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IMPACT OF CONNECTED AND AUTONOMOUS VEHICLES ON SIGNALIZED INTERSECTIONS WITH TRANSIT SIGNAL PRIORITY

Final Report

by

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DISCLAIMER

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EXECUTIVE SUMMARY

Transit signal priority (TSP) is a critical operational strategy that can be applied to improve the performance of transit vehicles on the road. However, this control strategy generally causes adverse effects on other traffic, which limits its widespread adoption. Connected and autonomous vehicles (CAVs) have the ability to exchange traffic data and vehicle information in real-time with other vehicles and infrastructure in their vicinity, which can certainly facilitate the development of TSP control strategies. As a result, research on TSP combined with CAV technology has increasingly gained a lot of attention.

This study evaluates the traffic performance of two general TSPCV control strategies, namely actuated TSP with CV (connected vehicle) and optimized TSP with CV, and compares them with two conventional signal control strategies, i.e., actuated signal control without TSP, and actuated signal control with TSP. Simulation experiments based on a signalized intersection in Charlotte, North Carolina, are conducted to compare the traffic performance of proposed control strategies under different market penetration rates, traffic demand, and bus arrival frequency conditions.

Results indicate that the proposed Genetic Algorithm (GA) optimization control strategy can reduce the average bus delay by 24.50% while minimizing the adverse impact on competing traffic under high traffic demand conditions. Fully actuated control with TSP using CV has the best performance in terms of average delay under low traffic demand conditions. In addition, the fully actuated with TSP using CV control strategy only requires the bus to be equipped with CV technology, which can be easily achieved due to its low cost. The proposed optimization control algorithm can provide certain priority to buses even at low rates of CV market penetration. The sensitivity analysis shows that the proposed optimization control algorithm is not very sensitive to either the bus occupancy or bus arrival frequency. The results of this study will provide a solid and systematic reference for both researchers and practitioners to better understand, plan, design, and operate TSP control strategies in CAV environment.

Chapter 1. Introduction

1.1. Problem Statement

Public transportation is playing a more and more prominent role in the urban transportation system. Strategies that ensure transit priority can provide higher quality transit services to the public, which can greatly help in developing a more sustainable, equitable, and efficient urban transportation system. The implementation strategies include the formulation of policies to prioritize public transportation, the provision of financial subsidies for public transportation, the construction of high accessible public transportation system, and the granting of priority to transit vehicles, etc. Among them, transit signal priority (TSP) is a critical operational strategy that can be applied to improve the performance of transit vehicles on the road. TSP generally adjusts the signal plan to ensure priority for transit vehicles at intersections, arterials, or networks (Skabardonis, 2000). However, this control strategy generally causes adverse effects on other traffic, which limits its widespread adoption.

It is widely accepted that the development of Connected and Autonomous Vehicle (CAV) technology will have a profound impact on the transportation systems. Numerous studies have been conducted to investigate the impact of CAV technology development. At the macro level, the economic, social and environmental impacts of CAVs development have been studied, while at the micro level, research mainly focused on the impact of various specific CAV technologies. The results showed that the development of CAVs technology can significantly improve the performance of transportation systems, thus bringing us a better world. The most important feature of CAV technology is real-time traffic data exchange, which also facilitates the development of TSP control strategies. Advances in TSP that benefit from CAV technology have gained a lot of attention. Hill and Garrett (2011) stated that Transit Signal Priority with Connected Vehicle (TSPCV) is a key application of CAV technology that will greatly enhance mobility and safety. The USDOT has also included TSPCV in its list of high-priority applications and development approach. With the benefit of CAV technology, more progress can be made in improving TSP efficiency.

This study evaluates the traffic performance of two general TSPCV control strategies, namely actuated TSP with CV and optimized TSP with CV, and compares them with two conventional signal control strategies, i.e., actuated signal control without TSP, and actuated signal control with TSP. Simulation experiments based on a real-world signalized intersection are conducted to compare the traffic performance of proposed control strategies under different market penetration rates, traffic demand, and bus arrival frequency conditions. The results of this study will provide a systematic reference for both researchers and practitioners to better understand, plan, design, and operate TSP control strategies in CAV environment.

1.2. Objectives

The objectives of this study are to:

1) Conduct a comprehensive literature review on CAV technologies and TSP control strategies.
2) Build a signalized intersection based on real-world configurations in the simulation environment.
3) Develop different simulation scenarios considering the TSP control strategies, and CAV market penetration rates, etc.
4) Conduct simulation experiments and collect the traffic performance data.
5) Analyze and discuss the simulation results in different scenarios.

1.3. Report Overview

The report is organized as follows. A comprehensive literature review is presented in Chapter 2. The methodology used to minimize the total person delay is described in Chapter 3. Chapter 4 details the configuration of studied intersection and the settings of different scenarios. The results that are obtained from conducting simulation experiments are analyzed and discussed in Chapter 5. Finally, in Chapter 6, the conclusions from this study are summarized and the future work are suggested.

Chapter 2. Literature Review

2.1. Introduction

This chapter provides a comprehensive review of the development of CAV and intersection management. Furthermore, the development of TSP and the latest state-of-the-art and state-of-the-practice in the field of TSP control are also reviewed.

The following sections are organized as follows. Section 2.2 presents the background of CAV technologies, such as definitions, taxonomies, impacts, and the prospects. Section 2.3 discusses the existing research and practices on intersection management. The development of TSP research and the studies on the integration of TSP and CAV are reviewed in section 2.4. Finally, a summary of the chapter is given in section 2.5.

2.2. Background of Connected and Autonomous Vehicle

2.2.1. Definition of Connected and Autonomous Vehicle

2.2.1.1. Connected Vehicle (CV)

Connected vehicles (CVs) refer to vehicles that are equipped with communication technologies (such as cellular technology), which enable them to communicate within a certain range with other vehicles on the road (V2V), roadside infrastructure (V2I), and other traffic participants (V2X) (Guo et al., 2019). V2V technology enables CVs to communicate with surrounding CVs for applications such as cooperative collision warnings, hazard alerts, and cooperative collision avoidance. V2I technology enables CVs to exchange detailed traffic information with nearby infrastructure, such as speed, acceleration/deceleration, volume, queue length, and signal phase and timing (SPaT). V2X enables the ability to transfer information with every entity around a CV that may affect the CV.

2.2.1.2. Automated Vehicle (AV)

NHTSA defines an autonomous vehicle as “those in which operation of the vehicle occurs without direct driver input to control the steering, acceleration, and braking and are designed so that the driver is not expected to constantly monitor the roadway while operating in self-driving mode” (USDOT, 2019). With the emergence of AV technologies, different organizations have proposed different taxonomies. In 2013, the NHTSA introduced a 4-level classification for the automation level of vehicles. The Society of Automotive Engineers International (SAE) proposed a 6-level taxonomy in 2014. This taxonomy was adopted by NHTSA later in 2016 and has become the industry standard for general use (NHTSA, 2016).

There are six levels of vehicle automation from level 0 to level 5. Level 0 means that the vehicle has no automation and is fully operated by a human driver. In Levels 1 and 2, the driver is responsible for dynamic driving tasks (DDT), while the advanced driver assistance systems (ADASs) on the vehicle can sometimes assist the human driver with steering or/and brake/acceleration. ADASs have the potential to prevent or mitigate crashes by partially eliminating driver errors. In higher levels of automation, the automated driving system (ADS) performs the entire DDT when engaged. In Level 3, the DDT fallback-ready user needs to intervene when requested. On the other hand, Levels 4 and 5 of automation do not require a DDT fallback-ready user, and Level 5 has an unlimited operation design domain (ODD), unlike Levels 3 and 4. An ADS is expected to eliminate driver errors in its ODD; however, disengagement from ADSs in Level 3 of automation can be challenging. Table 2-1 provides a summary of different levels of vehicle automation. The AVs discussed in this report belong to level 5.

Table 2-1 Automation Levels and Corresponding Descriptions (SAE, 2021)

Level	Description
L0	No Driving Automation. Only warnings and momentary assistance are provided.
L1	Driver Assistance. Steering **or** brake/acceleration support are provided.
L2	Partial Driving Automation. Steering **and** brake/acceleration support are provided.
L3	Conditional Driving Automation. When conditions are not met, you must drive. Otherwise, the system can drive the vehicle under limited conditions.
L4	High Driving Automation. You are not required to drive under any conditions. The system can drive the vehicle under limited conditions.
L5	Full Driving Automation. The system can drive the vehicle under all conditions.

2.2.1.3. Connected and Automated Vehicle (CAV)

Connected and automated vehicle technology is a combination of connected technology and autonomous vehicle technology. CAV can be self-driving and communicate with its surroundings. Some examples of existing CAV technologies are active lane-keeping assistance (LKA), active park assistance (APA), automatic braking (ABS), blind-spot detection (BSD), cross-traffic alert systems (CTAS), and forward-collision warning (FCW). The development of CAV technologies will have a profound impact on mobility, environmental effects, and traffic safety.

2.2.2. Impacts of Connected and Autonomous Vehicles

The impacts of CAV technology have been a hot research topic in recent years. The benefits of CAV technology, including improvements in safety, enhancement in mobility and reductions in emissions, have been widely researched and accepted.

2.2.2.1. Safety

In a report published by the National Highway Traffic Safety Administration (Singh, 2018), the critical reason for 94% of the crash events was attributed to drivers. There is a general consensus that CAV technologies will greatly improve traffic safety by reducing or even eliminating human errors while driving.

Li et al. (2017) developed and used both theoretical and experimental approaches to investigate the impacts of cooperative adaptive cruise control (CACC), a CAV technology, on improving the highway traffic safety. This study identified two modified parameters to measure the risk of rear-end collisions. In the theoretical approach, linear stability analysis was performed. In the experimental approach, several microscopic simulation experiments were conducted using calibrated car-following models. Each car-following model represented a human driven vehicle (HDV), an adaptive cruise control (ACC) vehicle, and a cooperative adaptive cruise control (CACC) vehicle, respectively. Results showed that the CACC system could reduce the risk of rear-end collisions by more than 90%.

Bareiss et al. (2019) used a simulation software to reconstruct some selected left turn across path/opposite direction (LTAP/OD) crashes in the United States. They then introduced the intersection advanced driver assistance system (I-ADAS) into these simulated crashes and evaluated the performance of the system. Results showed that I-ADAS with automatic emergency braking could reduce 18-84% of all LTAP/OD crashes.

Wang et al. (2020) conducted a literature review study using a meta-analysis approach to quantitatively assess the effectiveness of CAV technologies. Of 826 CAV-related safety impact papers or reports that they reviewed, 73 studies were selected using predefined criteria. The unbiased effectiveness of each specific CAV technologies was evaluated by applying meta-analysis, funnel plots, and trim-and-fill method. The comprehensive safety effectiveness and compilation of safety effectiveness were then calculated using crash data from six countries. Results showed that if all the CAV technologies studied in this article were implemented, a total of 3.4 million crashes could be reduced each year in six countries. The comprehensive safety effectiveness was 54.24%, 51.55%, 48.07%, 45.36%, 44.71%, and 40.95 for India, Australia, USA, New Zealand, Canada, and the UK, respectively.

Arvin et al. (2021) calibrated the simulation model using real-world data and investigated the safety impacts of ACC and CACC in mixed traffic with human driving vehicles at intersections. An analysis of the automated vehicle (AV) crash data in California concluded that 72.8% of the crashes occurred at the intersections and 63.8% of the crashes were rear-end collisions. Two surrogate safety measures, the number of longitudinal conflicts (TTC) and driving volatility, were applied to evaluate the simulation outcomes in this study. Results indicated a nonlinear safety improvement. As the ACC and CACC penetration rates increased, the number of conflicts and driving volatility decreased significantly. The improvement in safety was more significant when the ACC penetration exceeded 40%. Meanwhile, vehicles equipped with CACC have a better safety performance than those equipped with ACC.

2.2.2.2. Mobility

Shorter headways, faster reactions, and more accurate operations can be achieved by adopting CAV technologies. Thus, enhanced mobility can be guaranteed.

