Simulation Comparisons of Vehicle-Based and Movement-Based Traffic Control for Autonomous Vehicles at Isolated Intersections

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Abstract—With the advent of autonomous driving technologies, traffic control at intersections is expected to experience revolutionary changes. Various novel intersection control methods have been proposed in the existing literature, and they can be roughly divided into two categories: vehicle-based traffic control and movement-based traffic control. Movement-based traffic control can be treated as updated versions of the current intersection signal control with the incorporation of the performance of autonomous vehicle functions. Meanwhile, vehicle-based traffic control utilizes some brand-new methods, mostly in real-time fashion, to organize traffic at intersections for safe and efficient vehicle passages. However, to date, no systematic comparison between these two control categories has been performed to suggest their advantages and disadvantages. This paper conducts a series of numerical simulations under various traffic scenarios to perform a fair comparison of their performances. Specifically, we allow trajectory adjustments of incoming vehicles under movement-based traffic control, while for its vehicle-based counterpart, we implement two strategies, i.e., the first-come-first-serve strategy and the optimization-based strategy. Overall, the simulation results show that vehicle-based traffic control generally incurs a negligible delay when traffic demand is low but lead to an excessive queuing time as the traffic volume becomes high. We also discover that the comparison results can be influenced by other factors such as intersection layouts, traffic distribution and maturity of the autonomous driving technologies.

Index Terms—Intersection control, autonomous vehicles, first-come-first-serve, traffic simulation.

I. INTRODUCTION

URBAN road systems contain a large number of intersections. At intersections, the trajectories of vehicles traveling from multiple directions conflict with each other, posing a risk of collisions. The introduction of traffic signals has contributed significantly to intersection collision avoidance, but it has also made intersections the bottleneck of the road traffic network. Delays will inevitably occur when vehicles encounter red lights, and the startup loss as well as the clearance interval also lowers the intersection capacity. Many previous studies have focused on minimizing delay by adapting signal timing according to the estimated traffic demand [1], [2]. However, in a human-driven environment without vehicle-to-infrastructure (V2I) communications, the potential for improving the intersection mobility with such adaptation is restricted due to the limitations on reaction time and car-following headway.

With the rapid development of artificial intelligence and wireless communications, connected and automated vehicle (CAV) technology is considered to be one of the most promising fields in future transportation. CAVs are able to interact with other vehicles on the road as well as roadside facilities, leading to improved driving trajectories to minimize travel delay, fuel consumption and network throughput [3], [4]. Moreover, benefiting from sensors installed onboard and inter-vehicle communication, vehicles can measure the headway in a more accurate and timely manner and thus make decisions much more effectively, allowing CAVs to maintain a shorter headway [5], [6]. Due to all of the desirable characteristics of CAVs, the form of traffic organization, particularly at intersections, may experience revolutionary changes in the coming years.

Studies performed to date have explored a variety of control strategies for isolated intersections, which can be roughly categorized into vehicle-based and movement-based schemes. The vehicle-based control determines the optimal passing orders and trajectories for each vehicle based on real-time traffic conditions, while movement-based strategies group vehicles belonging to certain movements to pass the intersection, in a form similar as vehicle platoons. The time allocation scheme among movements can be fixed depending on the knowledge of typical traffic demands of the subject intersection (referred to as pre-timed movement-based strategies) or accommodated to the actual arrivals of vehicles (referred to as actuated movement-based strategies).

With the two categories of intersection control strategies available, an interesting question is that which strategy can better accommodate the intersection management with the CAV traffic. Previous studies (e.g., [7]) suggest that vehicle-based controls outperform movement-based ones in terms of traffic delays, as they apply real-time trajectory determination for individual vehicles and allow vehicles to pass the intersection as early as possible. But intuitively, compared to movement-based controls, vehicle-based controls induce more “crossing-type conflicts”, i.e., two vehicles on two conflicting routes pass through the conflict point consecutively.
and crossing-type conflicts generally require a large time gap to ensure safety. Based on this intuition, one can naturally question the capabilities of vehicle-based strategies in handling heavy traffic. On the other hand, since the movement-based strategies allow vehicles to consecutively pass the intersection with smaller headway, we may expect this category of control strategies to have better performances at high traffic demand.

This paper attempts to answer the question by carrying out a systematic comparison between these two intersection control categories in the era of CAVs and suggesting their advantages and disadvantages. For a fair comparison, this study conducts numerical analyses on several intersection control protocols, including a pre-timed movement-based control (P-MBC), an actuated movement-based control (A-MBC), a vehicle-based control with the first-come-first-serve strategy (FCFS), and a vehicle-based control with the optimization-based strategy (OBC), under heterogeneous traffic demand patterns and intersection layouts. Specifically, in the P-MBC and A-MBC strategies, the approaching vehicles’ trajectories are adjusted to cater to the green phases; the OBC strategy requires the solution of mixed-integer programming models in real-time fashion, and to simulate its practical usage, we only allow a limited computational time. The testing scenarios include a variety of demand patterns from light to heavy, from balanced to imbalanced (in terms of arrival rates from different legs), and from stable to fluctuated. The tests are conducted with different intersection layouts, including four-leg and three-leg intersections. Additionally, we also incorporate scenarios with different levels of technological maturity to validate the performance characteristics of the two control philosophies.

The main contribution of this paper includes:

- We conduct a comprehensive performance comparison among various CAV-enabled control strategies under the same communication and safety settings. The main focus is on the comparison between vehicle-based and movement-based controls.
- The simulation comparisons cover a wide range of traffic and technological environments, including different intersection layouts, different traffic demand magnitudes, different traffic demand distribution among legs, as well as the technological maturities affecting the minimum inter-vehicle safety gaps.
- Insights concerning the relative performances of CAV-enabled control strategies under different situations are generated to provide guidelines for future implementation.

The remainder of this paper is organized as follows. Section II reviews related studies on the intersection control strategies in the CAV environment. Section III describes the control models compared in this paper. In Section IV, we simulate the control models under various traffic demand scenarios and intersection layouts and describe the simulation results. Finally, we conclude by presenting our findings in Section V.

II. Literature Review

In this section, we first review some related researches on the two categories of intersection control strategies (i.e., the vehicle-based and the movement-based intersection controls), followed by studies comparing the performances between them.

A. Vehicle-Based Intersection Control

Leveraging the connectivity and controllability of CAVs, intersection traffic signals can be totally abandoned, and central controllers can be placed on intersections to detect the approaching CAVs and arrange movements for them. Following this manner, various control concepts have been proposed. According to the study of Meng et al. [8], the signal-free vehicle-based intersection control can be categorized into two kinds: “ad-hoc negotiation based” [7], [9], [10] and “optimization-based” [11]. With the ad-hoc negotiation based methods, intersections are mainly organized under the rule of “first come first served” (FCFS), while planning based methods usually utilize optimization or searching approaches to determine the passing trajectories of multiple vehicles.

