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Review Article

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Enhanced Automated Intersection Control for Platooning AVs: A Fusion Model with Significant Traffic, Safety, and Environmental Improvements

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Abstract

An automated intersection control system for platooning AVs is developed by combining an existing AVs platooning model and a known intersection control system for AVs. The proposed model remarkably improves traffic and safety measures, specifically in extreme volume regimes compared to the regular DSCLS model. This model outperformed the other AV-based intersection control systems in traffic measures with a 9% delay reduction and 18% maximum throughput increment. The safety and environmental measures were also remarkably improved by the proposed model.

Keywords: Automated Intersection Control, Platooning AVs (Autonomous Vehicles), Traffic Measures, Safety Improvements, Environmental Measures

1. Introduction

Most urban highways are facing daily traffic congestion, especially during peak hours. Hence, related institutions intend to deploy innovative policies to improve roadway traffic flow. Referring to the recent development in vehicular and infrastructural communication technologies, new ATM policies could be considered a potential and affordable solution to improve the traffic network performance in the bottleneck sections [1]. To avoid potential risks on the budget and time, any traffic management policy must be carefully evaluated before deploying on the roadways. In conventional intersection control systems, an intersection controller such as a traffic light dictates the rules to the vehicles. However, the recent advances in vehicles' communication systems demand communication from vehicles to controller systems to take full advantage of the CAVs' communication capabilities. Therefore, the CAV-based intersection control logic has been a point of interest for the last couple of decades. Several approaches such as trajectory planning, real-time optimization, and rule-based intersection control logic have been developed to establish purposive vehicle-to-vehicle or vehicle-to-infrastructure communication at the intersections.

The most critical task in developing an intelligent intersection control system is to make the algorithm adjustable with stochastic or unprecedented circumstances. Since conventional optimization approaches are based on predefined models or fixed rules, making them work in a stochastic environment requires several adjustments and experiments. Finally, they are unlikely to produce a satisfactory outcome in extraordinary circumstances. Following DRL's astounding performance in playing multi-player video games within the last few years, it is considered an outstanding Machine Learning (ML) technique for decision-making in stochastic environments. The chain impact of taking sequences of random actions in a DRL agent's learning process will expose the agent to enormous different circumstances, regardless of how likely they may happen in a real-world environment. Pieces of literature exist in using DRL to optimize traffic light phasing and timing or processing aerial images to optimize traffic flow at intersections.

However, at an ultimate automation level, CAVs are expected to act as individual robots, and to the best of the author's knowledge, there is no DRL control system developed to control individual CAVs and make them accountable for decision-making in the traffic networks. A Decentralized Sparse Coordination Learning System (DSCLS) based on DRL is proposed in this study to control CAVs at the intersections. In this approach, vehicles try to reserve their desired cells ahead of time. Based on having a shared desired cell with other vehicles, they would be in an independent or coordinated state. Individual CAVs are set accountable for decision-making in both coordinated or independent states at each step. CAVs learn to minimize the overall delay and queue length at the intersection in the training process.

CACC is another promising technology that allows CAVs to be driven cooperatively. CACC introduces significant benefits to traffic flow and safety, and several CACC control systems have been developed within the last couple of decades. A noticeable portion of studies in this area is focused on the dynamic aspect of CACC, such as vehicle mass, tire friction, and vehicle powertrain. These aspects are vital in bringing CACC to fruition yet provide limited insights into the impacts of CACC on the overall traffic network. Alternatively, most of the models developed explicitly for traffic assessment of CACC have missed several critical aspects of platooning such as the platoon evolution process, communication range limitations, or interactions between platoons.

This study applies a classical physics-based model called Spring-Mass-Damper (SMD) that reflects the most critical dynamic aspect of vehicles, the mass, and covers the platoon evolution process for platooning CAV. A maximum communication range is reflected in the model to make it more compatible with real-world circumstances. Strings of vehicles are divided into sub-platoons to avoid lengthy platoons and accommodate potential merging vehicles, while the SMD model controls both inter-platoon and intra-platoon interactions. The model is coded into commercial simulation software to facilitate traffic-oriented and potential macroscopic or mesoscopic assessments.
Considering platooning capability and automated intersection control systems as essential characteristics of CAVs, numerous studies have focused on these two areas. However, CACC platooning models are mainly developed and tested in uninterrupted flow circumstances, and the impact of platooning models on interrupted flow has not been examined. Few CAV-based intersection control systems can deal with platoons of vehicles. However, these models still lack a robust logic for platooning. This study also develops a platooning CAVs-based automated intersection control system for CAVs by simultaneously deploying the DSCLS and SMD models.