Chen et al. (2017) developed a theoretic framework to evaluate the lane capacity in mixed traffic environment. AV penetration rate, micro/mesoscopic characteristics of AV and HDV, different lane policies such as exclusive AV and/or HDV lanes and mixed-use lanes were taken into account in this framework. Result showed that higher capacities can be realized by implementing mixed-use policies, while strict segmentation of AVs and HDVs might lead to lower capacity.

Ye and Yamamoto (2018) developed a two-lane cellular automaton model to evaluate the possible impact of CAVs on the traffic flow. Simulations were conducted under different CAVs penetration rates and the impact of CAVs on road capacity was quantitatively investigated. When the penetration rate was below 30%, the effect of penetration rate growth on the increase rate of road capacity was insignificant. When the penetration rate exceeded 30%, the increase rate of road capacity was largely decided by the capability of the CAV.

Shi et al. (2019) adopted the intelligent driver model (IDM) to simulate CAVs in mixed traffic environments under different penetration rates. Besides, a cooperative CAV lane-changing model with two lane-changing algorithms was developed to form more CAV platoons. Simulation results indicated that the capacity would increase as the penetration rate grew, and the peak growth rate occurred between 40% and 70% of the CAV penetration rate.

Liu and Fan (2020) investigated the impact of CAVs on freeway capacity with a simulation based-method approach. Calibration was conducted using genetic algorithm to mimic the driving behaviors of HDVs. Different penetration rates of CAVs and different speed limits were considered to evaluate the freeway capacity. Results showed that freeway capacity would increase as the penetration rate increased. Besides, speed limits had a significant positive influence on freeway capacity.

Song et al. (2021) investigated the impacts of CAV market penetration rate (MPR) on different signal intersection scenarios based on simulation experiments. In this study, different control strategies and car following models were adopted to mimic different types of vehicles. Specifically, there are CAVs with the CACC system, AVs with the ACC system, AVs with IDM system, and HDV with IDM system. Different scenarios, such as fixed signal, gap-based actuated signal, and delay-based actuated signal with low, medium, and high traffic demands, were modeled in the simulation platform. Results showed that CACC system outperformed AVs with ACC/ IDM. With only a 20% MPR, significant delay drops can be observed in CACC system. For AVs with the ACC/IDM system, large delay drops can be observed after 60% and 80% MPR.

2.2.2.3. Environment

The impact of CAV technology in the environmental realm has been something that is controversial. From a microscopic perspective, there is a common consensus that CAV technology can improve fuel economy and reduce emissions. However, from a macroscopic perspective, whether the effect of CAV technology is positive remains a question.

Wadud et al. (2016) used a coherent energy decomposition framework to analyze the impact of AVs on travel and energy demand and associated greenhouse gas (GHG) emissions. One major finding of this study was different energy efficiency and travel impacts resulting from different levels of automation. At relatively lower automation rates, the reduction of energy use resulting from energy efficiency might outweigh the increase in energy use due to increased travel demand. However, at a high level of automation, the energy outcomes depended on which effects come to dominate.

Taiebat et al. (2019) estimated the elasticities of vehicle miles traveled (VMT) demand with respect to fuel and time cost under the full adoption of CAVs from a microeconomic perspective. The travel demand and energy use induced by adopting CAVs were taken into account in this research. Results indicated that a net rise in energy use was possible, especially in high income groups.

Le Hong and Zimmerman (2021) investigated the impacts of CAVs development on emissions in metro Vancouver, Canada in 2030 and 2040. The US Environmental Protection Agency's Motor Vehicle Emission Simulator (MOVES) was used to assess the emissions with respect to varying future vehicle kilometers traveled (VKT), transit use, fuel-type, and CAV market penetration rate. In the best scenario, CAVs could reduce GHG emissions by 20% compared with no-CAV scenario in 2040. Under the worst scenario, a 6% reduction in GHG emissions could be achieved.

There are also many studies that have evaluated the impacts of CAV technology from multiple perspectives. Mahdinia et al. (2020) analyzed field test data of CAVs collected from the

Cooperative Automated Research Mobility Application (CARMA) program. Two scenarios were considered in this study, namely platooning and merging. Each scenario had two types of vehicle combinations. The safety, energy, and environmental impacts of specific CAVs technologies were evaluated by applying corresponding assessment methods. Compared with vehicles equipped with ACC, CACC equipped vehicles reduced driving volatility in a five-vehicle-platoon from 13.6% to 29%. The volatility of the merging CACC equipped vehicle was reduced by 6.2% when compared with the merging human-driven vehicle. The CACC vehicles increased minimum values of TTC by approximately 100% to reduce the risk of rear-end collision. In the five-vehicle-platoon scenario, CACC technology reduced overall fuel consumption by 0.5% to 6.7% compared with ACC, and the reduction of total emissions ranged from 3.1% to 4.9%. In merging scenario, the overall fuel consumption and emissions of the merging vehicle equipped with CACC increased by 0.54% and 4.1%, respectively, compared with the human-driven merging vehicle.

Liu and Fan (2021) investigated the mobility and environmental impacts of CAVs on signalized intersections using the simulatio-based approach. Simulation performace indicated that with a 100% MPR of CAVs, vehicle delay could be reduced by up to 46.06% and emissions could be reduced by up to 33.47% compared with the HDV only scenario.

Table 2-2 Literature Review on the Impacts of Connected and Autonomous Vehicles

Research Perspective	Authors	Year	Findings
Safety	Li et al.	2017	The CACC system could reduce the risk of rear-end collision by more than 90%.
	Bareiss et al.	2019	I-ADAS with automatic emergency braking could reducing 18-84% of all LTAP/OD crashes.
	Wang et al.	2020	If all the CAV technologies studied in this article were implemented, a total of 3.4 million crashes could be reduced each year in these six countries.
	Arvin et al.	2021	The improvement in safety was more significant when the ACC penetration exceed 40%. Meanwhile, vehicles equipped with CACC have a better safety performance than those equipped with ACC.
Mobility	Chen et al.	2017	Higher capacities can be realized by implementing mixed-use policies, while strict segmentation of AVs and HDVs might lead to lower capacity.
	Ye and Yamamoto	2018	When penetration rate below 30%, the effect of penetration rate growth on the increase rate in road capacity is insignificant. When the penetration rate exceeded 30%, the increase rate of road capacity is largely decided by the capability of the CAV.

	Shi et al.	2019	The capacity would increase as the penetration rate grew, and the peak growth rate occurred between 40% and 70% of the CAV penetration rate。
	Liu and Fan	2020	Freeway capacity will increase as the penetration rate increase. Besides, speed limits had a significant positive influence on freeway capacity.
	Song et al.	2021	CACC system outperformed AVs with ACC/IDM. With only a 20% MPR, significant delay drops can be observed in CACC system. For AVs with the ACC/IDM system, large delay drops can be observed after 60% and 80% MPR.
Environment	Wadud et al.	2016	At relatively lower automation, the reduction of energy use resulting from energy efficiency might outweigh the increase in energy use due to increased travel demand. However, at a high level of automation, the energy outcomes depended on which effects come to dominate.
	Taiebat et al.	2019	A net rise in energy use was possible, especially in high income groups.
	Le Hong and Zimmerman	2021	At the best scenario, CAVs could reduce GHG emissions by 20% compared with no-CAV scenario in 2040. At the worst scenario, a 6% reduction in GHG emissions could be achieved.
Multiple	Mahdinia et al.	2020	Safety: Compared with vehicles equipped with ACC, CACC equipped Vehicles reduced driving volatility in a five-vehicle-platoon from 13.6% to 29%. The volatility of the merging CACC equipped vehicle was reduced by 6.2% when compared with the merging human-driven vehicle. The CACC vehicles increased minimum values of TTC by approximately 100% to reduce the risk of rear-end collision. In the five-vehicle-platoon scenario, CACC technology reduced overall fuel consumption by 0.5% to 6.7% compared with ACC. Environment: The reduction of total emissions ranged from 3.1% to 4.9%. In merging scenario, the overall fuel consumption and emissions of the merging vehicle equipped with CACC increased by 0.54% and 4.1%, respectively, compared with the human-driven merging vehicle.
	Liu and Fan	2021	Mobility: With 100% MPR of CAVs, vehicle delay could be reduced by up to 46.06% Environment: Emissions could be reduced by up to

			33.47% compared with the HDV only scenario.

2.2.3. The Outlook for Connected and Autonomous Vehicles

CAVs have the potential to significantly change the transportation system around the world. With the rapid development of cutting-edge technologies, such as advanced sensor technology, cellular technology, big data technology, and artificial intelligence, CAV technology has made great progress. Newly produced vehicles in recent years were generally equipped with Level 1 and Level 2 automation systems. The Level 3 automation system is still under development and is being tested in many practical experimental projects. Moreover, it takes significantly more time to develop mature Level 4 and Level 5 automation systems. There are many studies focused on forecasting the market penetration rate of CAVs, with varying findings.

Lavasani et al. (2016) developed Generalized Bass diffusion models for predicting the AV technology market penetration based on similar technologies and previous trends in the United States. In this study, the saturated market size was set as 75% of households who would purchase AV with AV sales starting at year 2025. The AV sales would be 1.3 million, 36 million and 83.6 million in 2030, 2040 and 2050, respectively. The AV market would be saturated in 2059, and more than 87 million AVs would be sold.

Bansal and Kockelman (2017) developed a simulation-based fleet evolution framework to predict the market penetration rate of CAVs in the United States during 2015-2045. Based on a US-wide survey of 2167 responses, the willingness to pay (WTP) and vehicle purchases decisions of Americans were measured. Results indicated that approximately 98% of U.S. vehicles would be equipped with emergency automatic braking (ESC) and connectivity function in year 2025 and 2030, respectively. In addition, the market penetration rate of vehicles with full driving automation would be around 24.8-87.2% in 2045, depending on the WTP and vehicle price.

Talebian and Mishra (2018) predicted the adoption of CAVs using agent-based model coupled with the diffusion of innovations theory. A survey was conducted to demonstrate the applicability of the proposed approach. Results suggested that the vehicle fleet penetration rate would approach 100% around 2050 only if the CAV price falls significantly. In another word, assuming that the cost of full automation is $40,000 at 2025, this price would have to drop by 15-20% annually to reach 100% adoption of CAV in 2050.

Quarles et al. (2021) developed a statistical model to investigate decisions in terms of vehicle transactions, travel behavior, and land use. Simulation results showed a sharp increase in AV ownership since 2040, comprising 36.41% of private vehicle ownership by the year 2050.

Furthermore, the VMT from AV will make up around 60% of US VMT in 2050. Of this, half will be shared autonomous vehicles.

Litman (2022) assumed that the Level 5 automation vehicles would become commercially available in the late 2020s. In the 2060s, AV sales, fleet and travel market penetration rates would be up to 100%, 60% and 80% respectively. Six factors that affect the speed of AV deployment were presented in this article. They were speed of technologies development, testing and regulatory approval, incremental costs of AVs, consumer travel and housing preferences, quality and affordability of AV related service, and public policies.

The industry, such as professional consulting firms and automotive industry experts, has also tried to predict the market penetration rate of CAVs. KPMG (2015) presented an optimistic prediction that by the year 2030, the penetration rate of L3 automation vehicle production would be 100% and the penetration rate of L4 and L5 automation vehicle production would be 25%. Furthermore, the penetration rate of connected vehicle production would reach 100% in 2026. IHS Markit (2016) forecasted annual globally sales of AV would reach 21 million in 2035, with approximately 76 million vehicles with some degree of autonomy being sold by 2035. In the US, the penetration rate of L4 and L5 automation light-duty vehicle sales would reach 5.4% in 2030. PTOLEMUS (2017) predicted that L2 vehicles with partial automation features would comprise the majority of new passenger car sales in 2030. L4 and L5 passenger cars would be commercially available in about 2025 and 2030, respectively.