One of the earliest concepts of ad-hoc negotiation based intersection controls is to allow CAVs to make passing reservations while approaching an intersection, with the intersection central control (ICC) ensuring conflict-free outcomes. In this approach, Dresner and Stone [9] proposed a multiagent FCFS intersection control policy, and it has been widely studied in subsequent researches [7], [12]. The control divides the intersection into multiple tiles, and by applying the restriction that a given tile can only be occupied by one CAV at any given time, collision avoidance is realized. These studies claim that the FCFS policy outperforms the traditional signal control in a single intersection in terms of average traffic delays, which is verified by VISSIM simulations conducted by Li et al. [10]. According to the experiments in [13], the intersection efficiency could be further improved by introducing an auction-based system.

In a different approach, planning based intersection control can handle multiple vehicles at the same time instead of arranging vehicle trajectories exactly in the arrival order. In this case, the controller would perceive vehicles that arrive within a certain time period and determine their passing orders and trajectories by solving an optimization problem. Some existing studies achieve collision avoidance by preventing vehicles with intersecting trajectories from being in the intersection concurrently [8], [11]. In [11], a discrete time model (linear programming formulation for autonomous intersection control, or LPAIC) is formulated to achieve minimum traffic delay in a 4-leg, 4-lane intersection, with the outputs from each direction satisfying the demands. Meng et al. [8] studied a simpler intersection scenario with only one lane in each leg. Both planning based and ad-hoc negotiation based frameworks are adopted to organize the vehicle passing order, and the simulations show that the optimization-based approach is superior to the ad-hoc negotiation based approach with respect to both average value and standard deviation of vehicle delay, particularly when the traffic demand is high.

In a more elaborate method, Lee and Park [14] proposed a cooperative vehicle intersection control (CVIC) system to adjust the acceleration behavior of passing vehicles by solving
nonlinear constrained programming problems to minimize the overlapping length of the intersected trajectories. Moreover, to achieve a higher traffic efficiency, some studies allow vehicles with intersecting trajectories to enter the intersection simultaneously, as long as they do not pass the intersected point at the same time [15], [16]. In the conflict point intersection control (CPIC) model [15], the spatial trajectories of vehicles passing the intersection are predesigned, and the conflict points are accordingly defined as the nodes where two trajectories intercept. The model then introduces a mixed integer program to optimize the entering time and passing speed of each vehicle.

B. Movement-Based Intersection Control

Movement-based intersection control periodically alternates passing permissions among conflicting traffic movements, to provide a safe as well as efficient intersection organization. In a control cycle, conflict movements are instructed to pass the intersection in different time intervals. The assignment of phase length, in general, focuses on the overall traffic demand and the demand distribution pattern among conflict movements.

At the current stage, the instructions are delivered to drivers using a set of signal lights, for which the movement-based traffic control is also known as the signalized traffic control. Most signalized intersection take a pre-timed control strategy which fixes the phase timing based on typical traffic characteristics (e.g., traffic demands or the headway in average) for its simplicity and low-cost, while the actuated signalized control uses detectors to adjust phase timing based on real-time detected vehicles and pedestrians.

In the era of autonomous driving, the movement-based intersection control may develop in other forms with higher traffic efficiency. While in this approach we still borrow the terminology of traditional signal control, e.g., phases and green/red lights, but it should be noted that the actual traffic lights are not required; rather, the passing instructions can be conveyed through V2I communications. The movement-based traffic control under the CAV environment is essentially a “collective” approach of traffic organization that assigns passing allowances to a group of non-conflicting vehicle movements in the same period of time. From the vehicle’s perspective, the Green Light Optimized Speed Advisory (GLOSA) system ensuring that vehicles arrive the signalized intersection during the green duration and pass it at a high speed has been verified to be able to considerably reduce fuel [17], [18] or electricity [19] consumption. Moreover, in a pure CAV environment, the ICC can ensure the nonstop passing of all vehicles, reducing the total startup losses of the intersection; as a result, the cycle length can be strongly decreased. References [20] and [21] proposed a parsimonious shooting heuristic to optimize the detailed trajectories of multiple CAVs approaching an intersection simultaneously, and following this research direction, Li et al. [22] simplified the trajectory optimization approach and lowered the computational complexity while preserving most of the desirable features of the former model. These studies reveal that the pre-timed movement-based strategy can also be a practical intersection control method in the coming autonomous driving era; compared to its vehicle-based counterpart, movement-based traffic control is easier to implement, and the computational burden added to the controller is strongly alleviated since it is not necessary to solve complicated mathematical programming problems.

C. Comparison Between the Vehicle-Based Strategy and the Movement-Based Strategy

Limited work comparing the performance characteristics of the above two control philosophies (i.e., the vehicle-based strategy and the movement-based strategy) has been reported. In addition, when using signalized control strategy as a benchmark, most previous studies on signal-free intersection control do not consider the performance improvement through usage of CAV technologies [7], [10], leading to an underestimation of its potential to some extent. Recently, some researchers have observed that the vehicle-based control cannot always outperform the conventional signal control. Levin et al. [23] indicated some traffic scenarios for which signalized intersection controls outperform vehicle-based controls, and Patel et al. [24] investigated the optimal placement of vehicle-based and signalized intersections in urban networks. In [25], Yu et al. presented a numerical comparison among the actuated movement-based control strategy and four vehicle-based control strategies, including an FCFS strategy, an optimization-based strategy and two batch strategies. The results show that the actuated movement-based strategy have higher delay in low traffic demand scenarios but higher maximum throughput compared to most vehicle-based strategies. Nevertheless, the existing comparisons have been performed mostly under limited traffic scenarios or the description of the compared strategies are to some extent brief and lack of details, which are incapable of producing convincing and comprehensive conclusions.

III. CONTROL STRATEGIES

This study focuses on control strategy comparisons for an isolated intersection under the CAV environment. In this section, we present an introduction of the study frameworks, followed by brief reviews of the discussed intersection control strategies.

