Research Article

An Occupancy-Based Adaptive Signal Control for a Congested Signalized Intersection in the Low CV Penetration Environment

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Adaptive signal control (ASC) is a well-researched topic that offers an efficient way for traffic management. It possesses a powerful ability to accommodate complex and constantly changing urban transportation networks. With the development of vehicular communication, CV-based ASC shows remarkable advantages compared with the traditional ASC system. Though the existing CV-based ASC strategies were proposed in the past few years, however, there are still issues to overcome. Most of the studies on CV-based ASC are based on the assumption of high CV penetration rate, which often result in poor performance when applied to low CV penetration environments. Besides, the lack of consideration for mixed traffic flow, which is in terms of both the vehicle types and CV penetration of different types of vehicles. To solve these issues, this paper developed an Occupancy-Based ASC strategy for a congested signalized intersection to optimize signal timing and reduce total passenger delay in the low CV penetration environment. Focused on the issues existing in the low CV penetration environment, a Maximum Likelihood Estimation (MLE) model was proposed to estimate vehicle arrivals, and two traffic models, MicroDM and MacroDM, were developed to model the mixed traffic flow and estimate passenger delay. With the purpose of offering fair treatment to passengers approaching the intersection, we proposed an Occupancy-Based Adaptive Signal Control strategy. By transforming the complex signal control problem into a mixed-integer linear programming problem, we found the optimal solution for minimizing total passenger delay. We then evaluated the proposed Occupancy-Based ASC strategy using simulation case studies. The results show that changing traffic status could be captured and estimated with the real-time CV trajectory data as input. Applying the Occupancy-Based ASC control strategy, phases with HOVs or more vehicles will be allocated more travel time. In particular, optimization results show that the proposed Occupancy-Based ASC strategy effectively balances passenger travel demands during peak volume periods.

1. Introduction

Traffic congestion is always a thorny issue in urban transportation networks. Limited by land resources, the traffic capacity hardly meets the growing traffic demands [1]. Especially during morning and afternoon rush hours, traffic volume may surge, leading to traffic jams and inefficiency. In response, an effective traffic management system is necessary for urban transportation networks.

Having been researched for decades, traffic signal control is one of the most efficient traffic management methods, resolving conflicts between multiple participants [2]. If properly optimized, the traffic demand in all directions can be balanced to improve efficiency and mitigate congestion. Numerous studies have investigated traffic signal control systems, and we find that those systems can be divided into three categories: fixed-time, actuated, and adaptive signal control [1–5]. The fixed-time and actuated signal control
systems operate based on predefined static parameters, which means they perform poorly when the traffic state changes [6]. The adaptive signal control (ASC) has shown a powerful ability to accommodate complex and constantly changing urban transportation networks. The ASC applies real-time traffic data to predict near-future traffic conditions and generated the optimal signal timing plan [7]. Especially in recent years, the introduction of continuous and multi-dimensional traffic information brought by connected vehicle (CV) technology significantly promotes the development of the ASC system [8–10]. Given this, adaptive signal control is the focus of the current research.

With real-time traffic data as input, numerous ASC strategies optimize the timing plan by minimizing vehicle delay, queue length, or vehicle stops to improve the capacity and efficiency of intersections [11–16]. However, such vehicle-based ASC strategies may lead to the unfair treatment of passengers in high occupancy vehicles, such as transit vehicles. To be fair, the signal timing optimization should be based on passenger demand rather than solely the number of waiting vehicles. With this in mind, several studies have developed ASC strategies to balance the traffic demands of all passengers and provided several examples under different traffic states [17, 18]. High occupancy vehicles, in this case, would be given greater right of way and fairer treatment. It is kind of like the Transit Signal Priority (TSP) strategy, except that the TSP only focuses on traffic demands of transit vehicles and ignores cars.