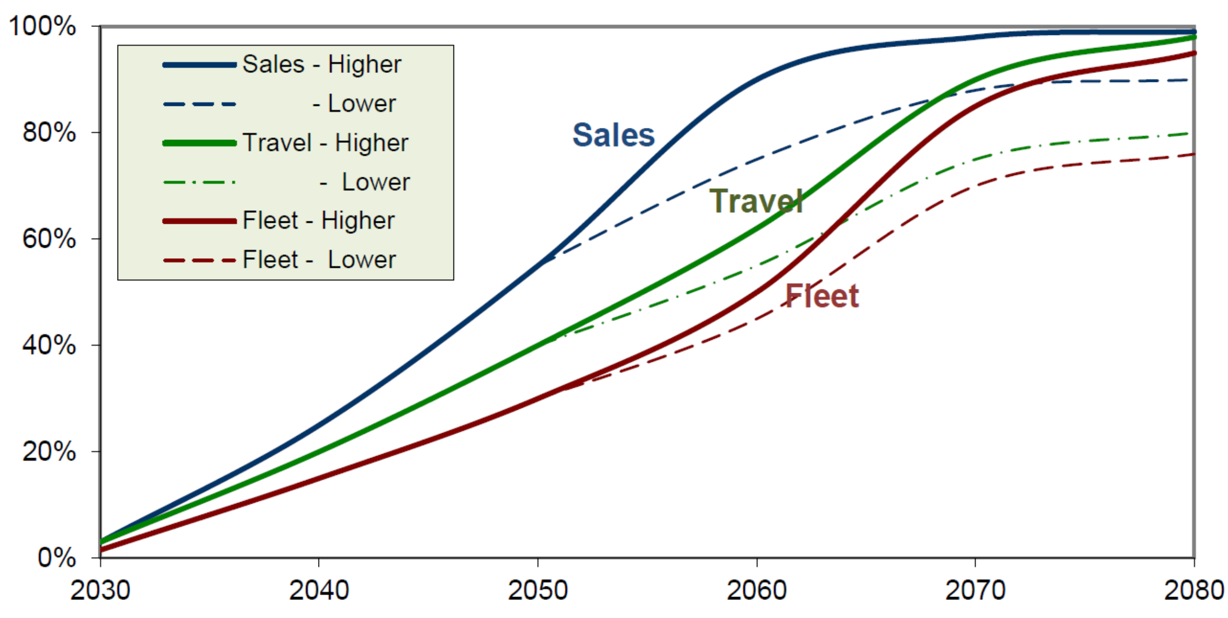


Figure 2-1 Autonomous Vehicle Sales, Fleet and Travel Projections (Litman, 2022)

Table 2-3 Literature Review on the Outlook for Connected and Autonomous Vehicles

Research Entity	Authors	Year	Prediction
Academia	Lavasani et al.	2016	The AV sales will be 1.3 million, 36 million and 83.6 million in 2030, 2040 and 2050, respectively. The AV market would be saturated in 2059, and more than 87 million AVs would be sold.
	Bansal and Kockelman	2017	The market penetration rate of vehicles with full driving automation would be around 24.8-87.2% in 2045, depending on the WTP and vehicle price.
	Talebian and Mishra	2018	Assuming the cost of full automation is $40,000 at 2025, this price would have to drop by 15-20% annually to reach 100% adoption of CAV in 2050.
	Quarles et al.	2021	AV will comprise 36.41% of private vehicle ownership by the year 2050. The VMT from AV will make up around 60% of US VMT in 2050.
	Litman	2022	In the 2060s, AV sales, fleet and travel market penetration rates would be up to 100%, 60% and 80% respectively.
Industry	KPMG	2015	In 2030, the penetration rate of L3 automation vehicle production will be 100% and the penetration rate of L4 and L5 automation vehicle production will be 25%.
	IHS Markit	2016	Annual globally sales of AV would reach 21 million in 2035. In the US, the penetration rate of L4 and L5 automation light-duty vehicle sales will reach 5.4% in 2030.
	PTOLEMUS	2017	L2 vehicles with partial automation features would comprise the majority of new passenger cars sales in 2030. L4 and L5 passenger cars will be commercially available in about 2025 and 2030, respectively.

2.3. Intersection Management

Intersections play a critical role in traffic delays and crashes, as well as traffic emissions. Intersection management is a complex problem that has been consistently studied for over 60 years (Webster, 1958). With the development of CAV technology, more advantages can be gained to advance intersection management.

2.3.1. Fixed-time Signal Control

Fixed-time signal control is the most traditional and widely used control strategy because it is economically competitive and easy to implement. The signal phase and timing of this strategy are predefined and fixed, so it is suitable for intersections with stable traffic demand. And the control plans can be predefined for different traffic situations (e.g., peak, and off-peak). Generally, the fixed-time signal plans are set based on historic traffic data. Due to the fact that traffic demand is unstable most of the time, this strategy is not efficient. Nevertheless, in the field of CAV research, many studies focusing on vehicle control still employed a fixed-time signal control strategy to simplify the research problem.

Wu et al. (2010) applied the simulation-based approach to investigate the energy and emission impacts of a specific CAV application. This CAV application is was advanced driving alert systems (ADAS), and two types of ADAS were proposed in this paper, i.e., stationary ADAS and in-vehicle ADAS. Two-phased fixed-time signal control strategy was employed in the simulation scenarios. Results demonstrated that proposed ADAS could reduce fuel consumption and CO_2 emissions by up to 40%.

Katsaros et al. (2011) proposed a Green Light Optimized Speed Advisory (GLOSA) application to control vehicles passing through fixed-time signal intersections. The fuel and traffic efficiency of GLOSA were proved by a simulation-based approach. Results suggested that the impact on fuel consumption could be noticed when more than 50% vehicles on the road were equipped with GLOSA. In the high traffic density scenario, the benefits could be up to 80% reduction in stop time and 7% reduction in fuel consumption.

Ubiergo and Jin (2016) presented a hierarchical green driving strategy based on the V2I technology. Signal control with fixed time was set up in simulation scenarios and the effectiveness of the proposed strategy was demonstrated. Results showed that by using the proposed vehicle control strategy, about 15% in traffic delay and about 8% in fuel consumption and GHG emissions would be saved.

Tang et al. (2018) introduced a speed guidance strategy aimed at eco-driving on a single-lane road with multiple intersections. Some numerical tests were conducted to investigate the effectiveness of the proposed strategy. Results showed that due to the speed guidance strategy, total fuel consumption was reduced by 13.92% and 16.45% in two scenarios studied in this paper, respectively. Besides, the proposed strategy could also be beneficial to improve traffic efficiency in studied scenarios.

2.3.2. Actuated Signal Control

Actuated signal control was first proposed by Dunne and Potts (1964). Since then, many studies have focused on this topic. This signal control strategy is based on real-time data collected from infrastructure-based sensors (e.g., inductive loops, and cameras). It utilizes some relatively simple control logic, such as green phase extension, gap out, and max out (Eom and Kim, 2020). Compared with the fix-time signal control strategy, the actuated signal control strategy can improve the traffic efficiency to some extent. However, this improvement may not necessarily lead to global optimization in the long run since future traffic conditions are not considered. CAV technology can provide more accurate real-time traffic conditions when compared with traditional sensors. This advantage can be of great benefit to the actuated signal control strategy.

Day and Bullock (2016) statistically analyzed the thresholds for CV market penetration rate that could provide feasible traffic data to implement detector-free optimization in signal control practice. A simulation-like approach was then applied to investigate the performance of the optimized signal on a nine-intersection corridor in Indiana under different market penetration rate scenarios. Results suggested that effective offline optimization with a 3-hour window required only a 1% CV market penetration rate. Moreover, successful offline optimization required only 0.1% penetration rates if using multiple days of data. At least 5% penetration rates were needed for online optimization with 15-min windows.

Day et al. (2017) used vehicle trajectory data collected from a private-sector vendor for two corridors comprising 25 signalized intersections as a proxy for CV data. The CV-like data had penetration rates between 0.09% and 0.80% on the studied corridors. These data were compared with those data obtained from physical detectors on the same corridors and showed statistically significant goodness of fit at a 90% confidence level. These data were then used to optimize the signal plans and compared to those optimized signal plans based on the data collected from physical detectors. Results indicated that these CV-like data could provide good-quality optimized signal plans even with low penetration rates.

2.3.3. Adaptive Signal Control

The adaptive signal control strategy utilizes predicted short-time traffic conditions to optimize the signal adjustments. An accurate and comprehensive traffic detection system is required to obtain the real-time traffic conditions in a network. Additionally, effective prediction algorithms are needed for signal adjustment. These systems (e.g., SCATS, and SCOOT) are mature and have been implemented in many cities. In combination with the CAV technology, these control strategies will gain more advantages.

He et al. (2012) introduced a platoon-based optimization model named PAMSCOD to control arterial signals to deal with the request of multiple travel modes. To identify the platoon, a headway-based platoon recognition algorithm was developed. Considering the platoon information, signal status, and priority requests from special vehicles, the signal control problem was then formulated into a mixed-integer linear program (MILP). The use of platoon rather than individual vehicles made the problem easier to solve by reducing the number of variables. Simulation results showed that, under a 40% penetration rate, PAMSCOD could reduce the overall traffic delay by about 20-30% compared to the transit signal priority (TSP) control plan optimized by SYNCHRO, while the average bus delay increased by only 3%. In addition, the throughput could be increased by more than 10% in congested scenarios.

Beak et al. (2017) proposed an integrated algorithm that consists of two levels of optimization to control the signals on the corridor. The lower level of the model used dynamic programming approach to optimize the SPaT in each intersection. At the higher level, a mixed-integer linear program was developed to solve the optimization problem for the signal offsets along the corridor. The coordination constraint for the lower level optimization was the optimized offsets derived from the higher level. Simulation experiment was then conducted to evaluate the effectiveness of proposed model. Results indicated that, at penetration rates as low as 25%, the average delay and the average number of stops in the coordinated route were still reduced by 6.3% and 3.4% compared to the actuated coordination control strategy. The network performance was more sensitive to the penetration rate than the corridor performance. At the 25% penetration rate, the average network delay and the number of stops increased by 0.72% and 2.56%, respectively, compared to the actuated coordination control strategy.

Liang et al. (2018) developed a real-time traffic signal optimization algorithm in the mixed traffic environment. Platoons were identified with a predetermined headway value using the information obtained from CVs approaching the intersections. SPaT was then optimized with the objective of allowing these platoons pass through the intersection to minimize total vehicle delay. Furthermore, longitudinal trajectory guidance was provided to the leading AV in platoons to control travel behaviors and thus minimize the total number of stops. Comparative simulation tests indicated that the proposed platoon-based algorithm reduced the computational burden by more than 95% with respect to a previous planning-based algorithm. Evaluation tests also showed that traffic performance improved with the increase in CAVs penetration rate. However, after CAVs in the platoon exceeded 40%, the marginal benefits decreased significantly.

2.3.4. Signal Vehicle Coupled Control

Traditionally, signal control and vehicle control have been studied separately, despite the fact that signal control and vehicle control interact with each other. By adopting the CAV technologies, the ability to exchange information between signals and vehicles in real time makes it possible to implement the signal vehicle coupled control (SVCC) strategy. Furthermore, when the CAV penetration reaches 100%, autonomous intersection management has the potential to eliminate the stops in intersections while ensuring safety of conflicting movements (Zhong et al., 2021).

Li et al. (2014) developed an algorithm for a signalized intersection with single-lane through approaches to optimize the signal timing and vehicle trajectories simultaneously based on V2V and V2I technologies. Based on basic constraints such as signal cycle, minimum and maximum green time, all feasible timing plans were enumerated. Considering the minimum average travel time delay (ATTD), the optimal vehicle trajectories were computed, and related signal timing plan were identified. For consecutive vehicles entering the communication areas, a rolling horizon scheme was developed to perform the optimization process over the time horizon.

Two measurements, ATTD and throughput, were used to evaluate the performance of the proposed algorithm. Results showed that this algorithm could reduce the ATTD by 16.2-36.9% and increase the throughput by 2.7-20.2%, compared to traditional actuated signal control.