2. Literature Review
This chapter reviews selected studies in two critical CAV-related research areas, including 1) CAV-based intersection control systems and 2) Cooperative Adaptive Cruise Controls (CACC). Based on the existing literature, CAV-based intersection control systems are clustered into three main groups, including 1) rule-based algorithms, 2) optimization-based algorithms, and 3) Machine Learning (ML)-based algorithms. Several studies in each group are reviewed, and it is clarified if any proposed intersection control logic can consider platoons of AVs instead of single vehicles. It should be noted that several studies have proposed a combination of the mentioned methodologies. In that case, they are included in the most related group.

Regarding the CACC systems, a brief history of vehicles' longitudinal control systems' evolution from basic Cruise Control (CC) systems to Cooperative Adaptive Cruise Control (CACC) is presented in this chapter. Several proposed CACC models and their impact on traffic flow measures are reviewed, and a brief background on the Spring-Mass-Damper (SMD) model is provided. It also explains how previous studies have used the SMD model to reflect the impact of several variables such as driver aggressiveness, vehicle mass, and vehicle stability on CAVs' platooning behavior.

A combination of Transportation Engineering-based policies with conceptual deep reinforcement learning has been used by Mirbakhsh et al to optimize ambulance dispatch in a pandemic or natural disaster circumstances [2]. Dresner et al divided the intersection area into an n×n grid of reservation tiles. Each approaching vehicle at the intersection attempts to reserve a time-space block at the intersection area by transmitting a reservation request to the intersection manager. The reservation request includes information such as speed and arrival time. According to the intersection control policy, the intersection manager decides whether to approve the request, provide more passing restrictions to the driver agent, or reject the reservation request. Dresner et al. adopted the First Come First Serve (FCFS) control policy, in which the passing priority is assigned to the vehicle with the earliest arrival time, and other vehicles have to yield to it. In a following study by Dresner et al. in 2008, several complimentary regulations were added to FCFC policy to make it work more reliably, safely, and efficiently [3]. Simulation results revealed that FCFS policy noticeably reduces the intersection delay compared to traffic light and stop sign control systems. The reservation-based approach can be combined with various control policies and has been deployed by several researchers since 2008.

Zhang et al. proposed a state-action control logic based on a Priority First in First Out (PriorFIFO) [4]. This control model assumes autonomous motion with spatial-temporal and kinetic parameters based on a centralized scheduling mechanism. The target was to reduce control delay for vehicles with higher priority. The simulation results with a combination of high, average, and low-priority vehicles showed that the algorithm works well for vehicles with higher priority. Meanwhile, causing some extra delay for regular vehicles compared to those with lower priority.

Carlin et al. developed an auction-based intersection control logic based on Clarke Groves tax mechanism and pixel reservation [5]. If commonly reserved tiles exist between vehicles, an auction is held between the involved vehicles. All vehicles in each direction contribute to their leading vehicle to win the auction, and the control logic decides which leading vehicles receive a pass order first. The bid's winner and its contributors (followers) have to pay the runner-up bid amount with a proportional payment (based on their contribution value in the bid). A "system wallet" component was added to auction-based intersection control to ensure low-budget vehicles or emergency vehicles would not be over-delayed. A comparison of simulation results showed that the auction-based control logic outperforms the FIFO logic.

Vasirani et al. approached the intelligent intersection management problem on a mesoscopic scale and designed a competitive computational market to control a set of intersections in urban roadway networks [6]. In this algorithm, buyers are driver agents, the suppliers are the intersection managers, and the traded resource is the intersection capacity. Each vehicle communicates with the intersection manager and provides its desired route. The intersection manager adjusts the prices based on demand and supply values. Vehicles can reroute if the offered price is not desired, and the transactions are made as the equilibrium price is obtained. Mesoscopic simulation runs for a roadway network consisting of several intersections showed that deployment of the algorithm leads to travel time reduction for CAVs and density reduction at the network's critical sections.