A. Comparison Frameworks

The investigated intersection area is shown as Fig. 1, including the intersection core (the conflict area) and the adjusting area with a length of several hundred meters on each leg. Within such areas, it is assumed that the intersection as well as the vehicles is able to operate under an intelligent framework. On the road side, the intersection central controller (ICC) is equipped with necessary infrastructures to detect traffic, calculate desired passing trajectories and convey the instructions to the vehicles. On the vehicle side, the onboard units enable the vehicle to understand the instructions and to follow the desired trajectories within a limited bias.
Under this setting, we present a thorough comparison among four control models for isolated intersections. The four models are two movement-based intersection control models with pre-timed and actuated phase timing strategies and two vehicle-based models with the first-come-first-serve strategy and the optimization-based strategy. To fairly compare the intersection control models, we should guarantee the equality of the parameters involved in the models, including the vehicle specifications and the intersection layouts. Over the four models, the involved vehicles share the same performance characteristics, including the physical sizes and the maximum acceleration/deceleration rate. Also, vehicles would enter the area at the same cruising velocity, and the speed limits are equally set. We also guarantee a same level of safety, for which the minimum inter-vehicle gap in the conflict area is equally set. The Gipps’ safe distance rule \cite{26} is introduced which the minimum inter-vehicle gap in the conflict area is equal to
\[ d_{min} = \frac{a}{2}t^2 + \frac{a}{4}t^3. \]
where \( a < 0 < \bar{a} \). In addition, some factors may further limit the feasible interval of \( t_o \). The safety concern, which forces two adjacent vehicles to maintain a spatial gap, is the major limitation in this case. Meanwhile, vehicles cannot enter the intersection in red intervals. The \( t_o \) is therefore determined as the earliest feasible time (considering the travel speed constraint and the safety constraint) during a green interval.

Given \( t_i \) and \( t_o \), the determination of the entire vehicle trajectory is still difficult because this determination is an infinite-dimension problem. To simplify the planning process, all of the vehicles are arranged for a trajectory with five quadratic segments according to the method proposed in \cite{22}. As illustrated in Fig. 2, \( t_1 \leq t_2 \leq t_3 \leq t_4 \in [t_i, t_o] \) denote the joint moments between segments. Vehicles first cruise at the entrance speed \( \bar{v} \) in time interval \([t_i, t_1]\) and then decelerate at a constant deceleration rate \( \bar{a} \) during \([t_1, t_2]\). In some cases, vehicles have to stop completely at \( t_2 \), and the length of \([t_2, t_3]\) denotes the duration that vehicles must remain stationary. Otherwise, \( t_2 \) is equal to \( t_3 \), and the third segment does not exist. Then, during the next segment starting at \( t_3 \), vehicles accelerate at \( \bar{v} \) until their velocities reach the leaving speed \( \bar{v}_o \) at \( t_4 \). In the fifth segment during \([t_4, t_o]\), vehicles cruise at \( \bar{v}_o \) and enter the intersection at \( t_o \).

It is straightforward that when the trajectory satisfies \( t_2 = t_3 = t_4 = t_o \), as shown in Fig. 3(a), the travel time \( d \) reaches its minimum and equals \( d_{min} \). When \( d = d_{min} \), the driving trajectory has a unique solution. However, when \( d > d_{min} \), the trajectory cannot be uniquely determined. Fig. 3(b) illustrates some feasible trajectories with the same \( t_i \) and \( t_o \).

Considering the safety constraint which requires the following vehicle to maintain a safety gap throughout the adjusting area between the preceding vehicle, the feasible region of the trajectory is further reduced. As illustrated in Fig. 4, the upper boundary of the feasible trajectories is shown by the solid line, in which the distance from the preceding vehicle (for which the trajectory is shown in the dot dash line) at any time is equal to the minimum gap. Since this paper only concerns the efficiency metrics of the intersection such as traffic delay and...
vehicle throughput, the “extreme acceleration” (EA) strategy in [22] is adopted, which allows vehicles to accelerate or decelerate at the maximum rates and pushes back the deceleration time $t_1$ as much as possible to leave more viable space for the following vehicles. Thus, the optimal trajectory will be the one that is tangent to or coincident with the upper boundary at some point. In Fig. 4(a), the selected trajectory is shown as the dashed line. Fig. 4(b) adds the constraint of signal phases, delaying the entry of the vehicle to the intersection.

The trajectory planning method can be applied on intersection with the fixed phase timing strategy (P-MBC) or actuated phase timing strategy (A-MBC). A brief introduction on how this method is used in the two strategies is presented as follows.

1) Fixed Timing Strategy: For the pre-timed phase settings, the phase length is determined based on the traffic demands and average headway. Webster signal timing formula [27] is widely adopted in the field of conventional signalized intersection control. Nevertheless, the calibration of the Webster formula is depended on the characteristics of human-driven traffic, which may be of distinctive difference with those in the connected and automated traffic. Therefore, in this study, the optimal cycle length is determined through a grid search by conducting a series of simulations. For each arrival pattern, we generated 10 arrival sequences and simulated them in different cycle lengths: from 16 s to 120 s in 4-leg intersections, and 12 s to 90 s in T-type intersections. The cycle length with the lowest average delay is then selected as the optimal cycle length for this traffic pattern.

2) Actuated Timing Strategy: The actuated timing strategy [28] dynamically adjusts the phase timing scheme depending on the real-time detected traffic information. In this strategy, a phase from the minor direction is activated only when a vehicle is detected in the corresponding movement, and based on the current timing scheme, the ICC determines the time $t_0$ that the vehicle should enter the intersection. Since the phase is activated, it is allocated a minimum green duration of 1 second, and every detected vehicles that are from the same movement and are able to arrive the intersection within the allocated green duration will add another $u$ seconds to the length of the green interval, where $u$ is determined based on the approaching speed, the length of the vehicle and the safety distance. The green interval ends if no vehicle is to enter the intersection in $u$ second from the same movement or a maximum green duration is achieved. In addition, the change of the timing scheme in one phase would result in the delay of green starting time of other phases, and therefore the trajectories of vehicles from the involved movements need to be re-planned. Algorithm 1 presents the process of the actuated timing strategy.

![Algorithm 1 Procedure of the A-MBC Strategy](image)

C. First-Come-First-Serve Control

For the ad-hoc negotiation based intersection control strategy, the first-come-first-serve (FCFS) control proposed in [7]
Fig. 4. Feasible region of the vehicle trajectory under the constraints of the preceding vehicle (a) and signal lights (b).

is one of the most seminal works in the literature. As its name suggests, the ICC provides reference trajectories for vehicles exactly in the order of their arrivals. Without knowledge on future traffic, the given trajectories aim to lead vehicles to pass the intersection as soon as possible without collisions with any other vehicles.

To realize collision avoidance, the ICC must record the occupancy status of the intersection space at every moment. In the study of [7], the authors present a simplified method by dividing the intersection area into multiple tiles, and replacing the occupancy of road space as the occupancy of tiles. In this paper, we adopt the conflict-point-based method to describe the occupancy of the intersection, of which the core idea is to pre-define several conflict points and record the occupied time intervals of each conflict point. The conflict-point based collision-avoidance method was previously developed for aircraft management in airports [29] and the open air [30]; in the field of intersection control, Levin and Rey [15] define conflict points as locations where the vehicle trajectories of vehicles traveling from different directions intersect. An illustration of the conflict points in a 4-leg intersection is shown in Fig. 5. The conflict points are numbered from 01 to 60, while numbers from 01 to 24 represent the entry and exit points on the 24 lanes. Here, right-turn movements from lanes 01, 05, 09 and 13 are ignored due to their negligible influence on the intersection traffic.