Sun et al. (2017) developed an innovative intersection operation method named as Maximum Capacity Intersection Operation Scheme with Signals (MCross). To utilize all approaching lanes of a road simultaneously, some unconventional intersection designs were introduced, such as continuous flow intersection (CFI) and tandem intersection (TI). CAVs were grouped as platoons to control their uninterrupted arrival and were assigned to specific lanes according to their destinations. In order to control the SPaT, mobility and safety objectives were then considered in formulating the optimization problems as a multi-objective mixed-integer non-linear programming (MO-MINLP) problem. Numerical results indicated that the proposed method could almost double the throughput of the intersection compared to the conventional signal plan.

Xu et al. (2017) presented an algorithm based on V2I technology to control the SPaT and vehicle trajectory simultaneously. The proposed cooperative algorithm consisted of two components, which are the roadside signal timing optimization and onboard vehicle speed control. The former was used to calculate the optimal signal timing to minimize the travel delay. Based on the signal plans determined in the former, the latter aimed to control the acceleration/deceleration of the vehicle to minimize the energy consumption. Simulation tests were conducted using MATLAD and VISSIM to evaluate the performance of the cooperative algorithm. Results indicated that the proposed algorithm could significantly improve traffic efficiency and fuel consumption by 19.7% and 23.7%, respectively, compared to the actuated signal control algorithm.

Du et al. (2021) proposed a signal vehicle coupled control algorithm considering the mixed traffic environment. The objective of this algorithm was to minimize the total delay as well as the fuel consumption. The performance was evaluated and compared to the traditional CACC control and GlidePath (a classic eco-driving model). Simulation results showed that proposed algorithm could significantly improve the traffic performance at intersections in a mixed traffic environment. The algorithm could save 6-14% in fuel consumption and increase average speed by 1-5% when the CAV penetration rate was greater than 40%.

Table 2-4 Literature Review on the Intersection Management with CAV

Control Strategy	**Author**	**Year**	**Findings**
Fixed-time	Wu et al.	2010	Proposed ADAS can reduce fuel consumption and CO_2 emissions by up to 40%.
	Katsaros et al.	2011	In the high traffic density scenario, the benefits of GLOSA could be up to 80%

			reduction in stop time and 7% reduction in fuel consumption.
	Ubiergo and Jin	2016	By using the proposed vehicle control strategy, about 15% in traffic delay and about 8% in fuel consumption and GHG emissions would be saved.
	Tang et al.	2018	The speed guidance strategy could reduce total fuel consumption by 13.92% and 16.45% in the two scenarios studied in this paper, respectively.
Actuated	Day and Bullock	2016	Effective offline optimization with a 3-hour window required only a 1% CV market penetration rate. Successful offline optimization required only 0.1% penetration rates if using multiple days of data. At least 5% penetration rates were needed for online optimization with 15-min windows.
	Day et al.	2017	These CV-like data could provide good-quality optimized signal plans even with low penetration rates between 0.09% and 0.80%.
Adaptive	He et al.	2012	Under a 40% penetration rate, PAMSCOD could reduce the overall traffic delay by about 20-30% compared to the transit signal priority (TSP) control plan optimized by SYNCHRO, while the average bus delay increased by only 3%. In addition, the throughput could be increased by more than 10% in congested scenarios.
	Beak et al.	2017	At penetration rates as low as 25%, the average delay and the average number of stops in the coordinated route were still reduced by 6.3% and 3.4% compared to the actuated coordination control strategy. However, the average network delay and the number of stops increased by 0.72% and 2.56%, respectively.
	Liang et al.	2018	The proposed platoon-based algorithm reduced the computational burden by more than 95% with respect to a previous planning-based algorithm. The traffic performance improved with the increase in

			CAVs penetration rate. However, after CAVs in the platoon exceeded 40%, the marginal benefits decreased significantly.
Signal Vehicle Coupled	Li et al.	2014	This algorithm could reduce the ATTD by 16.2-36.9% and increase the throughput by 2.7-20.2%, compared to traditional actuated signal control.
	Sun et al.	2017	The proposed method could almost double the throughput of the intersection compared to the conventional signal plan.
	Xu et al.	2017	The proposed algorithm can significantly improve traffic efficiency and fuel consumption by 19.7% and 23.7%, respectively, compared to the actuated signal control algorithm.
	Du et al.	2021	The algorithm could save 6-14% in fuel consumption and increase average speed by 1-5% when the CAV penetration rate was greater than 40%.

2.4. Transit Signal Priority

The main purpose of transit priority is to provide higher quality transit services to the public. The implementation measures include the formulation of policies to prioritize public transportation, the provision of financial subsidies for public transportation, the construction of high accessible public transportation system, and the granting of priority to public transportation on the roads. At the micro level, transit priority generally consists of two categories, namely facility-based design and signal-based control. Facility-based design measures typically ensure transit priority by implementing facilities, including dedicated transit vehicle lanes, bus bays and bus bulbs. Signal-based control strategies generally adjust the signal plan to ensure priority for transit vehicles at intersections, arterials, or networks (Skabardonis, 2000). This report mainly focuses on the control strategies for transit signal priority.

2.4.1. Conventional Transit Signal Priority

As early as 1962, the concept of transit signal priority was introduced and tested in Washington, D.C. (Chada and Newland, 2002). With the development of Intelligent Transportation System (ITS) technology, the TSP has evolved over the decades. Early studies focused on extending green time or reducing red time for buses to cross intersections as quickly as possible (Finger, 1992; Jacobson and Sheffi, 1981; Ludwick and John, 1975; Seward and Taube, 1977). While positive benefits can be identified for buses, competing traffic may experience extra delays. TSP control strategies can be categorized into two types: passive priority and active priority (Sunkari et al., 1995).

2.4.1.1. Passive Priority

In passive priority, priority is given to buses by predetermining the signal plan based on the bus schedule. There are several methods to adjust the signal plans, including adjustment of cycle length, splitting phases, areawide timing plans, and metering vehicles (Lin et al., 2014).

- Adjustment of Cycle Length

In general, a shorter cycle length may reduce the bus delay at intersections since a shorter cycle length can serve more buses over time (Balke, 1998). However, there is a tradeoff between shorter cycle lengths and reduction in total throughput.

- Splitting Phases

Splitting the green time into multiple shorter phases can also reduce the bus wait time by increasing the chances of a bus arriving at the green time. Applying this method does not require shortening the cycle length. However, it may increase the total delay due to the frequent signal phase transitions. Moreover, short phases may not provide sufficient green time for pedestrians to cross the intersection. Based on simulation analysis, Garrow and Machemehl (1999) found that this method can offer more efficiency and reduce the impact on the entire intersection compared to adjustment of cycle length.

- Areawide Timing Plans

Based on the bus travel times, areawide timing plans provide priority for buses by controlling signal offsets in a coordinated signal system. This method is difficult to implement because of the high fluctuation of bus travel time due to boarding and dropping off passengers at bus stops. By using a signal timing optimization program TRANSYT-7F, Skabardonis (2000) developed a passive priority strategy to optimize the traffic performance in favor of buses on a major arterial with 21 signalized intersections. Simulation results indicated that the proposed strategy reduced bus delays by 14%. Stevanovic et al. (2008) combined genetic algorithm (GA) and TRANSYT-7F to optimize the offline signal timing plans with transit priority settings. Simulations were performed to evaluate the effectiveness of this GA-based signal optimization program on an urban corridor with transit operations. Results indicated that the proposed program could improve overall traffic performance.

- Metering Vehicles

This method provides priority to buses by restricting other traffic, such as passenger cars, from entering congested areas. While the reliability and efficiency of transit can be guaranteed, other traffic may experience significant delays. This disadvantage makes it difficult to be applied in urban road networks.

The cost of implementing passive priority is low, as no extra hardware or software investment is required beyond the normal equipment. However, effective passive priority requires a determined transit arrival time or a high transit demand environment. Such strict application conditions have limited the research and popularity of this control strategy.

2.4.1.2. Active Priority

This control strategy applies TSP only when the transit vehicles are approaching the intersection. In the traditional active priority strategy, sensors needed to be installed upstream of the intersection to detect the arrival of transit vehicles. In general, there are four types of active priority methods that have been most widely used: phase extension, early start, special phase, and phase suppression (Sunkari et al., 1995). Each of these methods is detailed below.

- Phase Extension

This method is applied when a transit vehicle is detected arriving at the intersection at the end of a green phase. The green time will be extended until the transit vehicle crosses the intersection or the predefined maximum green extension is reached. The maximum green extension is determined to prevent excessive disruption to conflicting traffic.

- Early Start

Early Start (or Red Truncation) is adopted when the transit vehicle is detected arriving at the intersection during a red phase. The red phase will be truncated, the priority green phase will start earlier in the cycle, and the green time of other non-priority phases may be shortened. This method can also be used to clear long queues before the arrival of transit vehicles, so they do not have to wait in line.

- Special Phase

When a priority request is made, a special phase favoring the transit vehicle will be inserted into the normal phase sequence. This special phase is generally very short and can be inserted at any point in the cycle.

- Phase Suppression

With Phase Suppression, some non-priority phase with low demand may be skipped to facilitate the transit priority phase.

In addition, there is a concept of compensation in the active priority signal control strategies. Extra green time can be added to the non-priority phases as compensation to keep traffic on the non-priority approaches from deteriorating as a result of granting transit priority. The methods mentioned previously can be adopted individually or in combination, which is very flexible and depends on the application scenario.

Based on computational complexity, the active priority strategies can be further categorized into rule-based priority and model-based priority (Imran et al., 2021).

2.4.1.2.1 Rule-based Strategy

This strategy generally grants priority for transit vehicles based on some predefined logics, which are developed according to the presence of transit vehicles, headway adherence, and duration of lateness. Rule-based strategies are relatively simple and have a relatively low computational burden, which makes them widely used in practice.

Ludwick and John (1975) introduced an unconditional TSP strategy to grant the priority based on the presence of transit vehicles at signalized intersections. If a bus was detected arriving at the end of the green phase, the green time would be extended by 10-20s to clear the detected bus. This strategy was validated via simulation experiments under different traffic configurations. Results showed that the proposed strategy with 10s green time extension could save 20% of bus travel time while only causing a 7% increase in cross street traffic travel time, even with a half-minute headway frequency. However, with the development of public transit, the signal control agency may receive multiple priority requests at the same time. A basic policy to address this issue is first-come-first-serve (FCFS). The agency responds to the request once at a time in sequence and ignores other requests until the served transit vehicle crosses the intersection (Francois and Hesham, 2005; Muthuswamy et al., 2007). Meanwhile, alternative solutions for multiple request scenarios have been proposed (Kim et al., 2005; Lin et al., 2013; Tlig and Bhouri, 2011).

As the TSP study evolved, researchers found that granting priority to all transit vehicles without considering other traffic on the road could result in serious degradation of overall traffic performance. In order to mitigate the negative impact of TSP on other traffic, several basic rules were introduced.

1. The performance of non-priority traffic cannot be severely degraded after adopting TSP.

2. On a coordinated arterial, the adoption of TSP cannot disrupt the designed signal progressions or cause overflow at the downstream intersections.

3. The TSP cannot frequently disrupt the phase sequence as the change in the phase sequence may confuse drivers.

4. Only the transit vehicle that is behind schedule can be granted priority.

5. For multiple priority requests, the transit vehicle being served should be determined based on the delay of each transit vehicle.

With the development of advanced signal control and traffic sensor technologies, more sophisticated active priority control strategies with consideration of overall traffic performance emerged in the 1990s. Bowen et al. (1994) first integrated TSP control into the split cycle offset optimization technique (SCOOT), a mature adaptive signal control system. Simulation results indicated that it is feasible to provide bus priority in SCOOT. After that, TSP control was also added into other well-known adaptive signal control systems, such as Sydney coordinated adaptive traffic system (SCATS), real-time advanced priority and information delivery (RAPID), and balancing adaptive network control method (BALANCE).

Balke et al. (2000) summarized the limitations of TSP applied along an arterial and proposed a comprehensive bus priority control framework to solve this problem. Four basic modules were introduced according to the functional requirements, i.e., arrival time prediction module, priority assessment module, strategy selection module, and strategy implementation module. Simulation tests were performed under three volume-to-capacity levels: 0.5, 0.8, and 0.95. Results suggested that the proposed TSP approach could significantly reduce the bus travel time at all three levels while resulting in only minor decreases in overall traffic delay at moderate traffic levels (volume-to-capacity less than 0.9).