Chen et al. developed the win-fit intersection control logic. In this algorithm, the “win” logic scores clusters of approaching vehicles to the intersection by the value of delay imposed on all other yielding clusters [7]. The cluster with the lowest delay impact on other clusters obtains the passing priority. The control algorithm's “fit” function assigns idle time slots (resulting from turning movements) to the vehicles in lower priority groups. Unlike the previously reviewed control system, the win-fit control logic could consider a cluster of vehicles instead of a single vehicle at each decision-making step. However, holding on to the platoon was not a priority. So, the vehicles could leave their platoon to pass the intersection. A simulation run in SUMO revealed that the average delay at the intersection was improved compared to both FIFO and actuated traffic lights.

Mirbakhsh, et al. proposed an SMD-based platooning logic to control AVs car following behavior. The proposed model was tested in a commercial microsimulation software and the results showed that the model gains gained noticeable improvements in traffic measures, safety. pollution, and emission [8].

3. Methodology

One of the main goals of this study is to develop a platooning CAV-based intersection control system, which includes the simultaneous deployment of SMD platooning logic and an automated machine learning-based intersection control system for Avs developed by Mirbakhsh et al. [9]. It also requires adjusting the models to be compatible. A general layout of platooning CAV-based intersection control system based on the SMD model and DSCLS is shown in Figure 1. This model is called DSLCS&SMD.

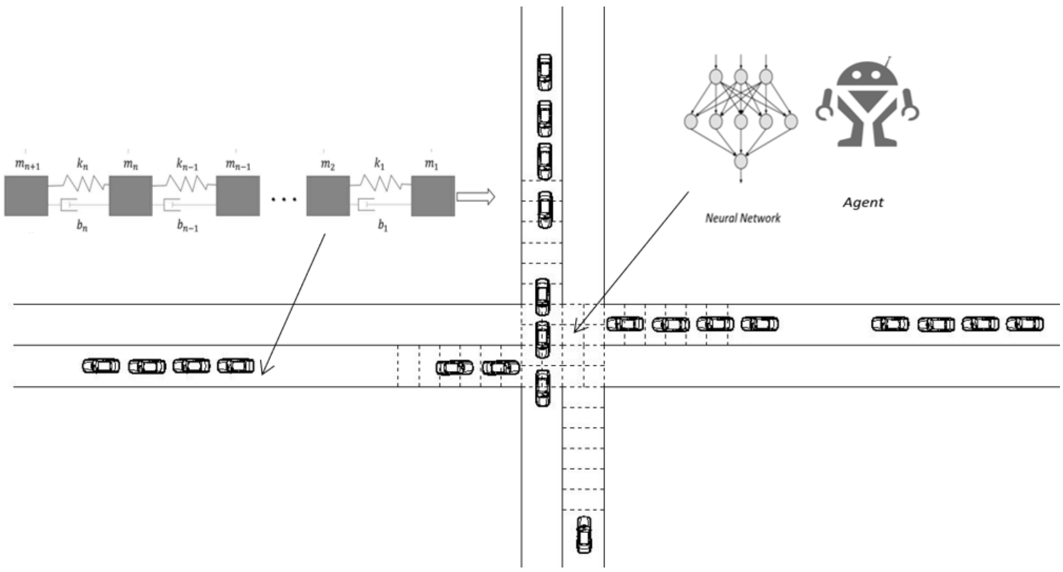

Figure 1: Platooning CAV-Based Intersection Control System

In this experiment, a full MPR of CAVs is assumed, meaning that the SMD car-following model controls all vehicles in the network. The leading vehicles of the first platoon approaching the intersection will be forwarded to the DSCLS to define passing order priority. Once the leading vehicle receives an acceleration or deceleration command from DSCLS, all the following vehicles in its platoon follow that command till the platoon passes the intersection. In this case, the DSCLS needs to be reconfigured to consider a platoon of vehicles instead of a single vehicle. To this end, the platoon length has been added to each leading vehicle’s state, as appears in Equation 1. The training course has been rerun with the new settings.

$$State_{Li} = (Speed_{Li}, Current\ Cell_{Li}, Queue_{Li}, Platoon\ Lenght_{Li}) \qquad (1)$$