Though the existing CV-based ASC strategies were proposed in the past few years, however, there are still key issues requiring answers. Firstly, most of the studies on CV-based ASC are based on the assumption of high CV penetration rate. Admittedly, such a hypothesis is forward-looking, but the low penetration rate condition will still continue for many years. The low penetration rate causes incomplete traffic information, which will accumulate disturbances, and degrade the performance of these CV-based ASC control. Therefore, how to estimate the status of non-CVs in low CV penetration is the first issue we want to solve. Second, the low CV penetration traffic flow is mixed. The “mixed” refers to both vehicle types and CV penetration of different types of vehicles. Some vehicles, such as transit vehicles, are 100% CV penetration rate for the efficiency improving purpose, while cars will be low penetration in the near future. Most existing CV-based ASC treated the mixed flow with the same microscopic models, which is limited utility when the CV information is incomplete. Hence, proposing a mixed traffic flow model, and estimating the travel demands of different vehicles, it is the second issue we want to solve.

To further our knowledge of proposing an ASC strategy for low CV penetration environment, and offering fair treatment to passengers, this study developed an Occupancy-Based ASC strategy for a congested signalized intersection in Wuhan, China. The research purpose is to optimize signal timing and reduce total passenger delay in the low CV penetration environment. The contributions are as follows: first, to solve the issue of the incomplete traffic information caused by the existing non-CVs, a Maximum Likelihood Estimation (MLE) model was proposed to estimate vehicle arrivals. To benefit by the high frequency CV data, estimation results were constantly updated in real-time to capture the rapidly changing traffic status. Second, to model the mixed traffic flow and estimate passenger delay, we built a Microscopic Delay Model (MicroDM) for HOVs with 100% CV penetration and a Macroscopic Delay Model (MacroDM) for car with low CV penetration. On this basis, we proposed an Occupancy-Based ASC strategy aimed at minimizing total passenger delay to offer fair treatment to passengers approaching the intersection. The evaluation was conducted by numerical simulation.

The remainder of this paper is organized as follows: in the next section, we define the problem of the timing plan optimization for a congested signalized intersection. The subsequent Methodology section outlines the models for CV data-based traffic state estimation and HOV and car passenger delay estimation, as well as the proposed Occupancy-Based ASC strategy. Section 4 describes the testing and evaluation of the proposed algorithm conducted for this study. Section 5 outlines our conclusions and suggests recommended future work.

2. Literature Review

As one of the most efficient traffic management methods, traffic signal control has been proposed and researched for decades. The literature and applications of traffic signal control can be divided into fixed-time, actuated, and adaptive signal control. Fixed-time control strategy makes the timing plans based on historical traffic data. It is the most widely used signal control strategy, even though its disadvantages are manifestly evident. As an off-line solution, it cannot accommodate the changing traffic demands in actual environments and usually results in poor performance [2]. As a real-time control strategy, actuated signal control collects data from infrastructure-based sensors, such as cameras, radars, and loops, and changes the signal timing to react to current traffic demands. Red truncation, green extension, and phase insertion are usually used to change the signal timing. However, this kind of signal control strategy is made based on a set of predefined static parameters, making it perform poorly when the traffic state changes [6]. Adaptive control’s input is similar to active signal control, but the signal timing parameters can be adjusted in real-time according to the control target. The adaptive control strategy has proven to better respond to the changing traffic state than passive and active control. Thus, it is the focus of the current research [1, 2].

As mentioned, implementing an adaptive control strategy relies on traffic data acquired by infrastructure-based sensors in early research. Based on these sensors, several adaptive signal control systems have been developed and applied, such as SCOOT (Split Cycle Offset Optimization Routine) [19], SCATS (Sydney Coordinated Adaptive Traffic System) [20], and OPAC (Optimization Policies for Adaptive Control) [21]. However, problems continue to exist for the data collected by the traditional sensors. For instance, fixed sensors can only provide the spatial and...
temporal information of traffic flow measured at specific points, which is discontinuous and limited. Furthermore, if the queue length of the intersection increases beyond the detection range during the peak volume period, it is challenging to get arrival information due to perception range limitations. In addition, infrastructure-based sensors are vulnerable to weather and environmental factors, which may hamper data collection, sometimes making it inaccurate [8, 9].