Skabardonis and Geroliminis (2008) proposed an active priority control strategy to grant the priority based on real-time estimation of travel time and the bus arrivals along the arterials. This strategy tried to minimize the adverse impacts on competing traffics while favoring efficient bus operations through aforementioned active priority methods at unsaturated intersections, taking into account queuing, headway adherence, remaining green time and progress of bus routes.

2.4.1.2.2 Model-based Strategy

In a model-based strategy, priority is granted to specific transit vehicles based on a model that optimizes certain traffic performance criteria. The most commonly used criteria have been passenger delay and vehicle delay. Using the actual traffic conditions as input and minimization of passenger/vehicle delays as the objective, the models calculated the optimal signal timing plans (Christofa et al., 2013; Christofa and Skabardonis, 2011; Han et al., 2014; Head et al., 2006; Liao and Davis, 2007; Yu et al., 2017).

Head et al. (2006) developed an optimization model to handle multiple priority requests based on the traditional North America traffic signal controller. The objective of the model was to minimize the total delay for all the requesting vehicles (not all vehicles). A relatively simple example was presented in the paper, and the results showed that the proposed model can perform better than FCFS in terms of multiple priority requests.

Christofa and Skabardonis (2011) proposed a real-time, traffic-responsive TSP system aimed at managing multiple priority requests from conflicting transit routes while minimizing the negative impacts on other traffic. In order to grant priority equitably, the optimization model minimized the total person delay by considering the passenger occupancy of both passenger cars and transit vehicles in the network. Meanwhile, it can also assign priority to the approaches with long queues to reduce the negative impact on other traffic. The simulation test for this system was conducted on a complex signalized intersection in Greece. Results showed that the total person delay for all passengers and bus passengers was reduced by 9.5% and 35.5%, respectively, compared to the vehicle-based optimization results. In the meantime, the delay for passengers in other vehicles increased by only 2.8%.

There are also TSP studies that focused on ensuring the reliability of transit service, such as transit schedule adherence. Ma et al. (2010) developed a TSP control strategy with the optimization model to minimize the bus headway deviation. Unlike studies that focused on minimizing traffic delays, the optimization model in this paper generated the optimal combination of two priority strategies (increase and decrease bus delay strategies) to ensure that the buses traveling along the corridor adhere to the bus schedule. A corridor with four signalized intersections in China was selected as the test bed to evaluate the proposed coordinated and conditional bus priority (CCBP) strategy. Compared with the no priority and unconditional priority, CCBP could reduce bus headway deviation to guarantee the reliability of bus service while not greatly reducing delays of other traffic.

Instead of considering a single traffic performance criterion, some model-based TSP strategies used a weighted summation of various criteria as the optimization objective to reflect the weights of different traffic performances (Han et al., 2014; Xu et al., 2019; Ye and Xu, 2017).

Han et al. (2014) formulated the adaptive TSP strategy into a quadratic programming problem and the global optimization results were solved by MATLAB. The objective function of this optimization problem was the sum of the weights of bus delay and average traffic delay, where the appropriate weights were determined by sensitivity analysis. In the case study, VISSIM was used to evaluate the performance of the proposed strategy on a 7.4 km corridor in Edmonton, Alberta. Results showed that the proposed strategy significantly outperformed the conventional active TSP strategy in reducing bus delay while balancing the services of the non-TSP approaches.

Xu et al. (2019) developed a bi-level optimization model to solve the problem of multiple priority requests on the corridors. The upper level controlled the signal phases between every two adjacent bus stops to maximize the green bandwidths. The lower level controlled intersections on the corridor, and its optimization objective was to minimize the weighted sum of in-bus passenger delay and passenger waiting delay at the downstream stop. The proposed optimization model was solved by using hybrid genetic algorithm and tested by simulation approach. Three other models were used to conduct the performance comparison, i.e., baseline model without TSP, model 1 with regular TSP and the classical coordination, model 2 with low level and the classical coordination. Results indicated that proposed model could significantly reduce the average delay and stops for buses compared to those three models. Moreover, the advantage of the proposed model over other models increased with the increase of traffic demand.

2.4.2. Transit Signal Priority with Connected and Autonomous Vehicle

Recently, researchers are incorporating CAV technology to advance the TSP control strategies. Hill and Garrett (2011) stated that combining CV technology with TSP (TSPCV) is a key application of CV technology that will greatly enhance mobility and safety. The USDOT has also included TSPCV in its list of high-priority applications and development approach. In general, there are three ways to improve the transit signal priority control: enhancing the arrival time prediction accuracy, extending the TSP logic library, and improving the priority selection algorithm (Hu et al., 2014). Among them, the most fundamental problem has been to accurately predict the trajectory of transit vehicle. With the emergence of CAV technology, real-time information such as vehicle trajectory can be easily obtained (Yang et al., 2019; Zeng et al., 2015; Zeng et al., 2021).

Zeng et al. (2015) utilized the advantage of CV technology and proposed a TSP control optimization model. The objective of this model was to minimize the total person delay during the planning period. Since real-time vehicle speed, location, and the number of passengers on board were available by using CV technology, it was possible to calculate the person delay for every vehicle traveling through the intersection more accurately, which provided a more reliable basis for optimization. The performance of proposed model was evaluated using the simulation approach. Compared with the signal plans optimized by SYNCHRO, the proposed model reduced the bus passenger delay by 39%, 49%, and 30% with one, two, three conflicting bus routes, respectively. Meanwhile, person delays in other vehicles decreased by 8-11%. Moreover, the proposed model could perform well even at the CV penetration rates as low as 30%.

Zeng et al. (2021) proposed two types of real-time TSP optimization models, i.e., intersection-based optimization model and route-based optimization model. The objective of these models was to minimize the timing and progression deviation along the route. For simplicity, both models were formulated as mixed integer linear models without considering the uncertainty of the bus travel time. Instead, the models were continuously formulated and re-solved utilizing real-time travel data obtained via CV technology to account for the uncertainty of bus travel times. Considering various cycle lengths and different definition of progression deviations, five variants of proposed models were derived and tested in a simulation environment. Results suggested that the route-based model could reduce the progression deviation by as much as 98%, while causing as little as 5.5% increase in delay to other traffic. In contrast, the intersection-based model could not provide as many benefits for buses yet cause more negative impacts on other traffic.

With the explosion of machine learning (ML) and artificial intelligence (AI), some researchers have integrated data-driven approaches into TSP control strategies in recent years (Ghanim and Abu-Lebdeh, 2015). This trend was facilitated by the availability of real-time big data along with the rapid development of CAV technology.

Chow et al. (2021) refined their previous works (Chow and Li, 2017; Chow et al., 2017) using the reinforcement learning (RL) approach to manage the adaptive signal controller to improve bus service reliability on the corridor. By approximating the relationship between the traffic control variables and the corresponding states and system performances, RL techniques can address the curses of dimensionality when solving optimization problems on large networks in real time. The proposed RL signal controller was tested using a real-world configuration on a corridor with five intersections in London, UK. Results indicated that proposed model could significantly reduce the traffic delays and bus progression deviations. Meanwhile, compared with the simple linear regression model used in other studies such as (Cai et al., 2009), this model was more effective when applied to adaptive traffic controller because of the shorter computational time.

Additionally, with the adoption of CAV technology, SVCC can be implemented to improve the TSP control strategy. This kind of control strategy could guide transit vehicles to travel at a specific speed while adjusting the SPaT for better optimization (Hu et al., 2015, 2016; Seredynski et al., 2015; Wu et al., 2016).

Hu et al. (2015) proposed a person-delay-based optimization model to control both the transit vehicle and signals in a CV environment and to coordinate signals along the corridor. The vehicle/signal cooperation provided another perspective for solving the optimization problem. The coordination feature took the mobility benefits of all intersections along the corridor into consideration. With minimizing average person delay as the objective, the problem was formulated as a Binary Mixed Integer Linear Program (BMILP) and solved using the classical branch-and-bound approach. In addition, priority was granted only when the bus was behind schedule. Both analytical and simulation results indicated that the proposed model overperformed the conventional TSP and TSP with CV, and there was no statistically significant negative impact when the volume-to-capacity ratio was less than 1.0.

Wu et al. (2016) developed an optimization model to control not only the signal timings and bus speed, but also the dwell time at bus stops. The objective of this model was to minimize the average vehicle delays, including bus delays and competing traffic delays at isolated intersections, while in the meantime controlling the buses to pass the intersection without stopping. Numerical experiment showed that proposed model outperformed the models without TSP, TSP only, and TSP with controlled bus dwell time while causing little negative impact on general traffic. Compared with the three base models, the proposed model could reduce the average delay by 54%, 24.2%, and 32.6% and the average number of stops by 88.2%, 83.6%, and 72.9%, respectively. Sensitivity analyses demonstrated that the proposed model has the potential for real world application, as it was effective in different traffic conditions.

Table 2-5 Literature Review on Transit Signal Priority

TSP Type	Author	Year	Control Object	Research Object	Performance Measurements
Passive TSP	Jacobson & Sheffi	1981	Signal	Intersection	Total person delay
Active TSP	Bowen et al	1994	Signal	Network	Total passenger delay
Passive TSP	Skabardonis	2000	Signal	Corridor	Bus delay
Active TSP	Balke et al.	2000	Signal	Corridor	Bus travel time; Total delay; Approach delay
Active TSP	Kim et al.	2005	Signal	Network	Travel time; Bus headway; Speed
Active TSP	Head et al.	2006	Signal	Intersection	Total delay
Active TSP	Muthuswamy et al.	2007	Signal	Corridor	Travel time
Passive TSP	Stevanovic et al.	2008	Signal	Corridor	Person delay; Bus delay; Total delay; Total travel time; Number of stops; Throughput
Active TSP	Skabardonis & Geroliminis	2008	Signal	Corridor	Average bus delay; Average vehicle delay; Average person delay
Active TSP	Tlig & Bhouri	2011	Signal	Network	Total bus delay; Headway deviation
Active TSP	Christofa & Skabardonis	2011	Signal	Intersection	Total person delay; Bus passenger delay; Auto

					passenger delay
Active TSP	Lin et al.	2013	Signal	Corridor	Headway deviation; Bus passenger delay; Total person delay
Active TSP	Han et al.	2014	Signal	Corridor	Weighted sum of bus delay and average traffic delay
TSP with CAV	Zeng et al.	2015	Signal	Intersection	Total person delay
TSP with CAV	Hu et al.	2015	Signal and Bus	Corridor	Bus delay; Total delay
TSP with CAV	Wu et al.	2016	Signal and Bus	Intersection	Average bus delay; Average number of bus stops
Active TSP	Xu et al.	2019	Signal	Corridor	Weighted sum of in-bus passenger delay and passenger waiting delay at the downstream stop
TSP with CAV	Zeng et al.	2021	Signal	Corridor	Progression deviation; Bus delay; Passenger car delay
TSP with CAV	Chow et al.	2021	Signal	Corridor	Total delay; Schedule deviation; Headway deviation

2.5. Summary

A comprehensive review and synthesis of the current state-of-the-art and state-of-the-practice of historical research related to connected and autonomous vehicle technology, intersection management, and trasit signal priority control have been discussed and presented in the preceding sections. This is intended to provide a solid reference and assistance for formulating analysis methods for the impact of connected and autonomous vehicles on signalized intersections with transit signal priority and for developing effective simulation strategies for future tasks.

Chapter 3. Methodology

Since Foy et al. (1992) introduced genetic algorithm (GA) to optimize the SPaT, this approach has been extensively studied and has become one of the classical optimization methods in the area. Noting that many more sophisticated optimization methods have been proposed over the years, this research uses GA as a representative or baseline for these methods. A list of variables used in this paper is summarized in Table 3-1.