$Speed_{Li}$: platoon’s leading vehicle speed
$Current\ Cell_{Li}$: platoon’s leading vehicle current cell
$Queue_{Li}$: Queue length behind platoon’s leading vehicle
$Platoon\ Lenght_{Li}$: Leading vehicle’s platoon length

Since te simulation results for the single lane intersection, multilane intersection, and the corridor of four intersections comply in the aspect of gains or losses of the proposed model. The simulation testbed in this experiment is the same as the proof-of-concept test experiment presented. The proposed model is compared with four other intersection control systems, including fixed traffic light, actuated traffic light, LQF, and DSCLS, in three different volume regimes. The simulation settings are set the same as proof-of-concept test experiments, and the simulation results are presented in the following sections.

4. Analysis Results

According to the delay results comparison shown in Figure 2, the DSCLS&SMD model noticeably improves the delay in the extreme volume regime with a 31% delay reduction compared to the DSCLS. A delay reduction of 10% is observed in moderate and high-volume regimes. Since fewer platoons are formed in the moderate and high-volume regimes due to lower occupancy, the model is less effective in delay reduction than in the extreme volume regime. The delay results confirm that clustering vehicles into platoons can improve DSCLS decision-making efficiency.

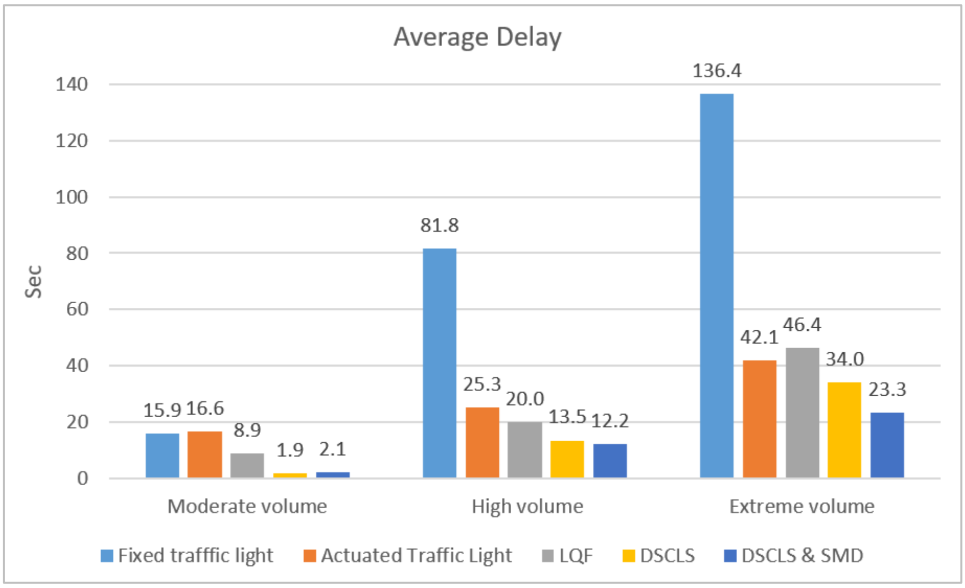

Figure 2: Average Delay Comparison, Including DSCLS & SMD

The DSCLS&SMD gains a 10.7% travel time reduction compared to the DSCLS in the extreme volume regimes. However, the impact of the model on travel time is not noticeable in moderate and high-volume regimes. The travel time results appear in Figure 3.

