown in Fig. 4.3.4.1, we can conclude that the benefit of the CVSC system is maximized at intersection offsets of 0.05-0.35, which is consistent with our calculation.



(a)



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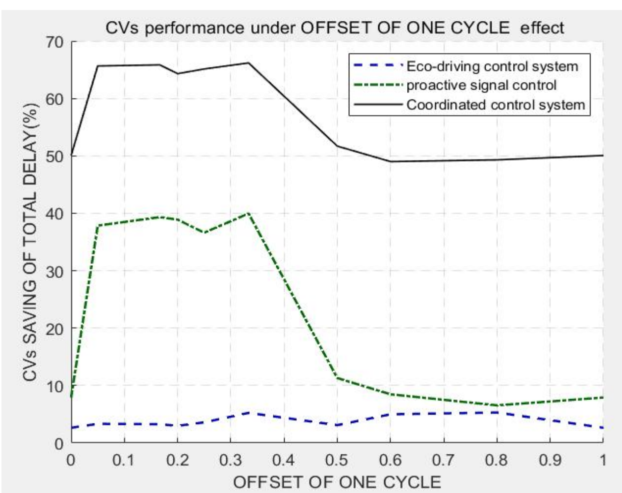
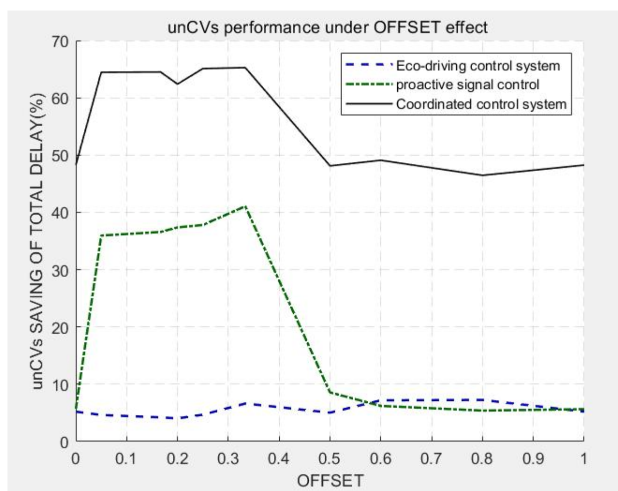


(c)



(d)

Fig. 4.3.4.1: Benefit comparison at different offsets: (a) savings in fuel consumption for CVs, (b) savings in fuel consumption for non-CVs, (c) savings in travel time delay for CVs, and (d) savings in travel time delay for non-CVs

4.3.5 Validate the effectiveness of the cooperated optimization model

Figures 4.3.5.1, 4.3.5.2, and 4.3.5.3 show the intersection delay, travel time, and fuel consumption when the penetration rate of connected vehicles varies under different saturations, respectively. Among them, when the penetration rate of connected vehicles is 0, the fixed timing plan is used as the benchmark signal control scheme. The rest use the cooperative optimization control method introduced in chapter three. The data results show that our proposed model performs well under different demand levels.Especially when the traffic demand is similar to the actual traffic demand, the delay reduction effect is obvious.