Table 3-1 List of Important Variables

Notation	Description
P_c	Probability of crossover
P_m	Probability of mutation
a	Private car index
b	Bus index
i	Vehicle index
j	Phase index
k	Cycle index
m	Travel direction index
A	Current car set at each decision time
B	Current bus set at each decision time
o_a	Passenger occupancy of car *a*
o_b	Passenger occupancy of bus *b*
$d_{a,k}$	Delay of car *a* in cycle *k*
$d_{b,k}$	Delay of bus *b* in cycle *k*
t_i	Time for vehicle *i* to reach the stop line
L_i	Distance to stop line for vehicle *i*
h_i	saturation headway for vehicle *i*
l_i	Vehicle length for vehicle *i*
gap_i	Minimum gap when vehicle *i* is stopped
d_i	Delay for vehicle *i*
g_j	Green time for phase *j*
w_i	Cumulative waiting time for vehicle *i*
$t_{j,k}$	Time between the start of optimization and the start of phase *j* in cycle *k*
$t_{j,k+1}$	Time between the start of optimization and the start of phase *j* in cycle *k*+1
v_i	Free-flow speed for vehicle *i*
q_m	Maximum queue length in travel direction *m*

3.1. Genetic Algorithm

GA is a meta-heuristic algorithm inspired by the natural selection process to efficiently search for optimal or near-optimal solutions (Holland, 1992). A genetic algorithm consisting of three basic components is used in this project.

3.1.1. Encoding and Decoding

Encoding refers to the use of chromosomes to symbolize traffic signal timing decision variables. Decoding is a reverse process of encoding, which refers to the process of translating these decision variables from chromosomes. Decision variables are the duration of green time for each phase.

3.1.2. Fitness/Evaluation

Each chromosome is decoded and sent to the fitness function to obtain the corresponding fitness value for the selection process. Elitism is a widely used selection process which is adopted in this project. For the problem being considered here, the objective of the fitness function is to minimize the total person delay at the intersection. The calculation method of the total person delay is described in detail in the next section.

3.1.3. Reproduction, Crossover, and Mutation

These three manipulations are used to produce new generations. Reproduction process copies elite chromosomes to produce new generations. During crossover, the elite chromosomes exchange their genetic materials with a predefined probability P_c. The mutation is conducted by selecting a random bit on the offspring's chromosome and then changing the value. The likelihood of mutation occurring on a given chromosome is determined by the probability P_m (Teklu et al., 2007).

3.2. Objective Function

The objective of this study is to minimize the total person delay of an isolated intersection. The objective function is given in equation 1.

$$\min \sum_{a=1}^{A} o_a d_{a,k} + \sum_{b=1}^{B} o_b \, d_{b,k} \tag{1}$$

The passenger occupancy of each vehicle can be obtained via CV technology. The most important part of this function is the accurate estimation of vehicle delay. Existing studies mainly used three kinds of approach to estimate the vehicle delay, i.e., Highway Capacity Manual (HCM) approach (Ghanim and Abu-Lebdeh, 2015), Webster's delay formula (Christofa et al., 2013), and individual vehicle trajectory-based delay estimation models (Hu et al., 2015; Yang et al., 2019; Zeng et al., 2015). The last type is a more delicate estimation approach but requires a large amount of real-time traffic data. However, in CV environment, these data are easily available.

In this research, a vehicle delay estimation model is developed accordingly. A simplified delay calculation method is used in this model. During the delay calculation process, not only the current cycle but also the next cycle is considered. In this way, the probability of myopic optimization results will be reduced. The individual vehicle delay is categorized into two types: (a) delay of vehicles that are already stopped and queuing before the stop line at the optimization time step, and (b) delay of vehicles that are still approaching the intersection at the optimization time step.

3.2.1. Queuing Delay

The queuing delay is calculated as follows. Based on the position of queuing, stopped vehicles can be divided into two groups:

Queuing 1. The vehicle *i* that can leave the stop line during the corresponding green time of the current cycle *k*.

Queuing 2. The vehicle *i* that cannot leave the stop line during the corresponding green time of the current cycle *k*.

First of all, the time for stopped vehicle *i* to reach stop line is calculated with equation 2.

$$t_i = (L_i * h_i)/(l_i + gap_i) \tag{2}$$

The delay for vehicles in Queuing 1 can be calculated with equation 3.

$$d_i = w_i + t_i + t_{j,k} - L_i/v_i \tag{3}$$

The delay for vehicles in Queuing 2 can be calculated with equation 4.

$$d_i = w_i + t_i + t_{j,k+1} - g_j - L_i/v_i \tag{4}$$

3.2.2. Delay for Approaching Vehicles

Based on the time that vehicle *i* arrives at the stop line, the delay for approaching vehicles can be divided into three groups. The arrival time of vehicle *i* is calculated by considering the vehicle speed and the maximum queue length for the corresponding travel direction.

Arrival 1. The vehicle *i* that reaches the stop line before the corresponding green start of the current cycle *k*.

Arrival 2. The vehicle i that reaches the stop line during the corresponding green start of the current cycle k.

Arrival 3. The vehicle i that reaches the stop line after the corresponding green end of the current cycle k.

For vehicles in Arrival 1, the delay can be calculated with equation 5.

$$d_i = t_{j,k} + q_m - t_i \quad (5)$$

For vehicles in Arrival 2, the delay is zero.

For vehicles in Arrival 3, the delay can be calculated with equation 6.

$$d_i = t_{j,k+1} + q_m - t_i \quad (6)$$

3.3. Control Logic

This research uses Simulation of Urban MObility (SUMO) as the simulation platform to evaluate the traffic performance of proposed TSPCV control strategies. SUMO is an open-source software and one can use Python to control the simulation loop through Traffic Control Interface (TraCI) provided by SUMO. The control logic is presented in Figure 3-1. The control horizon is set for every half cycle so as to capture vehicle trajectory data as comprehensively as possible during the control process.

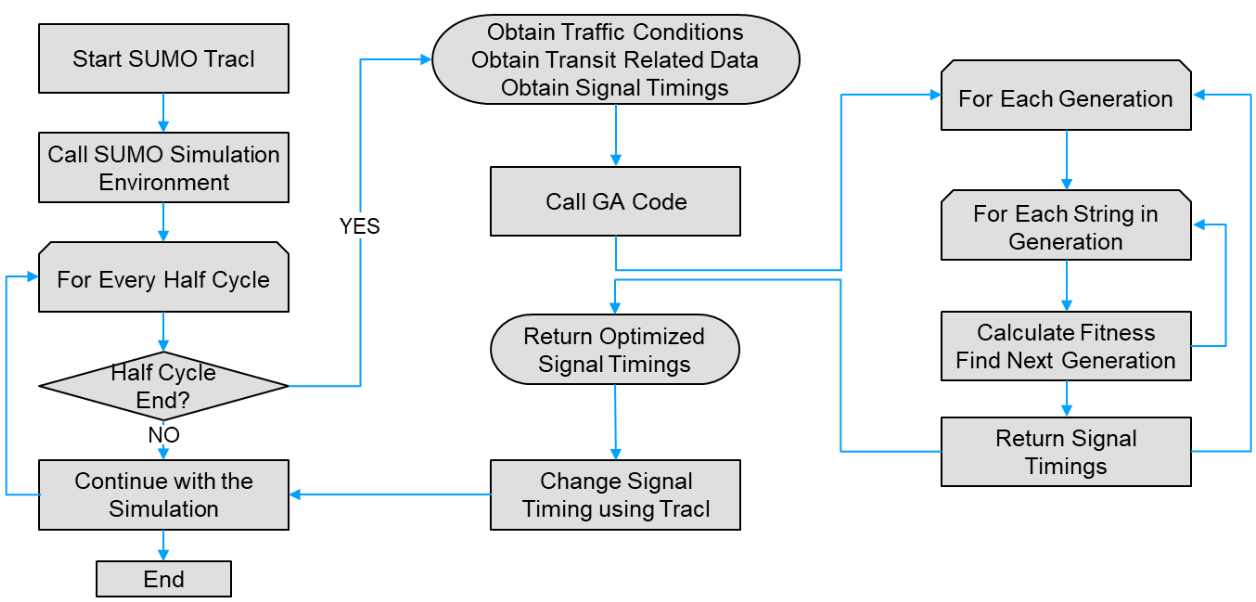


Figure 3-1 Flowchart for Optimization Process and Simulation Environment Integration

The optimization and signal control process is triggered at the end of each half cycle. Through TraCI, all the required data are obtained from the simulation environment, including vehicle locations, speeds, types, and signal timing parameters, etc. These data are passed along to the GA optimizer. The optimizer then finds an optimal or near-optimal signal timing plan by minimizing the total person delay calculated based on the delay estimation model. The optimized signal timing solution is returned to the simulation environment and used to control the signal phase and timing in the next half cycle. This process is iterated every half cycle until the end of the simulation experiment.

Chapter 4. Simulation Framework

4.1. Traffic Configuration

The test intersection is a real-world four-approach intersection of Central Avenue and Eastway Drive located in Charlotte, North Carolina, as shown in Figure 4-1. Each approach has four lanes. On the south-north street, there are two lanes for through traffic, one for left-turn traffic, and one for right-turn traffic. On the east-west street, there are two lanes for left-turn traffic, one for through traffic, and one for both through and right-turn traffic. Bus lines travel southbound and northbound. The bus arrival frequency depends on the scenario settings. The signal control strategy is varied in different scenarios, which will be described in the next section. The yellow time is 3 seconds and the red clearance time is 2 seconds. The traffic volume for each travel direction is listed in Table 4-1. The speed limit is 45 mph for the south-north street and 35 mph for the east-west street.

Figure 4-1 Layout for the Test Intersection

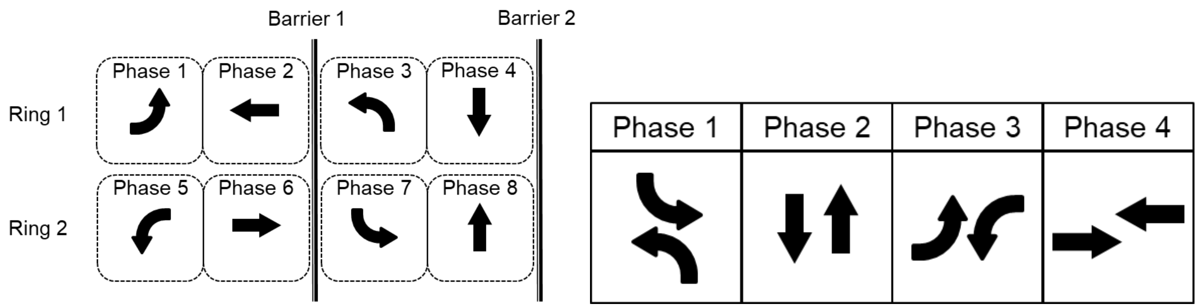
Table 4-1Traffic Volume of Each Travel Direction, veh/h

Time period	SB			WB			NB			EB		
	R	T	L	R	T	L	R	T	L	R	T	L
PM Peak	176	793	88	68	341	206	325	883	180	193	547	246
Off-peak	152	707	36	40	319	235	122	541	138	128	197	91

Note: SB=southbound; WB=westbound; NB=northbound; EB=eastbound; R=right turn; T=Through, L=Left turn.

4.2. Simulation Settings

The car following model used in the simulation is the IDM (Treiber et al., 2000), a model that has been widely used to simulate the CVs and also performs well for simulating human driving vehicles (HDVs). For simplicity, the passenger occupancy of the car is assumed to be 1.5 passengers per vehicle. Bus occupancy is also set to be constant but varies depending on the experimental settings. Based on different signal control strategies, five basic simulation environments are established. More specific scenarios are then developed taking into account the traffic demand, bus occupancy, and CV market penetration rate. Each scenario runs twenty times with a simulation time of one hour. The basic simulation environments and the corresponding signal control strategies are detailed as follows.



(a) Ring-and-barrier Phase Program (b) Stage-based Phase Program

Figure 4-2 Signal Phase Program Used in the Research

Environment 1. Actuated Signal Control without TSP (NTSP)

In this environment, the signal control strategy is fully actuated signal control. A typical National Electrical Manufacturers Association (NEMA) phase diagram is adopted, with the phase sequence shown in Figure 4-2(a). The minimum and maximum green time are set in accordance with the signal controller timing plan obtained from the Charlotte Department of Transportation. The buses and cars are HDVs.