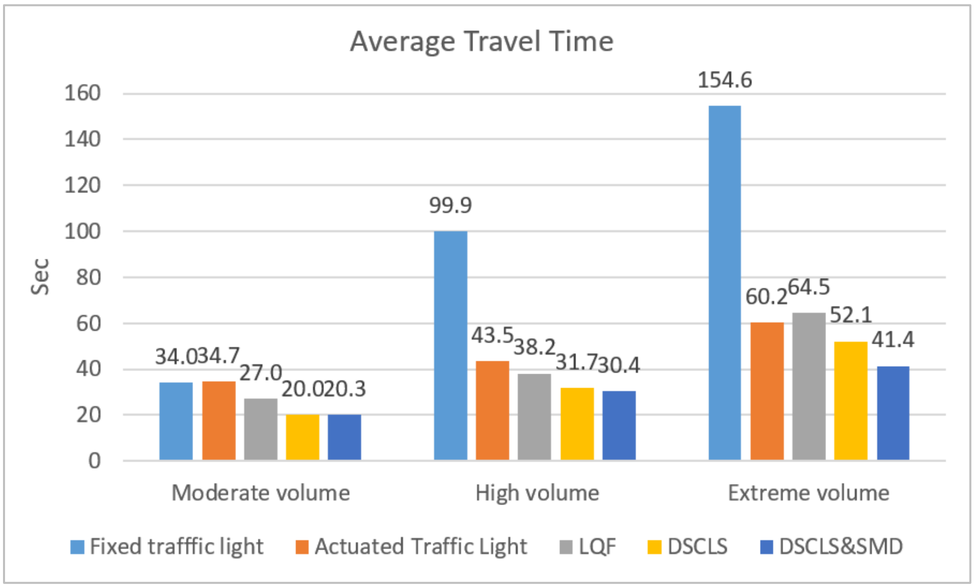

Figure 3: Average Travel Time Comparison, Including DSCLS & SMD

According to the maximum throughput results in Figure 4, the DSCLS&SMD noticeably outperforms the DSCLS by an 18% increment in the maximum throughput.

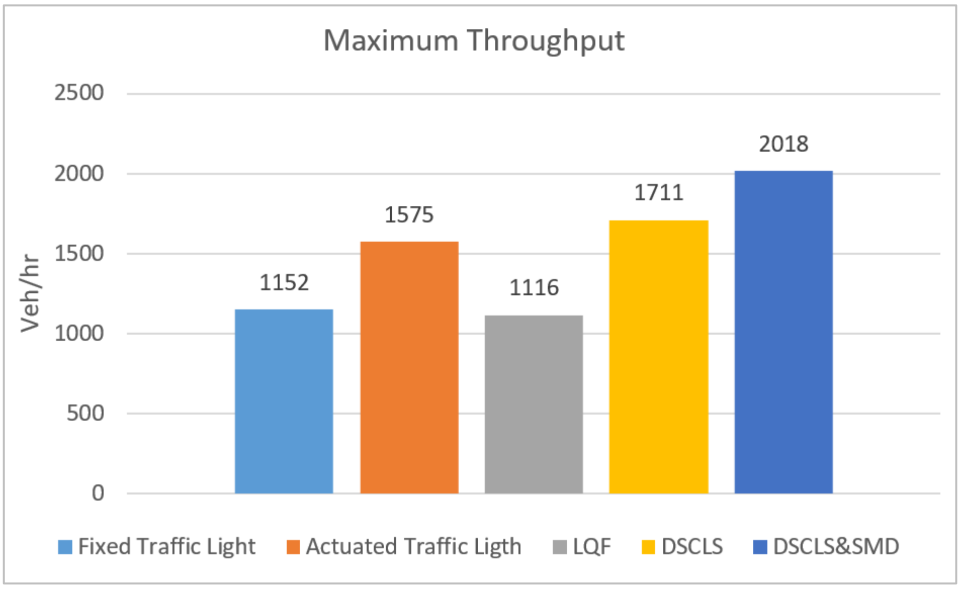

Figure 4: Maximum throughput Comparison, Including DSCLS & SMD

4.1. Other Measures Comparison

The average fuel consumption results appear in Figure 5. The DSCL&SMD increases the fuel consumption by 21%, 25%, and 31% compared to the DSCLS model in moderate, high, and extreme volume regimes. The fuel consumption increments result from the SMD model pushing all vehicles to strictly follow the leading vehicle, which is controlled by DSCLS with limited acceleration and deceleration rates. However, the DSCLS&SMD still has almost equal or better performance in fuel consumption compared to the conventional control systems and the LQF.