In recent decades, wireless communication technology was developed and applied in vehicular communication, known as CV technology. It enables vehicles to communicate with each other and with roadside infrastructure [10]. Leveraging CV technology, much continuous and multi-dimension traffic information can be captured, especially the CVs’ trajectories, which feature real-time and high reliability. With the introduction of CV data, some studies proposed methods of traffic state estimation, such as vehicle arrival and queue, as well as time-of-day breakpoints identification [22–25]. This use of data further completes the picture of the traffic states near an intersection and can be utilized for signal control [1]. These discussions contribute significantly to the development of ASC strategies.

The research on adaptive signal control (ASC) in the CV environment has generated key discussions where several issues are the focus. The mainstream of research is improving the capacity and efficiency of intersections. Feng Y et al. presented a real-time adaptive signal phase allocation algorithm to optimize the phase sequence and duration, aiming at reducing the total vehicle delay and queue length at the intersection [11]. CV data were used to estimate the traffic status and predict vehicle arrivals. In 2016, Younes and Boukerche proposed an intelligent traffic light controlling (ITLC) algorithm to minimize vehicle delay [12]. This algorithm considered the real-time traffic characteristics of the competing traffic flows at the signalized road intersection. Liu W et al. developed a distributed cooperative reinforcement learning-based adaptive traffic signal control model to solve the urban traffic congestion problem [13]. The V2X networks’ dynamic clustering algorithm was integrated to provide efficient and accurate traffic state information to traffic signal controls. The proposed model was proven to effectively improve the traffic throughput, reduce the average waiting time, and avoid congestion.

Aside from these control strategies for improving the capacity and efficiency of intersections, some studies concentrated on the strategy that served a subset of traffic participants, such as the traffic signal priority strategy. In 2011, He et al. presented a heuristic algorithm for serving public transport systems [14]. Buses were equipped with onboard equipment (OBE) that enabled them to send pass requests. In this model, buses were given priority via a first-come, first-serve (FCFS) rule. Again addressing public transport systems, Ye and Xu proposed a decision model to deal with conflicting requests [15]. This study focused on reducing delays for passengers, whereby the phase with the maximum delay would be first served.

Modern urban transportation networks involve multiple travel modes, and the ASC system serves varieties of vehicles in most cases. Therefore, a significant research question is how to reasonably allocate the right of way to maintain a balance among the competing modes. In 2014, He et al. proposed a request-based, mixed-integer linear program (MILP) to investigate the multi-modal traffic signal control problem [16]. The MILP formulation distinguished multiple requests by modes of vehicles, such as emergency vehicles, buses and cars, with the optimization target to reduce the weighted delay.

Some researchers focused on the passengers, and proposed the occupancy-based ASC strategies to optimize the signal timing based on passenger demand rather than solely the number of waiting vehicles. Christofa et al. [17] presented a person-based traffic responsive signal control system. A mixed-integer nonlinear program (MINLP) is formulated, which minimizes the total person delay at an intersection while assigning priority to the transit vehicles based on their passenger occupancy. Yu et al. [18] proposed a person-based signal timing optimization system with flexible cycle lengths and phase rotation. He extended the framework proposed by Christofa et al. [17] at isolated intersections to allow for flexible cycle lengths and to account for uncertainty in transit vehicle arrivals, both of which had not been previously considered. The results reveal that phase rotation reduces total passenger delays significantly at a high volume.

3. Problem Definition

During morning and afternoon rush hours, the traffic volume in several urban areas may surge, leading to traffic congestion and inefficiency. Figure 1 shows the intersection of Guanggu 3rd Rd, in Hoshan District, Wuhan, Hubei province, China. The traffic volume in this area varies at different times of day, with large volumes usually occurring during the morning and afternoon peak hours. It is a typical intersection that conforms to the standard dual-ring, eight-phase structure. The traffic flow in this area is mixed, mainly composed of cars (with low CV penetration rate) and HOVs (100% CV penetration rate). Cameras connected to the roadside equipment (RSU) are installed near the stop line, providing the queue information at an update rate of 1 Hz.