Environment 2. Actuated Signal Control with TSP Using the Traditional Detector (ATSP)

In this environment, the bus detectors are placed 100 meters before the stop line in the south and north approaches. When there is a bus cross the detector, the signal will be switched to the corresponding phase. Otherwise, the SPaT is the same as that in Environment 2. The buses and cars are HDVs.

Environment 3. Actuated Signal Control with TSP Using CV (ATSP-CV)

Buses in this environment are CVs and no bus detector is installed. When a bus approaches the intersection within 100 meters, the signal will be switched to the corresponding phase. Otherwise, the SPaT is the same as that in Environment 2. The cars are HDVs.

Environment 4. Optimized Signal Control with TSP Using GA (TSP-GA)

The stage-based signal phase shown in Figure 4-2(b) is adopted in the GA optimization. The decision variable is the duration of green time for each phase. The minimum green time for the left turn phases is 6 seconds and for the through phases it is 12 seconds. The maximum green time is 20 seconds for the left turn phases and 35 seconds for the through phases. Accordingly, the cycle length ranges from 56 seconds to 130 seconds. Buses are CVs, and the MPR of cars varies from 20% to 100% in 20% intervals.

For the parameters related to the genetic algorithm, the maximum generation is set to 250, the population size is 20, the probability of mutation is 0.7, and the probability of crossover is 0.7. Elitism is applied to retain the best solution in a generation.

Chapter 5. Results and Discussions

The average delay is used as the performance index to evaluate the traffic performance of each scenario.

5.1. Performance Evaluation

5.1.1. Average Delay in Major Scenarios

The performance of four major scenarios with different signal control strategies are compared. The performance of NTSP is used as the baseline. In these scenarios, the bus occupancy is 30 passengers per vehicle, and the bus arrival frequency for southbound and northbound is five minutes.

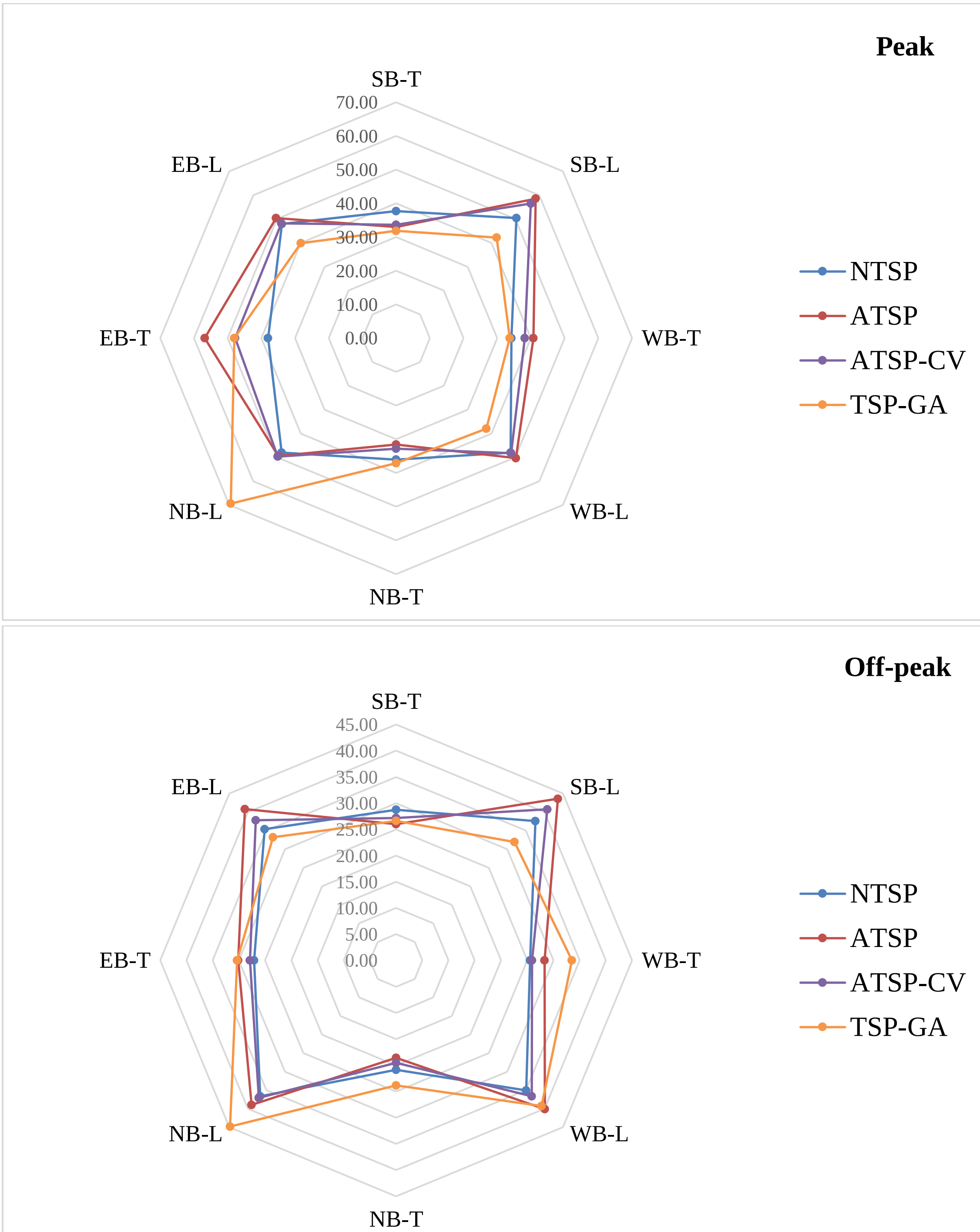
As shown in Table 5-1, the average bus delays for both ATSP and ATSP-CV scenarios are very low. Compared to the baseline, the average bus delays for these two scenarios during the peak hour decrease by 54.31% and 63.36%, respectively. Meanwhile, the average car delays during the peak hour increase by 7.54% in ATSP scenario and 2.46% in ATSP-CV scenario. A similar trend can be observed under the off-peak condition, with even better performances in terms of the average car delay. In addition, the comparison of the two actuated control strategies with TSP indicates that the CV technology offers a better performance than just using traditional fixed detectors to sense bus arrivals. As for the TSP-GA scenario, the average bus delay decreases by 24.50% and the average car delay increases by 2.58% during the peak hour. The average bus delay is reduced by 23.50% and the average car delay increases by 8.88% during the off-peak hour. These results shows that the GA optimization with TSP performs better in peak hours than in off-peak hours.

Table 5-1 Comparison of Average Vehicle Delay in Major Scenarios

Period	Vehicle Type		NTSP	ATSP	ATSP-CV	TSP-GA
Peak	Bus	Average Delay (s)	40.73	18.61	14.92	30.75
		Delay Change		-54.31%	-63.36%	-24.50%
	Car	Average Delay (s)	35.36	38.02	36.23	36.27
		Delay Change		7.54%	2.46%	2.58%
Off Peak	Bus	Average Delay (s)	28.93	13.73	11.11	22.13
		Delay Change		-52.52%	-61.60%	-23.50%
	Car	Average Delay (s)	25.66	26.00	25.40	27.94
		Delay Change		1.33%	-1.02%	8.88%

The detailed impacts for these four major control strategies on average car delays of each travel direction are shown in Figure 5-1. Compared to the baseline scenarios, the average car delays in ATSP and ATSP-CV scenarios increase in all conflicting travel directions. Eastbound through is the direction with the largest increase in terms of the average car delay, increasing by 49.56% in ATSP scenario and 25.72% in ATSP-CV scenario during the peak hour. During the off-peak hour, average car delays in conflicting directions still increase for the ATSP and ATSP-CV scenarios, but by a smaller percentage than during the peak hour. The increases for ATSP and ATSP-CV range from 6% to 16% and 1% to 8%, respectively. In the TSP-GA scenario, compared to the baseline during the peak hour, average car delays are reduced by 15-20% in almost all left turn directions, except for a 44.37% increase in the northbound left turn. This is understandable, as the traffic demand for northbound left turn is more than twice that of southbound left turn. As for the through traffic, the average car delay is reduced by 15.50% in southbound and increases by 26.38% in eastbound. The average car delays of other through traffic remain roughly the same as the baseline. In the TSP-GA scenario during the off-peak hour, average car delays decrease only in southbound through, southbound left, and eastbound left. The average car delays of other travel directions increase by ranging from about 12% to 30%.

These results imply that under high traffic demand conditions, GA optimization with TSP control strategy has the potential to provide conditional priority to buses while minimizing the negative impact on conflicting traffics. Under low traffic demand conditions, fully actuated signal control with TSP using CV technology has the best performance in terms of average delay. Note that the longer the cycle length, the larger the average delay will be. The actuated control strategy used in this study is very flexible since we only focused on isolated intersections. When it comes to coordinated actuated signal control scenarios, things can change significantly because the cycle length will be fixed. For example, according to the Charlotte Department of Transportation, at this test intersection, the cycle length is 130 seconds in order to achieve coordinated signal control.



Note: SB=southbound; WB=westbound; NB=northbound; EB=eastbound; T=Through, L=Left turn.

Figure 5-1 Average Car Delays of Each Travel Direction in Major Scenarios

5.1.2. Average Delay in Mixed Traffic Scenarios

The impacts of different CV market penetration rates on GA optimization with TSP control strategy is investigated. Five scenarios are designed for each of the peak hour and off-peak hour traffic demand conditions, with MPRs ranging from 20% to 100% and at intervals of 20%. Other scenario settings are the same as before. Figure 5-2 shows that, as the MPR increases, the average delays of both buses and cars decrease. During the peak hour, the average bus delay is less than the baseline, even with the MPR being as low as 20%. During the off-peak hour, the average bus delay is less than the baseline when the MPR reaches 40%. These results suggest that the proposed algorithm can provide priority to buses at low rates of CV market penetration and can be more effective in high traffic demand conditions.