During operation of the conflict-point-based strategy, the ICC needs to maintain a log file that records the occupied time intervals of each conflict point and the origins and destinations of occupying vehicles. The log file is updated in real time, and the outdated record items will be deleted so that the log file only has a limited size. We denote the occupied time interval of the subject vehicle as \((t_{i,j}^{-}, t_{i,j}^{+})\), where \(t_{i,j}^{-}\) is the time when the head of the vehicle arrives the conflict point while \(t_{i,j}^{+}\) represents the time when the tail leaves the point. When a new vehicle intends to pass through the intersection, its occupancy of all conflict points must not collide with any recorded time interval that has been reserved by other vehicles. The procedure of the FCFS strategy is presented in Algorithm 2.

![Algorithm 2](image)

If we notate \((t_{i,j}^{-}, t_{i,j}^{+})\) as the occupied time interval of the conflict point \(i\) of the subject vehicle, we have either

\[ t_{i,j}^{-} > t_{i,j}^{+} + t_{buff} \]  

(1)
for one time period. As previously stated, we guarantee collision avoidance by setting a minimum inter-vehicle distance of \( s \). Consider a situation where the subject vehicle and the \( j \)th recorded vehicle pass through the conflict point \( i \) from different routes, and their trajectories intersect at an angle of \( \theta_{i,j} \) at the conflict point. As illustrated in Fig. 6, to satisfy the minimum distance condition, when the two vehicles are closest to each other, the distance between the vehicles and the conflict point can be derived as

\[
s_{i,j} = \frac{s}{2\cos(\theta_{i,j}/2)} + \frac{W_{\text{max}}/2}{\tan([\pi - \theta_{i,j}]/2)}
\]  

(3)

where \( W_{\text{max}} \) represents the maximum width of all vehicles restricted by regulations, which is a constant. It is noted that Eq. (3) also holds when the subject vehicle and the vehicle \( j \) share the same route. In this case we have \( \theta_{i,j} = 0 \) and therefore \( s_{i,j} = \frac{s}{2} \), and the distance between two consecutive vehicles equals \( s \). Finally, the \( t_{i,j}^{\text{buff}} \) is derived as

\[
t_{i,j}^{\text{buff}} = \frac{2s_{i,j}'}{v_i} = \frac{2s_{i,j}'(t_{i,j}^{(+)} - t_{i,j}^{(-)})}{l_j}
\]  

(4)

where \( l_j \) is the length of vehicle \( j \), and the speed \( v \) to pass the conflict point \( i \) is estimated using the speed of the vehicle \( j \).

Under the assumption that vehicles maintain constant speed at the intersection, the occupied time interval of each conflict point can be derived from the intersection entry time \( t^{(\text{in})} \) and exit time \( t^{(\text{out})} \) of the vehicle, as

\[
t_i^{(+)} = (1 - \frac{d_i}{d})t_i^{(\text{in})} + \frac{d_i}{d}t_i^{(\text{out})}
\]

(5)

\[
t_i^{(-)} = (1 - \frac{d_i + l}{d})t_i^{(\text{in})} + \frac{d_i + l}{d}t_i^{(\text{out})}
\]

(6)

where \( d \) represents the distance between the entry point and the exit point, and \( d_i \) represents the distance between the entry point and the conflict point \( i \). \( l \) is the length of the subject vehicle.

We formulate an MILP problem over variables \( t^{(\text{in})} \) and \( t^{(\text{out})} \) to determine the trajectory of the subject vehicle. The objective is to minimize the \( t^{(\text{out})} \), as

\[
\min t^{(\text{out})}
\]  

(7)

The constraints include

1. Lower bound of \( t^{(\text{in})} \) based on the distance to the intersection entry. Enough time should be guaranteed for the subject vehicle to arrive at the intersection, even if it is required to decelerate and enter the intersection at \( v^{(\text{min})} \).

\[
t^{(\text{in})} \geq t^{(\text{min})}
\]  

(8)

2. Speed limits, as

\[
\frac{d}{v^{(\text{max})}} \leq t^{(\text{out})} - t^{(\text{in})} \leq \frac{d}{v^{(\text{min})}}
\]  

(9)

3. First-in-first-out (FIFO) conditions, as

\[
t^{(\text{in})} \geq t_{c_{\text{in}},0}^{(+)}
\]

(10)

\[
t^{(\text{out})} \geq t_{c_{\text{out}},0}^{(+)}
\]  

(11)

where \( c_{\text{in}} \) is the entry point of the intersection and \( c_{\text{out}} \) is the exit point. For example, for the bold route illustrated in Fig. 5, \( c_{\text{in}} = 3 \) and \( c_{\text{out}} = 21 \). \( f_0 \) is the last vehicle that shares the same route with the subject vehicle. Eqs. (10) and (11) guarantee the FIFO constraint when vehicles have the same spatial trajectory.

4. Collision avoidance conditions. To describe Eqs. (1) and (2) under the MILP framework, we introduce auxiliary 0-1 variables \( \delta_{i,j} \) and a large number \( M \). If the subject vehicle passes the conflict point \( i \) after the vehicle \( j \) does (as Eq. (1) shows), we define \( \delta_{i,j} = 0 \), and vice versa. The Eqs. (1) and (2) can be therefore rewritten as

\[
-t_i^{(+)} + (t_{i,j}^{(+)} + t_{i,j}^{\text{buff}}) \leq \delta_{i,j} M
\]

(12)

\[
t_i^{(+)} - (t_{i,j}^{(-)} - t_{i,j}^{\text{buff}}) \leq (1 - \delta_{i,j}) M
\]

(13)

\[
\delta_{i,j} \in \{0, 1\}
\]  

(14)

By solving the optimization problem from Eqs. (7)-(14), we have obtained the optimal intersection entry and exit times for the subject vehicle, based on the existing conflict point occupancy. In addition, the occupancy status of involved conflict points are calculated and then updated using Eqs. (5) and (6) for the optimization of future traffic.
**D. Optimization-Based Intersection Control**

Different from the FCFS strategy, the optimization-based intersection control (OBC) considers multiple vehicles simultaneously in a dynamic fashion. In this category of control, a large-scale optimization problem is usually formulated to determine the intersection passing order as well as the detailed passing trajectories for vehicles. In addition, a rolling horizon model is generally adopted in dynamic traffic scenarios for real-time implementation [8]. Theoretically, the OBC is considered to outperform the ad-hoc negotiation based control because the strategies adopted in ad-hoc negotiation based control are always feasible in the optimization process; however, constrained by the heavy computational burden in the optimization procedure, the OBC must compromise on optimization scope and suffer from performance loss in practice.