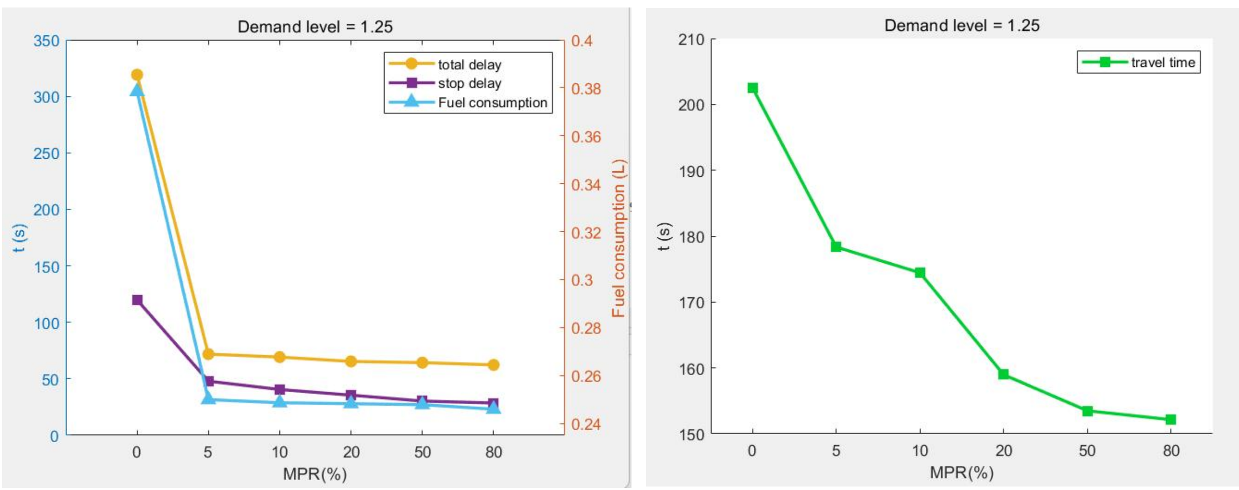


Fig. 4.3.5.1, Average delay and travel time as a function of MPR for saturation of 1.25

(1) Intersection with a demand level of 1.25

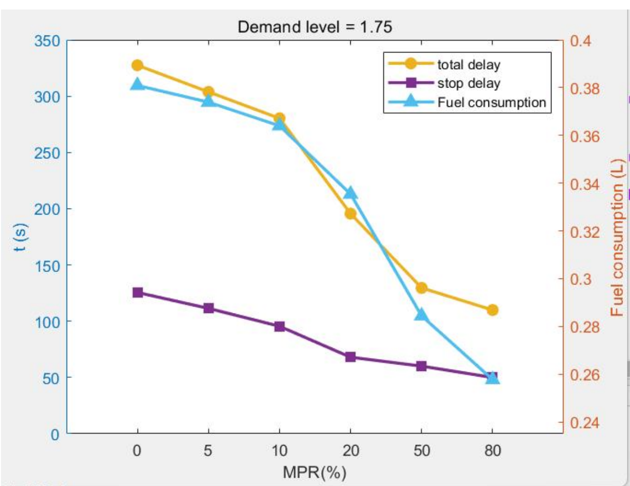
At oversaturated (demand level=1.25) intersections, the cooperative control strategy in this paper performs best. All evaluation index values change almost linearly with the increase in the penetration rate of connected vehicles. When MPR is different, Tab. 4.3.5.1 shows the percentage reductions in average delay, transit time and fuel consumption compared with pre-time control.

Tab. 4.3.5.1 Reduction Rate of Evaluation Indicators at Intersections with Demand Level 1.25

MPR (%)	5%	10%	20%	50%	80%
average delay saving rate	52.84%	54.05%	57.67%	58.54%	59.77%
Fuel consumption saving rate	17.58%	17.76%	18.33%	18.40%	18.68%

When the connected vehicle penetration rate is 5%, the delay and fuel consumption rates have been reduced by 52.84% and 17.58%, respectively. The optimization effect is relatively obvious even when the penetration rate is just 5%. And the reduction trend of stop delay in Fig. 4.3.5.1 is slightly higher than the reduction trend of total delay, indicating that the cooperative control strategy can reduce intersection delay and reduce fuel consumption by effectively reducing stop. It is also approved that when the demand level we set is similar to the real-word data, the performance of the saving of fuel consumption and delay time shows the best.

(2) Oversaturated state — Intersection with a demand level of 1.75



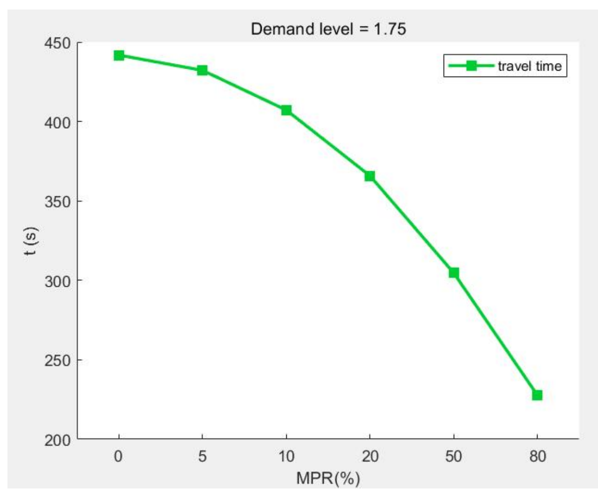


Fig. 4.3.5.2, Average delay and travel time as a function of MPR for saturation of 1.75

In oversaturated situations, the traffic flow has exceeded the road capacity, so even with coordinated optimization, the effect is not particularly significant at low MPRs. As shown in Fig. 4.3.5.2, the reduction in travel time, delay, and fuel consumption is not significant within the MPR range of 5% to 10%. This is because the ratio of connected vehicles is too low, and their impact may not be sufficient to reduce the delay and fuel consumption of the entire traffic system. Since connected vehicles can only communicate with other connected vehicles and not with traditional non-connected vehicles, the optimization effect of connected vehicles is limited. When the MPR increases to 20%, the effect can be clearly seen from the figure. But it can also be seen from the data that even when the traffic state is oversaturated, the optimal control method proposed in this thesis can still provide better performance, relieve traffic congestion, and reduce fuel consumption.