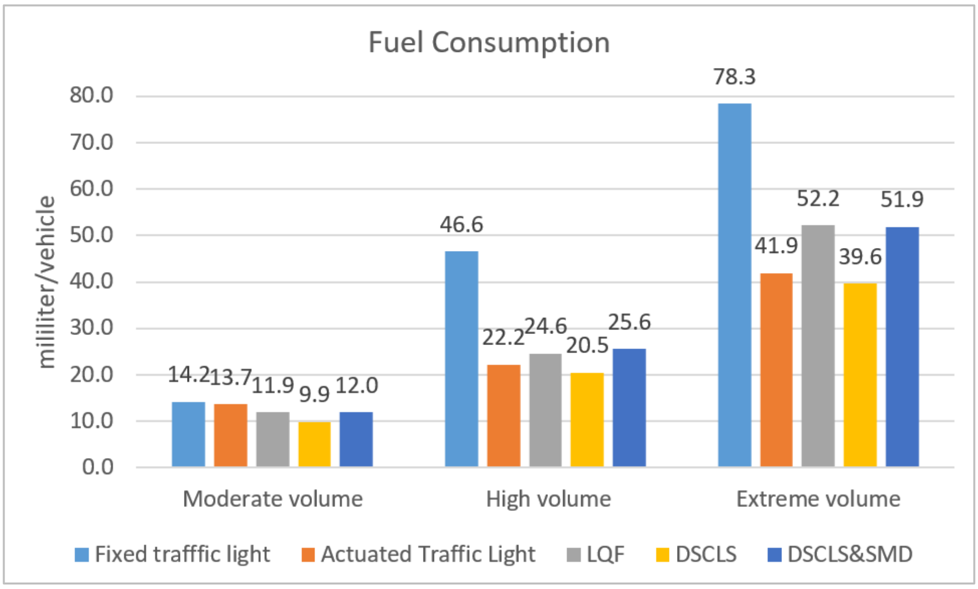

Figure 5: Average Fuel Consumption Comparison, Including DSCLS & SMD

The average CO_2 emission shown in Figure 6. follows the same pattern as fuel consumption with 20%, 24%, and 31% fuel consumption increments for platooning CAVs compared to the DSCLS.

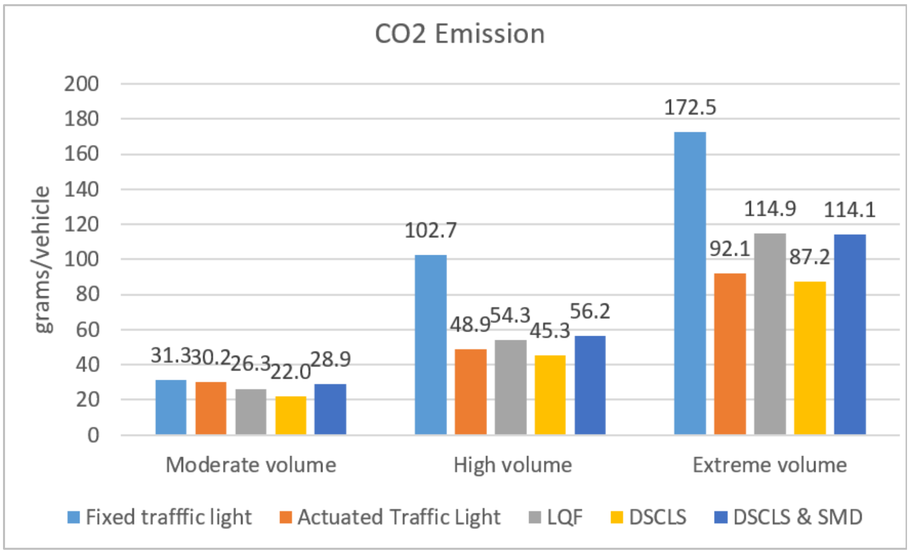

Figure 6: Average CO_2 Emission Comparison, Including DSCLS & SMD

The comparison of PET, shown in Figure 7, reveals that the platooning CAVs have a safer crossing maneuver at the intersections. The PET value is improved by 1%, 6%, and 10% in moderate, high, and extreme volume regimes. The reason is that instead of single vehicles being involved in a crossing maneuver, platoons of vehicles are involved, reducing the number of conflicts and the chance of side collisions.