Our realization of planning-based control is mainly based on the Conflict Point Intersection Control (CPIC) model proposed in [15]. The process of the strategy is as follows. As illustrated in Fig. 7, two control lines are set in the adjusting area. The outer line is regarded as “vision”, and the inner line suggests the minimum safety distance for a vehicle to adjust its speed to pass through the intersection. The ICC receives or detects the locations and the speeds of all approaching CAVs at every time step, and when a vehicle passes through the first control line, it will be added into the optimization set. In each time step, an MILP problem is formulated to find the optimal trajectories for the set members. The obtained solution is only conducted for the period of one step before another solution is given out. Presented as the “as late as possible” (ALAP) rule in [15], the trajectory for each vehicle remains adjustable until it passes the second control line. After that, the trajectories are determined, serving as constraints for undetermined vehicles. The procedure of the OBC strategy is presented in Algorithm 3.

The formulation of the MILP problem is also based on the definition of conflict points. Under this framework, the optimization problem can be formulated in a similar form with Eqs. (7)-(14), while since we organize multiple vehicles in a single optimization process, the decision and auxiliary variables involved in the MILP problem have significantly increased.

Let $V_1 = \{v_1, v_2, \ldots, v_n\}$ includes the $n$ vehicles between the control line I and II, and $V_2 = \{v_{n+1}, v_{n+2}, \ldots, v_{n+m}\}$ includes the $m$ vehicles who have passed the control line II and not yet left the intersection. We aim to minimize the sum of exit time of all vehicles in $V_1$, as

$$\min \sum_{j=1}^{n} t_j^{(\text{out})}$$

Similar to the constraints in the formation of the FCFS strategy, we have following constraints in the OBC strategy. The notations are similarly presented as before.

1. **Lower bound of $t_j^{(\text{in})}$ for all $v_j \in V_1$, as**
   $$t_j^{(\text{in})} \geq t_j^{(\text{min})}$$

2. **Speed limits of all $v_j \in V_1$, as**
   $$\frac{d_j}{v_j^{(\text{max})}} \leq t_j^{(\text{out})} - t_j^{(\text{in})} \leq \frac{d_j}{v_j^{(\text{min})}}$$

3. **FIFO conditions for all vehicle pairs that $v_k$ passes after $v_j$ on the same route with $1 \leq j, k \leq n + m$, as**
   $$t_k^{(\text{in})} \geq t_j^{(\text{in})}$$
   $$t_k^{(\text{out})} \geq t_j^{(\text{out})}$$

4. **Collision avoidance conditions. For every vehicle pairs $v_j, v_k$ that come from different directions and have intersecting trajectories at the conflict point $i$, we have**
   $$-t_{i,k}^{(-)} + (t_{i,j}^{(+)} + t_{i,j}^{(\text{buff})}) \leq \delta_{i,j,k} M \quad (20)$$
   $$t_{i,j}^{(+)} - (t_{i,j}^{(-)} - t_{i,j}^{(\text{buff})}) \leq (1 - \delta_{i,j,k}) M \quad (21)$$
   $$\delta_{i,j,k} \in \{0, 1\} \quad (22)$$

where $t_{i,j}^{(+)}$ and $t_{i,j}^{(-)}$ can be calculated using Eqs. (5) and (6) with $v_j$ ($v_k$) regarded as the subject vehicle.
Along the adjusting area is passes the conflict point and k roads. Similar to the 4-leg intersection, scenarios legs from the opposite direction were narrowed as secondary 1-A tested the model performance in a symmetric 4-leg intersection and imbalanced traffic demand patterns and intersection layouts. We first assess the model performance characteristics under different scenarios. By using heterogeneous intersection scenarios, we ran the simulation under both balanced and imbalanced traffic demand cases, obtaining an optimal solution of this problem is quite time-consuming. According to the simulation experiment conducted in [15], the trajectory arrangement for no more than 30 vehicles can be completed in real time. If the gap between the two lines is set to a too large value, too many vehicles will be involved in the optimization, and therefore, real-time trajectory allocation will be impossible; on the other hand, the performance of the solution will be damaged with a narrow gap. Therefore, we have to develop a mechanism to include as many vehicles as possible into the optimization, while ensuring that the optimization can be solved efficiently enough. In the simulations of this paper, the gap between the two control lines varies from 18 meters to 72 meters depending on the traffic demand.

IV. COMPARISONS OF NUMERICAL SIMULATIONS

In this section, we present the results of the numerical simulations on the four control models under a variety of scenarios. By using heterogeneous intersection scenarios, we assess the model performance characteristics under different traffic demand patterns and intersection layouts. We first tested the model performance in a symmetric 4-leg intersection (scenarios 1-A and 1-B). Then, in scenarios 2-A and 2-B, two legs from the opposite direction were narrowed as secondary roads. Similar to the 4-leg intersection, scenarios 3-A and 3-B test the performance in a T-type intersection. In each intersection layout, we ran the simulation under both balanced and imbalanced traffic demand. Moreover, under the same intersection layouts of scenario 1-A, we explored the possible impact of a fluctuated traffic pattern (in scenarios 4-A and 4-B), dominant traffic direction (in scenarios 5-A and 5-B) and different safety buffers (in scenarios 6-A, 6-B and 6-C). The numerical simulations were coded on MATLAB [31], and conducted using a personal computer with an AMD Ryzen 7 3700x CPU and 16GB RAM.

For an unbiased comparison of the performance of the vehicle-based and movement-based traffic control, we ensure that each control strategy shares exactly the same traffic scenario and environmental variables. The time step as well as the reaction time in simulations is 0.2 seconds. The length of the adjusting area is 600 m. Vehicles enter the area at the maximum allowable cruising speed (7), which is 18 m/s in simulations; the minimum speed v along the adjusting area is set 5 m/s. When passing through the intersection, the speed limit v0 is 15 m/s for through vehicles and 10 m/s for left-turn vehicles, while right turns are ignored from the model due to their negligible influence on the intersection traffic. The maximum acceleration and deceleration rates are 1.5 m/s\(^2\). All of the vehicles are cars with dimensions of 4 m × 1.8 m. In the movement-based traffic control, the method suggested by National Electrical Manufacturing Association (NEMA) is adopted to assign phases to movements, and the phase settings of the 4-leg and 3-leg intersection is illustrated in Fig. 8. Specifically, based on the traffic patterns involved in the simulations, phase pairs 1&5, 2&6, 3&7 and 4&8 in 4-leg intersections begin and end simultaneously, and in 3-leg intersections, westbound through vehicles are allowed to pass through the intersection if there are no conflicts with vehicles from other phases. The clearance interval between two consecutive phases is 3 seconds in accordance to the maximum required time for vehicles to pass through the intersection. In most scenarios, we adopt a static buffer size that does not vary with vehicle speed. In scenarios 1, 2, 3, 4 and 5, the minimum spatial gap between any two vehicles is 1.0 m, and we also test the performance of the control models under different safety gap settings of 2.3 m and 3.6 m in scenarios.
6-A and 6-B. In scenario 6-C, the inter-vehicle gap is set as a static time gap of 1.5 seconds for crossing-type or merging-type conflicts and 1.0 second for car-following.