Our study will implement an Occupancy-Based ASC strategy at the intersection to optimize the signal timing of this intersection and reduce passenger delay, all to maximize the traffic efficiency of the intersection. In the following sections, we will first discuss the method of traffic state estimation, and the mixed traffic flow modeling and delay estimation follows. To undertake the proposed Occupancy-Based ASC strategy and apply the optimization, we adopted red truncation, green extension, and phase jumping signal control strategies, which will subsequently be discussed.

4. Methodology

4.1. Traffic State Estimation. This section will develop a traffic state estimation model to estimate the vehicle arrival at the intersection. The arrival of vehicles at the isolated
intersections generally follows a time-dependent Poisson Distribution [26]. On this premise, we proposed a Maximum Likelihood Estimation (MLE) model to estimate the vehicle arrival on a lane basis. We then extended the model, modifying it from the traffic volumes estimation model proposed by Zheng et al. [22].

The basic idea is to acquire vehicle arrival information from real-time CV trajectories to estimate the changing arrivals. There are two types of CV trajectories we can capture: CVs passing through the intersection with and without a stop, as shown in the time-distance graph in Figure 2. Only trajectories with a stop were utilized in this study. For a CV passing an intersection with a stop, we extracted the moment \( t_{i,p} \) and location \( d_{i,p} \) where it stopped and queued. If two or more CVs passed the intersection with a stop within the red interval in the same signal cycle, such as the trajectories of CV1 and CV2 shown in Figure 2, the increased queue length and the time interval between two stop points would be calculated and saved. From this, we derived vehicle arrival rate sampling data, set as \( x_{p} \). Since the HOVs is longer than cars, for example, the vehicle length is 8–9 meters of buses and 4–5 meters of cars, we consider an increase in queue length for one HOV to be equal to an increase of two cars.

The arrival rate \( x_{p} \) was calculated as shown in equation (1a), in which \( C \) is the signal cycle length and \( H \) is the average space headway of cars. The parameter representing vehicle type was introduced to eliminate the error caused by HOV bodywork length: if vehicle \( i \) is a HOV, \( V_{i,p} \) is equal to 1; if vehicle \( i \) is a car, \( V_{i,p} \) is equal to 0. The \( p \) phase arrival rate set collected in the sampling time \( T \) was recorded as \( X_{p} = \{x_{p1}, x_{p2}, \ldots, x_{pn}\} \). As it was assumed that vehicle arrivals follow a time-dependent Poisson Distribution, we built a maximum likelihood estimator (MLE) model based on this distribution for arrival estimation, as shown in equation (1b). The parameter \( \lambda_{p}^{*} \) was the estimated result of the arrival rate. It should be noted that a shorter sampling time was preferred for this study since it helped to capture more details of the changing traffic demands. Based on the estimated arrival rate and the queue information collected by cameras, the queue of phase \( p \) at the \( t \) moment before the green interval started was derived as shown in equation (1c). The parameter \( Q(p, t_{Q}) \) is the queue length collected by a camera at \( t_{Q} \).