(3) Undersaturated state — Intersection with a demand level of 0.7

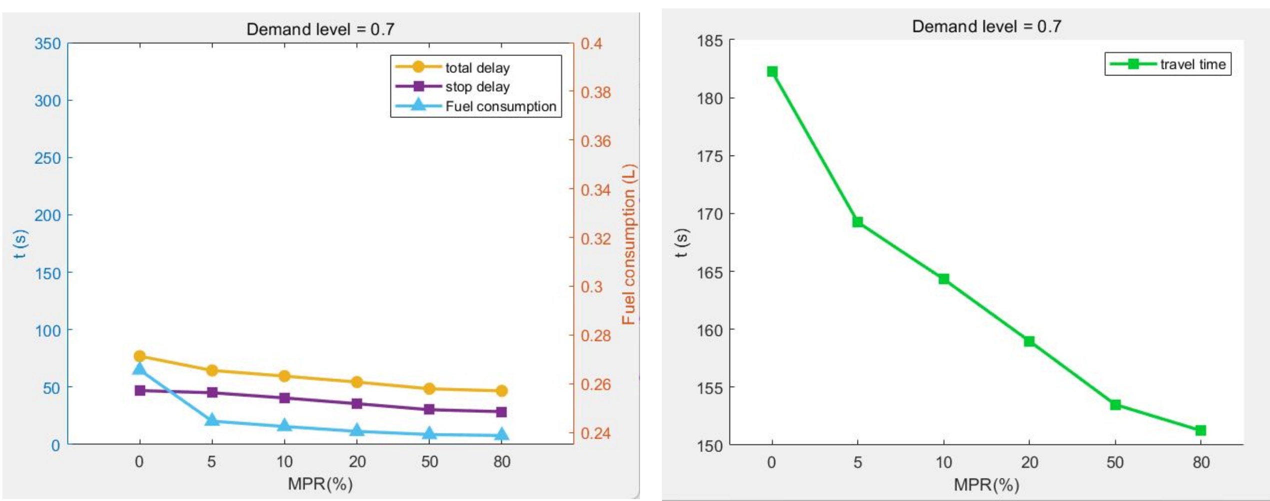


Fig. 4.3.5.3, Average delay and travel time as a function of MPR for saturation of 0.7

Tab. 4.3.5.2 Reduction Rate of Evaluation Indicators at Intersections with Demand Level 0.7

MPR (%)	5%	10%	20%	50%	80%
average delay saving rate	57.69%	60.48%	64.80%	68.72%	69.85%
Fuel consumption saving rate	19.33%	19.81%	20.90%	21.30%	22.06%

It can be seen from Fig. 4.3.5.2 that when the demand level is low (demand level=0.7), the three indicators all decrease because the intersection itself is not congested, but the value of total delay time and stop delay time do not decrease significantly. The main reason is that the green light in the system can easily release the queue at the red light even with pre-time signal control system under this level of demand, which is not much different from the optimized minimum delay time. When there are connected vehicles on the road section, the predicted Inflow rate is more accurate during proactive signal control, so the average delay and transit time are on a downward trend overall. When the penetration rate of connected vehicles is 5%, and the fuel consumption and average delay are reduced by 19.33% and 57.69% respectively compared with the intersection under pre-time signal control.

Conclusions

Aiming at the optimization problem of vehicle speed suggestion and proactive traffic signal cooperative control at continuous intersections on urban roads under the environment of mixed intelligent vehicle networking, the microscopic modeling of intersection traffic considering the individual characteristics of vehicles is respectively carried out. In order to simultaneously optimize vehicle delays and reduce fuel consumption, an algorithmic and experimental study is carried out on the cooperative control of traffic trajectories and signals. The main research conclusions and innovation points are summarized, and the future research direction prospects.