A. Traffic Generation

In the simulations, we use \( \lambda_0 \) to describe the traffic demand volume, which denotes the average number of total arrivals per hour in all lanes. In each scenario, we test 15 cases with \( \lambda_0 \) varying from 1,000 to 15,000. In addition to the total volume, we also specify the distribution pattern of traffic demands by setting the vehicle distribution ratio \( r_i \) on lane \( i \), where \( \sum_i r_i = 1 \). The traffic intensity of lane \( i \) is determined by the following Eq.(24).

\[
\lambda_i = \lambda_0 r_i \quad (24)
\]

For each vehicle arrival vector \( \lambda \), 10 realizations of vehicles arrivals in 65 minutes are randomly generated, and the first 5 minutes are regarded as the warm-up time. As suggested in [32], we supposed that the headway follows a shifted exponential distribution, and the minimum following headway is set to 1.0 s. In each time step of 0.2 seconds, the probability that a new arrival is generated is determined by Eq.(25).

\[
p_i = \begin{cases} 
0, & \text{if the time gap to the previous vehicle} < 1.0 \text{ s} \\
\frac{\lambda_1}{18000 - 5\lambda_1}, & \text{otherwise.}
\end{cases} \quad (25)
\]

With the generated arrival realizations, the four control models are tested, and the differences between the simulated travel times and the free flow times are calculated as the delay time. In some extreme cases, the queuing vehicles may spill back to the head of the adjusting area and therefore block new arrivals. If the generation of vehicles is blocked, the entrance will be postponed and the waiting time is also considered into the total delay. Additionally, for each traffic scenario, the maximum observed throughput in one hour is summarized as an estimation of the capacity of the corresponding strategy in the scenario.

B. Symmetric 4-Leg Intersection

As shown in Fig. 9, we model a 4-leg intersection with 6 lanes in each leg, among which 4 lanes are approaching the intersection and 2 lanes are departing. The lane width is 3 m. As illustrated, the lanes are numbered from 01 to 24. The possible routes between the lanes are fixed; for example, a vehicle that arrives from the south and intends to make a left turn heading west will enters the intersection from lane 08 and leaves at lane 21. The right-turn movements are omitted in this study, indicating that no vehicle is generated from lanes 1, 5, 9 and 13. Two traffic demand patterns are tested under this intersection layout: the balanced demand pattern and the imbalanced demand pattern.

In the balanced demand pattern (scenario 1-A), the traffic intensity of all lanes are equally set as 1/12 of the total traffic demand \( \lambda_0 \). Therefore, we have \( r_i = 1/12 \) for \( i \in \{2, 3, 4, 6, 7, 8, 10, 11, 12, 14, 15, 16\} \) and \( r_i = 0 \) otherwise, as shown in Fig. 9(a). For every traffic level \( \lambda_0 \) from 1,000 vph (or vehicles per hour) to 15,000 vph, Fig. 10(a) presents the average value of the delay time of 10 experiments, and the 25th and 75th values are expressed by the colored region around the curves. The comparisons across various intersection control models (FCFS, OBC, P-MBC and A-MBC) show notable differences in the average delay, particularly when traffic demand is high.

Benefiting from the reduced headway and start-up losses, the MBC under the CAV environment is able to achieve a short cycle length. When the traffic demand is quite low, a total green time ratio of 25% is verified to be sufficient to dissipate queuing vehicles, and the signal cycle time can be shortened to 16 seconds with the average delay shortened to no more than 8 seconds. In addition, we observe a relatively lower delay for the A-MBC strategy, since it activates phases from minor directions only when passing demand occurs. The two vehicle-based traffic control models show even better performance under low traffic volume. Most vehicles can maintain the maximum speed when passing the intersection, experiencing negligible delays. In most traffic demands, the OBC strategy outperforms the FCFS strategy, since the solution of the FCFS strategy is always within
the average delay of the FCFS strategy when
length of 32 s. On the other hand, as shown in Fig. 10(a),
P-MBC strategy is around 15.16 s under an optimal cycle
the numerical simulations show that the average delay of the
eties. Under the scenario that the traffic demand is 15,000 vph,
higher average delay. However, the increase in the average
delay is quite small compared to that of FCFS and OBC strate-
gies, which are another important category of

| Scenario | FCFS | OBC | P-MBC | A-MBC |
|----------|------|-----|-------|-------|
| Scenario 1-A | 11,611 | 11,822 | ≥15,000 | ≥15,000 |
| Scenario 1-B | 11,465 | 11,633 | ≥15,000 | 14,535 |

Fig. 10. Average delay of scenarios 1-A(a) and 1-B(b).

C. 4-Leg Intersections With Secondary Roads

We then examine the performances of the control models under a smaller intersection where a 6-lane main road intersects with a 4-lane secondary road. The balanced (scenario 2-A) and imbalanced (scenario 2-B) traffic patterns are included. The intersection layouts and the demand patterns are presented in Figs. 11(a) and 11(b), respectively. This type of intersections is prevalent in urban road networks, particularly on arterial roads.

The simulation results under the balanced and imbalanced traffic patterns are presented in Figs. 12(a) and 12(b), respectively, and the maximum throughput is shown in Table III. The basic trends of the average delay given by the four control models in this intersection layout do not differ much from those observed in scenarios 1-A and 1-B. It should be noted that in scenario 2-A, a relatively high demand of $\lambda_0 = 10,000$ caused a significant deviation among the 10 simulations under the OBC strategy. The results indicate that the performance of the OBC strategy in busy intersections is unreliable with the potential risks for intersection failure.

D. T-Type Intersections

A series of simulations are also used to examine T-type intersections, which are another important category of

Remark 1: It should be noted that the success of the P-MBC strategy relies on the prior knowledge of the traffic demand and
distribution; otherwise, we may observe a higher average delay
when the optimal timing scheme is not chosen. This character-
istic suggests that the P-MBC strategy is less adaptive than its
vehicle-based counterparts. The following table presents the
average delay time (s) of the P-MBC strategy under different
traffic demands (vph) and cycle length settings (s).

In the imbalanced distribution pattern (scenario 1-B), we assumed that the traffic demand from the east and the south
is higher than average. Fig. 9(b) illustrates the distribution:
$\lambda_0 = 12,000$. In Table II, the capacities of the FCFS and OBC
strategies. Under the scenario that the traffic demand is 15,000 vph,
the numerical simulations show that the average delay of the
P-MBC strategy is around 15.16 s under an optimal cycle
length of 32 s. On the other hand, as shown in Fig. 10(a),
the average delay of the FCFS strategy when $\lambda_0 = 11,000$ is
7.58 s, while under the demand that $\lambda_0 = 12,000$, the delay
time increases to 71.92 s. Similar phenomena are also observed
in the OBC strategy when $\lambda_0$ reached 12,000. In Table II, the
maximum throughput in one hour of simulation is presented,
and the results indicate that the capacities of the FCFS and the
OBC strategy in this scenario are 11,607 vph and 11,822 vph,
respectively.