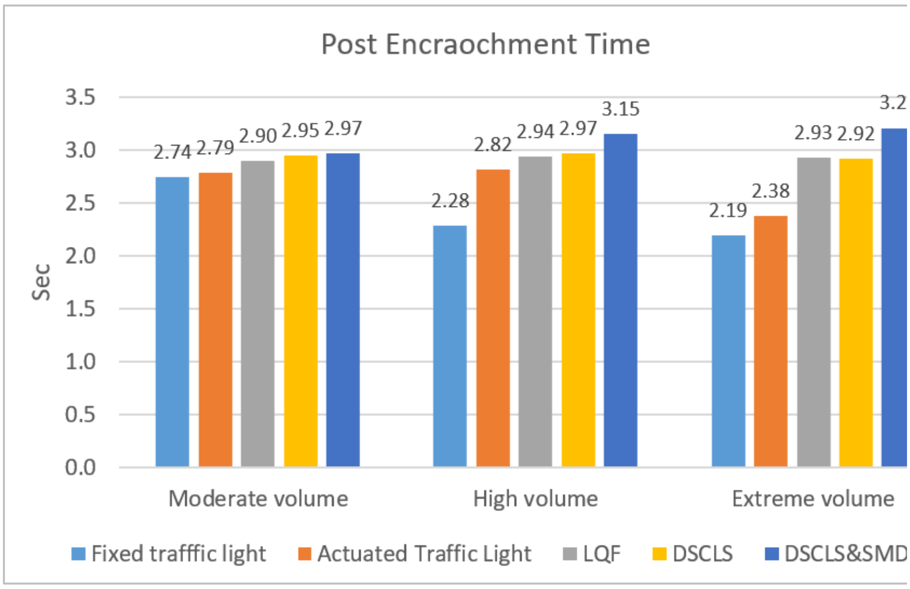

Figure 7: Average PET Comparison, Including DSCLS & SMD

The TTC measure comparison appears in Figure 8. The platooning CAVs have a better performance than the DSCLS in the TTC measure, with around a 45% increment in all volume regimes. The reason is that in DSCLS&SMD, all vehicles in the network are controlled by the SDM model, catching up with the leading vehicle's acceleration and deceleration smoothly.

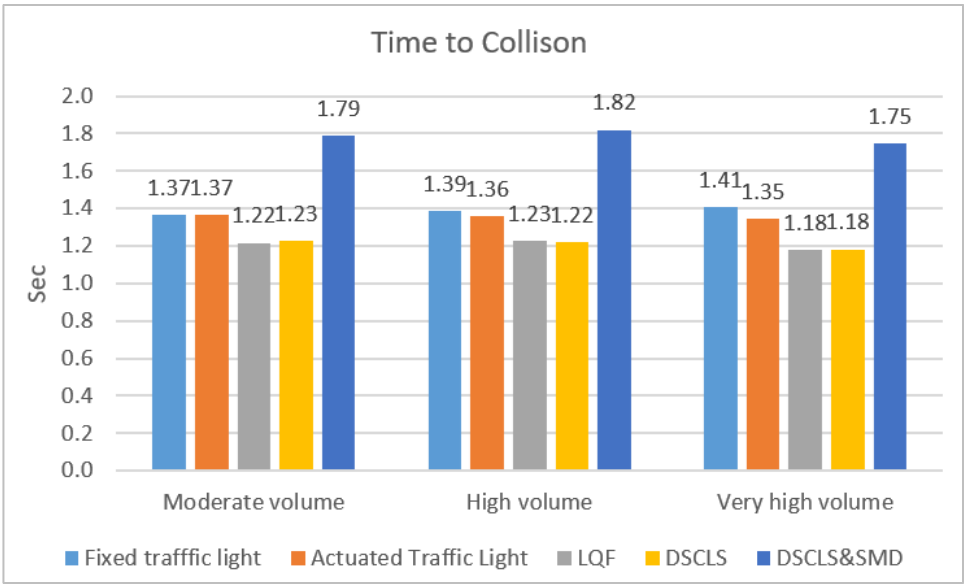

Figure 8: Average TTC Comparison, Including DSCLS & SMD

4.2. Statistical Analysis of the Simulation Results

The t-test results between DSCLS&SMD and four other control systems are shown in Table. Differences in fuel consumption are not statistically significant between DSCLS&SMD and LQF in the high-volume regime, and differences in CO_2 emissions are not statistically significant in the extreme-volume regime for the two models.