This thesis presents the development of a cooperative vehicle-signal control system aimed at minimizing travel time delay and fuel consumption for vehicles at signalized intersections. The system utilized CVs to collect the dynamics of individual vehicles and signal timing plans for the estimation of queue lengths and traffic conditions at intersections. The CVSC system integrated an Eco-CACC system and a proactive signal control system to optimize both the signal timing plan and the speed profiles of connected vehicles (CVs) in the vicinity of an intersection. The system was evaluated under a real-world network, FM528, which consisted of three consecutive intersections. The results showed that the system was able to reduce average vehicle stop delays by 57%, the number of vehicle stops by 10%, and fuel consumption by 22%, resulting in savings of up to $474 per day on the test road. On this basis, the sensitivity analysis was performed on the MPRs of CVs at multiple intersections. The analysis shows that the higher MPRs, the greater the benefit of the proposed system. When the MPR is high enough (>70%), the system can almost achieve the optimal control effect.

Also, the cooperative model is transferable to other areas, as it is designed for general intersections. The Eco-CACC system is generally applied to straight road segments with multiple lanes, enabling the control of individual vehicle speeds to ensure a smoother trajectory when passing through intersections. As a result, eco-driving can be applied to any road and intersection. Regarding signal optimization, the cooperative model can define any phase sequence in the intersections and predict time delays, allowing for proactive signal control deployment at any intersection. Both systems can function for any intersection and segment and can be transferred to other networks. Applying the proposed system to other intersections only requires recalibrating parameters such as traffic flow, road features, capacity, free flow speed, the geometry of intersections, the number of phases and so on.

With the ever-evolving advancements in intelligent vehicle-road network technology, the model and algorithm proposed in this thesis serve as valuable references for real-world traffic control application deployment and related research. Nonetheless, intersection traffic control within the intelligent vehicle-road network environment, as a prominent aspect of the integration of artificial intelligence, multi-mode collaboration, and intelligent vehicle-road network, presents a highly complex and challenging research task, both in terms of depth and breadth. Building on this research, future studies can be conducted from the following perspectives:

(1) Conduct sensitivity analysis on other parameters affecting the cooperative control model to obtain optimal system settings. Certain parameters in the CSVC system, such as the semaphore update interval and control region length for each method, are arbitrarily set in this study. Hence, further exploration of their performance is required in the future.

(2) Consider other types of vehicles in the road network. In this research, we assume that all vehicles are passenger cars. With connected vehicles, information about vehicle types, such as buses, vans, and other emergency vehicles, can be acquired. Therefore, we can utilize this collaborative system to enable emergency vehicles to navigate mixed traffic more efficiently and apply it to real-world scenarios more effectively.

(3) Supplement the modeling of other traffic participation entities. Under the intelligent human-vehicle-road tripartite network connection, in addition to various types of vehicles, models for pedestrians and various types of non-motorized vehicles should be established. Furthermore, the detectability, guide ability, predictability, and controllability of various traffic parameters and entities' behavior in the mixed environment should be improved. We should analyze the intricate interactions and constraints of different traffic participants in the mixed environment and realize the detection of various random or abnormal traffic conditions in the model design, thereby enhancing the algorithm's stability and practicability.

(4) Investigate the solution efficiency of more complex optimal control models. When a considerable volume of real-time traffic information is input, the system's current state and forecast state are continuously and rapidly updated during optimization. In order to

accurately predict traffic conditions at intersections, more complex prediction models must be employed to enhance system efficiency.

(5) The impact of the coordinated control system on the surrounding network. While we observed excellent performance for the three tested intersections, the impact on their surrounding intersections or the entire network in the city could be positive or negative is not sure and depend on the traffic condition. For instance, if there is an upstream intersection adjacent to the test area and the control system is applied to only these three intersections, the control taken downstream may be insufficient, leading to increased flow at the upstream intersection and causing congestion. This could have a potentially negative impact, as we are essentially pressurizing the upstream intersection and creating congestion.

On the other hand, adding the cooperative system to resolve congestion in the most congested area of the road, such as the three intersections in our test, could bring some positive benefits. If these three intersections are already bottlenecked, the cooperative system can resolve their congestion. Then it is likely to alleviate congestion throughout the entire network, leading to significant positive impacts.

Therefore, while the performance of the coordinated control system may vary depending on the traffic conditions, it has the potential to provide significant benefits to the entire network, provided it is implemented correctly.

(6) Apply the continuous intersections' joint traffic control strategy to road networks or cities on a larger scale to improve the overall traffic condition performance indicators at the city level, rather than on a road section. Therefore, based on the research in this thesis, a multi-point collaborative fine-grained control model and solution method for the overall optimization strategy of the large-area road network can be studied.

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