For this intersection layout, we can briefly summarize
the performance of the different intersection control models under various demand levels. The vehicle-based traffic control
performs well under low demand, but the capacity of these
models is relatively low, i.e., the models cannot accommodate
to large demands well. On the contrary, the movement-based
trafﬁc control shows higher delay under low trafﬁc volume
scenarios, but in high demand cases ($\lambda_0 \geq 12,000$ in this
scenario), it becomes the only method that can stabilize the
intersection queues.

Remark 1: It should be noted that the success of the P-MBC strategy relies on
prior knowledge of traffic demand and

### Table I

| Sensitivity Analysis Under Different Cycle Lengths | 9000 | 10000 | 11000 | 12000 | 13000 | 14000 | 15000 |
|-------------------------------------------------|------|-------|-------|-------|-------|-------|-------|
| 22                                              | 10.16 | 11.12 | 13.94 | 33.51 | 86.61 | 180.83 | 331.52 |
| 24                                              | 10.62 | 10.92 | 11.91 | 15.41 | 38.41 | 99.65 | 209.96 |
| 26                                              | 10.78 | 11.01 | 11.32 | 11.98 | 13.19 | 17.13 | 48.28 |
| 28                                              | 11.38 | 11.55 | 11.76 | 12.15 | 12.84 | 14.51 | 21.36 |
| 30                                              | 12.00 | 12.13 | 12.29 | 12.52 | 12.86 | 13.54 | 15.51 |
| 32                                              | 12.62 | 12.77 | 12.91 | 13.11 | 13.40 | 13.92 | 15.16 |

### Table II

| Maximum Throughput in Scenarios 1-A and 1-B |
|---------------------------------------------|
| Scenario 1-A | 11,611 | 11,822 | ≥15,000 | ≥15,000 |
| Scenario 1-B | 11,465 | 11,633 | ≥15,000 | 14,535 |
intersections. In the junction connecting one main road (from the west and east) and a secondary road (from the south), traffic from the main road is dominant. The intersection layouts and the demand distributions are presented in Figs. 13(a) and 13(b), including a balanced demand pattern and an imbalanced one.

The simulation results are shown in Fig. 14 and Table IV. The results indicate that the conclusions we draw from 4-leg intersections also hold on T-type intersections. Moreover, combining the results from scenarios 1-A and 3-A, it can be seen that in cases with low traffic demands, the difference between the FCFS strategy and the OBC strategy is negligible. It indicates that in low demand scenarios, organizing vehicles in the order of their arrivals might be near optimal.

### E. Symmetric 4-Leg Intersection Under Fluctuating Arrival Rates

In following scenarios, we examine the impact of fluctuating arrivals in a symmetric 4-leg intersection. The intersection layouts and the demand distributions are the same as those in scenarios 1-A and 1-B, which are shown in Figs. 9(a) and 9(b),

#### Table III

| Maximum Throughput in Scenarios 2-A and 2-B | FCFS | OBC  | P-MBC  | A-MBC  |
|-------------------------------------------|------|------|--------|--------|
| Scenario 2-A                              | 9,600| 9957 | ≥15,000| ≥15,000|
| Scenario 2-B                              | 10,044| 10,117| 13,588 | 12,594 |

Fig. 11. Intersection layouts and demand distribution under the scenarios 2-A(a) and 2-B(b).

Fig. 12. Average delay of scenarios 2-A(a) and 2-B(b).

Fig. 13. T-type intersection with balanced (a) and imbalanced demand patterns (b).
respectively. The differences lie in the traffic generation procedure. In scenarios 4-A and 4-B, the vehicle generation rate varies every 2 minutes between 0.5$\lambda_0$ and 1.5$\lambda_0$. For instance, for the demand volume such that $\lambda_0 = 6,000$, the average vehicle arrival rate is set to 3,000 vph in the first two minutes of the simulation and 9,000 vph in the next two minutes. The purpose of these experiments is to study the ability of the control models to deal with temporary queues. In traditional traffic scenarios, joining a growing queue generally leads to an additional queuing delay. Considering the notable startup loss in manual driving, it will take even more time for a queue to dissipate, giving rise to a degradation in the intersection efficiency. However, due to the shorter reaction time of CAVs, it is expected that the fluctuating arrival process will lead to a weaker impact on autonomous driving intersections.

From the simulation results presented in Fig. 15 and Table V, it can be observed that the fluctuations in the traffic arrivals do not have much influence on the efficiency and capacity of the vehicle-based control strategies, while the movement-based strategies are revealed to have higher delay in such scenarios.

We take the scenario with a traffic demand of 8,000 vph as an example to illustrate the variation of the delay time under different control strategies. Fig. 16 shows the delays of individual vehicles entering the intersection during the one-hour simulated time and the average delay (marked as the dashed line) of each strategy. When demand volumes shift from low to high, both vehicle-based strategies demonstrate differing delay times; on the other hand, under P-MBC, delay times are evenly distributed within a control cycle, with only a few vehicles waiting more than one cycle. Under the A-MBC strategy, we also observe a reduction in average delay during periods of low demand. However, due to the A-MBC strategy not being fully actuated, the reduction in average delay is less apparent than with vehicle-based strategies.

### F. Symmetric 4-Leg Intersection With Dominant Directions

In this series of scenarios, we examine the impact of dominant directions in a symmetric 4-leg intersection. As shown in Fig. 17, the traffic demand on the straight lanes from the east and the west is three times of that on other lanes. In scenario 5-A, the traffic arrivals are stable, while in 5-B the traffic demand fluctuates in the same manner with scenarios 4. The average delay and the maximum throughput in the two scenarios are presented in Fig. 18 and Table VI.

Compared to the scenario 1-A, the observed traffic delay in case 5-A is lower under most traffic demands, especially with the movement-based FCFS and OBC strategies. It is because less intersected trajectories are generated since most vehicles are from the dominant direction and do not conflict with
each other. In addition, the A-MBC strategy has more distinct advantages compared to the P-MBC strategy in low traffic demands, since phases from the minor directions are more likely to be skipped in low demand cases with the A-MBC strategy.

G. Intersection Performance Under Different Safety Gaps

Finally, we examine the intersection performance under different safety gap settings to reflect the impact of technological maturity of autonomous driving. In previous simulations, the minimum allowable gap between vehicles is 1.0 m. This setting only considers a possible trajectory tracking error of up to 0.5 meters (which is validated to be realistic in [33] and [34]), while the GPS location error and communication delay are omitted. It requires a relatively high autonomous driving technology level, which is unlikely to be achieved in the near future. Therefore, to examine the impact of immature autonomous driving technologies, we conducted simulations with different safety gap settings. As suggested in [35], it is currently possible to achieve a communication delay within 20 milliseconds and a GPS location error within 1 meter. Based on the maximum speed of 15 m/s, we set a safety gap of 3.6 meters as a value that CAVs may achieve in the initial stage in scenario 6-B, and a gap of 2.3 meters that may be realistic in the near future in scenario 6-A. The simulations are conducted under the same intersection layout and demand pattern of scenario 1-A.