	Fixed Traffic Light					
	Moderate volume					
	Delay	Travel Time	Fuel Consumption	CO2 Emission	PET	TTC
DSCLS & SMD	<0.05	<0.05	<0.05	<0.05	<0.05	<0.05
	High Volume					
	Delay	Travel Time	Fuel Consumption	CO2 Emission	PET	TTC
	<0.05	<0.05	<0.05	<0.05	<0.05	<0.05
	Extreme volume					
	Delay	Travel Time	Fuel Consumption	CO2 Emission	PET	TTC
	<0.05	<0.05	<0.05	<0.05	<0.05	<0.05

	Actuated Traffic Light					
	Moderate volume					
	Delay	Travel Time	Fuel Consumption	CO2 Emission	PET	TTC
DSCLS & SMD	<0.05	<0.05	<0.05	<0.05	<0.05	<0.05
	High Volume					
	Delay	Travel Time	Fuel Consumption	CO2 Emission	PET	TTC
	<0.05	<0.05	<0.05	<0.05	<0.05	<0.05
	Extreme volume					
	Delay	Travel Time	Fuel Consumption	CO2 Emission	PET	TTC
	<0.05	<0.05	<0.05	<0.05	<0.05	<0.05
	LQF					
	Moderate volume					
	Delay	Travel Time	Fuel Consumption	CO2 Emission	PET	TTC
DSCLS & SMD	<0.05	<0.05	<0.05	<0.05	<0.05	<0.05
	High Volume					
	Delay	Travel Time	Fuel Consumption	CO2 Emission	PET	TTC
	<0.05	<0.05	>0.05	<0.05	<0.05	<0.05
	Extreme volume					
	Delay	Travel Time	Fuel Consumption	CO2 Emission	PET	TTC
	<0.05	<0.05	<0.05	>0.05	<0.05	<0.05

	DSCLS					
	Moderate volume					
	Delay	Travel Time	Fuel Consumption	CO2 Emission	PET	TTC
DSCLS & SMD	<0.05	<0.05	<0.05	<0.05	<0.05	<0.05
	High Volume					
	Delay	Travel Time	Fuel Consumption	CO2 Emission	PET	TTC
	<0.05	<0.05	<0.05	<0.05	<0.05	<0.05
	Extreme volume					
	Delay	Travel Time	Fuel Consumption	CO2 Emission	PET	TTC
	<0.05	<0.05	<0.05	<0.05	<0.05	<0.05

Table: P-values for T-test Results - DSCLS&SMD

References

1. Mirbakhsh, A., Lee, J., Jagirdar, R., Kim, H., & Besenski, D. (2023). Collective assessments of active traffic management strategies in an extensive microsimulation testbed. Engineering Applications, 2(2), 146-153.
2. Mirbakhsh, A. (2023). How hospitals response to disasters; a conceptual deep reinforcement learning approach. Advanced Engineering Days (AED), 6, 114-116.
3. Dresner, K., & Stone, P. (2008). A multiagent approach to autonomous intersection management. Journal of artificial intelligence research, 31, 591-656.
4. Zhang, K., De La Fortelle, A., Zhang, D., & Wu, X. (2013, December). Analysis and modeled design of one state-driven autonomous passing-through algorithm for driverless vehicles at intersections. In 2013 IEEE 16th International Conference on Computational Science and Engineering (pp. 751-757). IEEE.
5. Carlino, D., Boyles, S. D., & Stone, P. (2013, October). Auction-based autonomous intersection management. In 16th International IEEE Conference on Intelligent Transportation Systems (ITSC 2013) (pp. 529-534). IEEE.
6. Vasirani, M., & Ossowski, S. (2011). A computational market for distributed control of urban road traffic systems. IEEE Transactions on Intelligent Transportation Systems, 12(2), 313-321.
7. Chen, G., & Kang, K. D. (2015, October). Win-fit: Efficient intersection management via dynamic vehicle batching and scheduling. In 2015 International Conference on Connected Vehicles and Expo (ICCVE) (pp. 263-270). IEEE.
8. Mirbakhsh, A., Lee, J., & Besenski, D. (2023). Spring–Mass–Damper-Based Platooning Logic for Automated Vehicles. Transportation research record, 2677(5), 1264-1274.
9. Mirbakhsh, A., Lee, J., & Besenski, D. (2023). Development of a Signal-Free Intersection Control System for CAVs and Corridor Level Impact Assessment. Future Transportation, 3(2), 552-567.