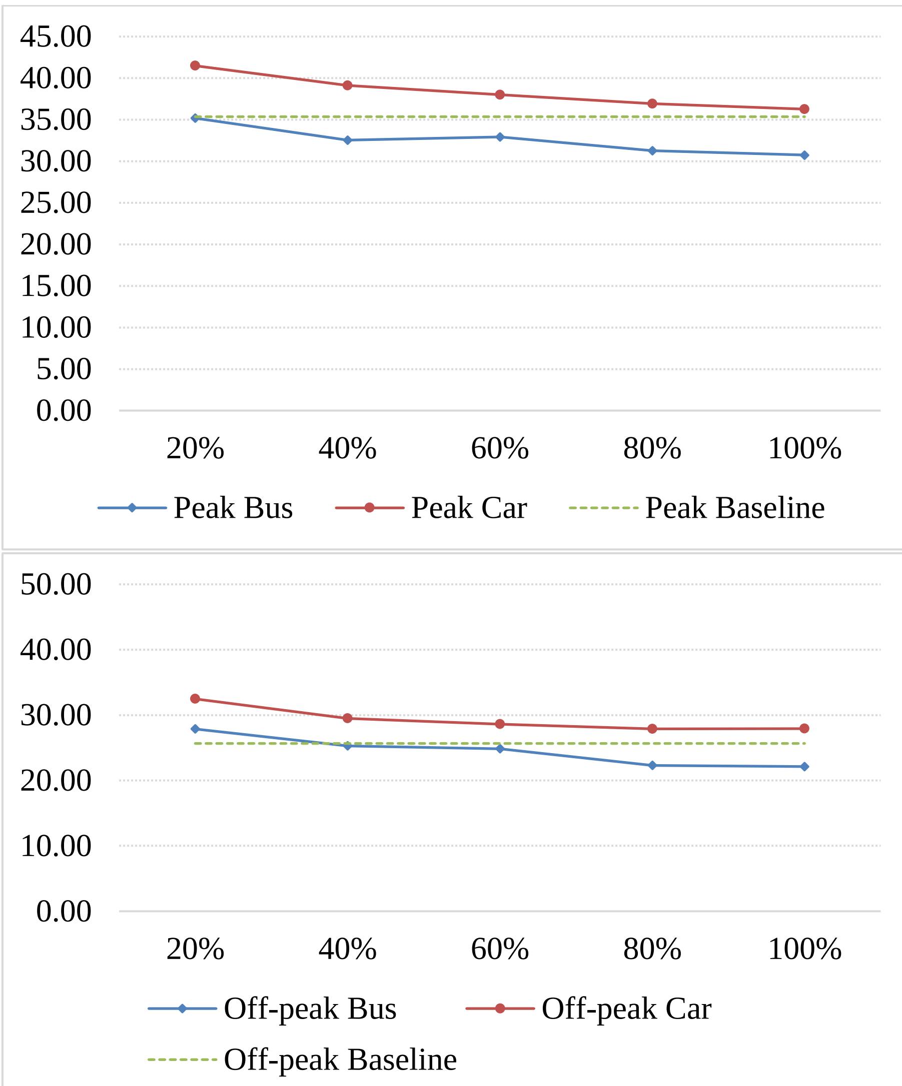


Figure 5-2 Average Delays in Different CV Market Penetration Rates

5.2. Sensitivity Analyses

5.2.1. Bus Occupancy

The bus occupancy can be easily obtained via CV technology and is varied in real-world. This study investigates the sensitivity of proposed GA optimization algorithm to the bus occupancy. Except for bus occupancy, other scenario settings are the same as the major TSP-GA scenario. As shown in Figure 5-3, during the off-peak hour, as the bus occupancy increases, the average bus delay decreases. However, during the peak hour, the proposed algorithm is not sensitive to the bus occupancy after it is greater than 10 passengers per vehicle. One possible explanation is that it is difficult to reduce the average bus delay due to the high traffic volumes.

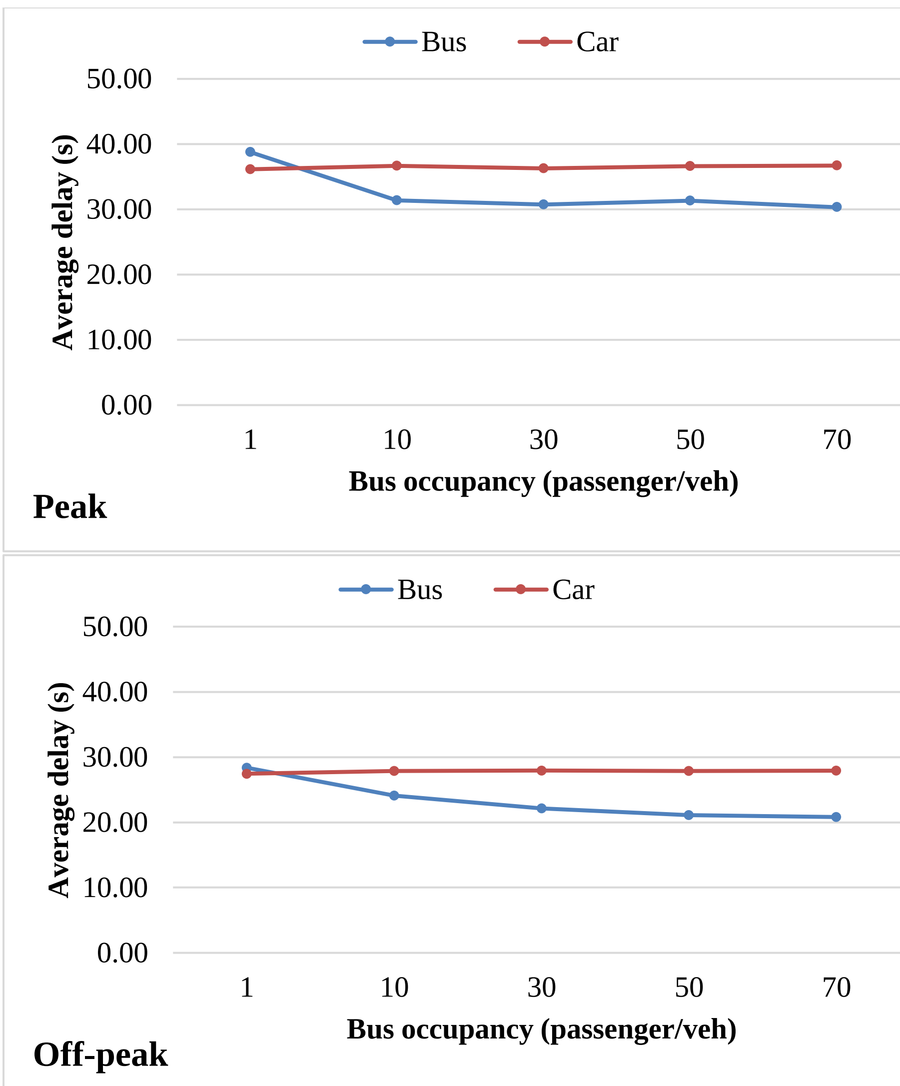


Figure 5-3 Sensitivity of GA Optimization with TSP to Bus Occupancy

5.2.2. Bus Arrival Frequency

Bus arrival frequency is a possible important factor that can influence the effectiveness of the GA optimization algorithm. Based on two traffic demand conditions, four different bus arrival frequencies are investigated in this research, i.e., 2 minutes, 5 minutes, 10 minutes, and 15 minutes. Other scenario settings are the same as the major TSP-GA scenario. As shown in Figure 5-4, the average delays for both buses and cars decrease as the frequency of bus arrivals decreases. Compared with the 2-minute arrival frequency scenarios, the average delays for buses and cars in the 15-minute scenarios are reduced by about 20% and 5%, respectively, in both peak and the off-peak conditions. The reduction in the average bus delays is much larger than the average car delays. This is because the number of cars is much higher compared to the number of buses and therefore, changes in the frequency of bus arrivals have a smaller impact on the average car delay.

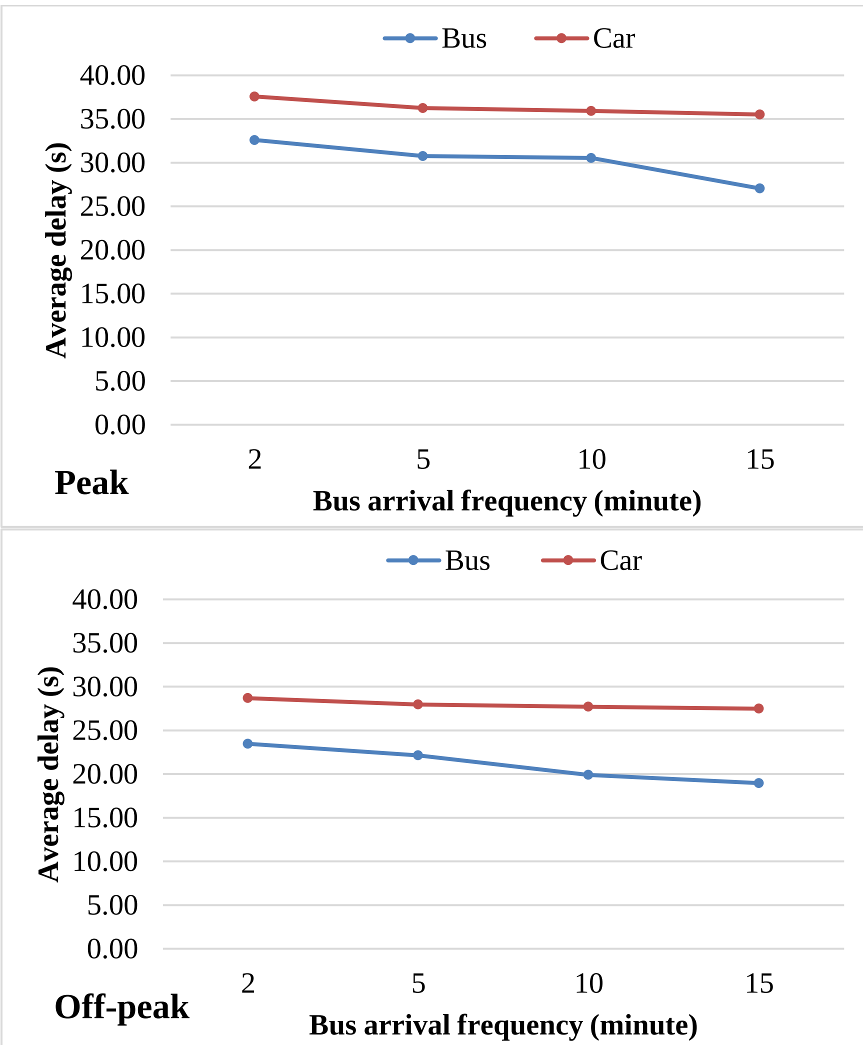


Figure 5-4 Sensitivity of GA Optimization with TSP to Bus Arrival Frequency

Chapter 6. Conclusions

This study investigates two typical signal control strategies that apply CV technology to provide priority to transit vehicles at signalized intersections, which are actuated TSP with CV and optimized TSP with CV. The optimization algorithm used in this study is GA, a classical algorithm in the field of signal optimization. A real-world intersection is modeled in SUMO to evaluate the performance of proposed control strategies. The results are compared with fully actuated signal control strategies with and without TSP. The impacts of MPR, bus occupancy, and bus arrival frequency on the performance of proposed optimization algorithm are also investigated.

Results indicate that the proposed GA optimization control strategy can reduce the average bus delay by 24.50% while minimizing the adverse impact on competing traffic under high traffic demand conditions. Fully actuated control with TSP using CV has the best performance in terms of average delay under low traffic demand conditions. In addition, the fully actuated with TSP using CV control strategy only requires the bus to be equipped with CV technology, which is easily achieved. The proposed optimization control algorithm can provide certain priority to buses even at low rates of CV market penetration. The sensitivity analysis shows that the proposed optimization control algorithm is not very sensitive to both the bus occupancy and bus arrival frequency. This is useful because in the real-world, bus occupancy and arrival frequency are quite random.

In the future, progresses can be achieved by (a) considering more comprehensive traffic conditions, e.g., multiple transit priority requests, and under oversaturated traffic flow situations, (b) expanding the control object, e.g., along a corridor or even throughout the network, (c) developing more advanced control algorithms, such as integrating data-driven approaches into control strategies.

Appendix

Appendix 1 Average Delay in Each Vehicle Type and in Each Direction in Major Scenarios (second)

Period	Control Strategy	Bus	Car	SB			WB			NB			EB		
				R	T	L	R	T	L	R	T	L	R	T	L
Peak	NTSP	40.73	35.36	8.71	37.71	50.45	30.03	34.22	47.98	10.57	36.03	48.06	35.10	37.98	47.91
	ATSP	18.61	38.02	8.64	32.97	58.53	35.64	40.71	50.30	10.33	31.54	49.41	54.79	56.81	50.38
	ATSP-CV	14.92	36.23	8.81	33.68	56.50	32.74	38.18	48.28	10.43	32.76	49.69	44.60	47.75	48.18
	TSP-GA	30.75	36.27	11.76	31.86	42.18	28.09	33.70	37.90	14.40	37.09	69.38	44.50	48.00	39.92
Off Peak	NTSP	28.93	25.66	8.77	28.74	37.57	21.19	25.54	35.06	7.11	20.84	36.64	21.26	27.10	35.44
	ATSP	13.73	26.00	8.67	26.00	43.63	23.05	28.32	40.11	6.96	18.55	38.96	23.14	30.12	40.83
	ATSP-CV	11.11	25.40	8.77	27.14	40.77	21.48	25.93	36.62	6.98	19.55	37.06	21.73	27.88	37.84
	TSP-GA	22.13	27.94	11.04	26.61	31.94	27.68	33.53	39.25	8.73	23.84	44.81	23.97	30.31	33.25

Note: SB=southbound; WB=westbound; NB=northbound; EB=eastbound; R=right turn; T=Through, L=Left turn.

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