Fig. 19(a) illustrates the simulation results when the minimum allowable safety gap is set to 2.3 m. The change would have impacts on the headway of two consecutive vehicles from the same direction; furthermore, the minimum time gap between two conflict vehicles increases significantly, especially in conflict points with small angle $\theta$ (see Fig. 6). As shown in Fig. 19, the performance comparisons of the four control models follow similar patterns as in other scenarios: vehicle-based traffic control is dominant in the low demand cases, while the movement-based traffic control shows better performance in busy intersections. However, compared to the results of scenario 1-A (shown in Fig. 10(a)), the intersection

| Scenario  | FCFS | OBC  | P-MBC | A-MBC |
|-----------|------|------|-------|-------|
| 5-A       | 13,979 | 14,703 | 15,000 | 15,000 |
| 5-B       | 13,299 | 14,119 | 15,000 | 15,000 |
The performance is degraded in all the four control models. The delay under all demand levels increases and the maximum throughput decreases. For the vehicle-based strategies, the average delay begins to rise rapidly when $\lambda_0$ exceeds 8,000. Among the four control models, the MBC strategies are found to be affected the least by the increased safety gap. The critical traffic demand level at which the MBC strategies outperform the OBC strategy is around 8,000 vph, which is much smaller than the value in scenario 1-A (around 11,000 vph). The results of the simulations conducted under a much higher safety gap setting are shown in Fig. 19(b). When the minimum allowable safety gap is 3.6 m, the advantages of the MBC strategies are more distinct. The average delay of the vehicle-based traffic control exceeds the delay of the MBC strategy when $\lambda_0 = 7,000$.

In addition, a series of experiments are conducted to explore the performance of the four strategies when the safety gap is chosen as the similar values in the human-driving environment. In scenario 6-C, we set the minimum car-following headway as 1.0 second, and the minimum time gap between the passing of two crossing-type conflicting vehicles on the conflict point is 1.5 seconds. The simulation results are shown in Fig. 20. In this scenario, we observe a sharp performance decline under all intersection control strategies. The maximum throughput of the vehicle-based strategies is lower than 5,000 vph, and the MBC strategies are forced to deploy a long cycle, which increases the average delay. Nevertheless, we can still notice that the MBC strategies have larger capacities and better abilities to handle high traffic demands. The results indicate that the MBC strategies may be more suitable when autonomous driving technologies are not sufficiently advanced.

Table VII shows the maximum throughput of the four strategies in different safety gap settings.

| Scenario | FCFS | OBC | P-MBC | A-MBC |
|----------|------|-----|-------|-------|
| Scenario 6-A | 8,481 | 8,906 | $\geq$ 15,000 | $\geq$ 15,000 |
| Scenario 6-B | 6,524 | 7,571 | $\geq$ 15,000 | 13,481 |
| Scenario 6-C | 4,617 | 4,904 | 7,342 | 6,646 |

V. CONCLUSION

To supplement the existing studies on the isolated intersection control in the CAV era, this paper compared the performances of two intersection control philosophies, i.e., movement-based and vehicle-based traffic control, through a series of numerical simulations. Specifically, we implement four intersection control strategies: one ad-hoc negotiation based FCFS strategy, one optimization-based control strategy (OBC), pre-timed and actuated movement-based control (P- and A-MBC). For a fair comparison of the four control strategies, all of the environmental factors, including the safe gap, the adjusting area length and the speed limits, were set to be the same to ensure that all control strategies benefited equally from autonomous driving technologies. The comparisons were conducted under multiple intersection layouts, including symmetric and asymmetric 4-leg intersections as well as a T-type intersection. In each layout, we simulated various traffic demand levels from 1,000 to 15,000 vehicles per hour and distributed the demand in both balanced and imbalanced manner. Furthermore, we compared the intersection performances under different settings, such as fluctuating vehicle arrival sequences, dominant directions and larger safe gaps.

The simulation results lead to some interesting conclusions. When the traffic demand is low, the vehicle-based traffic control strategies (FCFS and OBC) show negligible delay. As the demand level increases, their delay increases rapidly, making the movement-based traffic control a relatively better choice. Specifically, the actuated movement-based control achieves lower delay in low demand scenarios, while the pre-timed one owns larger maximum throughput. Nevertheless, in traffic scenarios with less conflicting vehicles (e.g., when there are dominant directions and most vehicles drive on
the main road) or imbalanced traffic pattern (e.g., when the traffic demand differs a lot between the two movements that share the same signal interval), the relative advantages of vehicle-based methods over the movement-based methods are more distinct. On the contrary, when autonomous driving technologies are immature so that the CAVs are forced to maintain a larger headway, the advantages of movement-based control are more remarkable. In addition, since the performance of the P-MBC strategy relies on an elaborate selection of the cycle length, it might be more suitable to choose the A-MBC or vehicle-based strategies when the traffic predictions are unavailable.

In general, findings of this study reveal that the vehicle-based and movement-based strategies each have their own scope of applicability. The movement-based strategies that employ a logic similar to traditional signal timing are not entirely defeated, as many might expect, by vehicle-based strategies; rather, they have proven irreplaceable in high demand scenarios. The advantages of movement-based strategies in such scenarios mainly come from the reduced cycle length with CAVs. It is also supported in the study by [36], which suggests that the vehicle-based strategy tends to exhibit a signal-like behavior and group vehicles from different movements to enter the intersection in turns under high demands. Barring the traffic intensity, other factors such as intersection layouts and traffic distributions could also lead to a shift in preference between the two categories of strategies. Furthermore, the findings of this study offer a promising future for combining concepts of vehicle-based and movement-based strategies and exploiting the strengths of each.

This paper discussed several representative intersection control strategies in the autonomous driving era, and our comparisons cannot cover all possible control strategies. From the results derived from this study, we believe it a worthwhile endeavor to explore mixed intersection control strategies for improved performances in general traffic scenarios; furthermore, to acquire more reliable results, deriving the theoretical performances of intersection control under general settings is a topic worth investigating. Regarding the comparison between vehicle-based and movement-based strategies, the required safe gap is assumed to be fixed in this paper, which is not always reasonable, and the effects of a flexible gap should be examined in future studies. Finally, since some existing studies (e.g., [24]) have revealed that the selection of control strategies at different intersections may affect the efficiency of traffic network, in the future it is necessary to generalize the comparisons to network level in order to obtain a comprehensive understanding of the performance of the network traffic control.

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