According to the shockwave theories, the process of traffic flow passing through the intersection could be divided into three parts: queue formation, queue discharge, and queue clearance [27]. The shockwave speed of these three states was calculated as in equations (2a)–(2c). The parameters \( q_{m} \) and \( k_{m} \) were the capacity volume and density, respectively, and \( k_{j} \) was the jam density; they were fixed. \( q_{a}^{p} \) and \( k_{a}^{p} \) were the arrival volume and density of phase \( p \).
\[ x_{pi} = \left( \frac{d_{p,i+1} - d_{p,i}}{t_{p,i+1} - t_{p,i}} \right) C - V_{i,p} \]  

(1a)

\[ \lambda'_{p}^{\ast} = e^{-\lambda_{p}^{\ast}} \sum_{i=1}^{n} \frac{\lambda_{p}^{\ast}}{x_{p,i}} \]  

(1b)

\[ Q(p, t) = Q(p, t_Q) + \lambda_{p}^{\ast} H(t - t_Q) \]  

(1c)

\[ v_1^p = \left[ 0 - \frac{q_m}{k_m - k_d^p} \right] = \left[ 0 - \frac{\lambda_{p}^{\ast} T}{k_m - k_d^p} \right] \]  

(2a)

\[ v_2^p = \frac{q_m - 0}{k_m - k_j^p} \]  

(2b)

\[ v_3^p = \frac{q_m - \lambda_{p}^{\ast} T}{k_m - k_d^p} \]  

(2c)

where:

(i) \( t_{i,p} \): the moment the CV stopped and queued;
(ii) \( d_{i,p} \): the location where the CV stopped and queued;
(iii) \( x_{p,i} \): the vehicle arrival rate sampling data;
(iv) \( V_{i,p} \): the vehicle type, if the vehicle is a HOV, \( V_{i,p} \) is equal to 1; if the vehicle is a car, \( V_{i,2} \) is equal to 0;
(v) \( Q(p, t_Q) \): the queue length collected by a camera at \( t_Q \);
(vi) \( q_m \) and \( k_m \): the capacity volume and density;
(vii) \( F_{020k} \): the arrival volume and density of phase \( p \);
(ix) \( T \): sampling time;
(xi) \( \lambda'_{p} \): the estimated result of the arrival rate;
(xii) \( v_1^p, v_2^p, v_3^p \): the value of queue formation, queue discharge, and queue clearance shockwave.

4.2. Microscopic Delay Model (MicroDM) for HOV Passengers.

In this section, we modeled the forecasted HOV passenger delay based on traffic state estimation results. Benefiting from the fully equipped HOVs, we built a microscopic delay model (MicroDM) to estimate the delays of each HOV. We then calculated the HOV passenger delay by multiplying the HOV delay by the occupancy. The MicroDM was designed based on the shockwave theory and extended and modified from that proposed by Han et al. [28].

The model of Han et al. divided vehicle delay into three parts according to several possible scenarios. As such, the process of vehicles passing through the intersection was described with greater detail, resulting in fewer delay estimation errors. We followed this model and made the following extensions. Firstly, the queue formation shockwave speed, based on which the HOV delay was estimation, was a real-time estimate as described above. In contrast to the delay estimation based on fixed shockwave speed, it better represented the actual traffic demand for HOVs. Secondly, benefitting from the continuous information collected by OBEs, the vehicle delay was estimated in real-time within the communication range. Thirdly, HOVs approaching an intersection may be in different motion states, i.e., HOVs in motion or stopped and waiting in the queue. The delay of HOVs in different motion states, therefore, was calculated, respectively. In addition, the ASC control strategy was continuously iterated and updated since the number and location of HOVs approaching the intersection are constantly changing.

The process of buses passing the intersection is described by a time-space diagram as shown in Figure 3(a) and divided into three parts. As such, bus queuing delay \( D_Q(i, p) \) is caused by the bus joining and waiting in the queue, the bus waiting delay \( D_B(i, p) \) is generated if buses cannot cross within one signal cycle, and the bus moving delay \( D_{sd}(i, p) \) is caused when the bus's desired speed is higher than the capacity speed. \( \theta_1(i, p) \), \( \theta_2(i, p) \) and \( \theta_3(i, p) \) are three flag parameters defined to determine whether the bus will experience the three parts of delay:

(a) If \( t_{v_{i,k}}(i, p) < t_{v_{i,k}}(p, k) \), then \( \theta_1(i, p) = 1 \), buses will join and wait in the queue, experiencing a queuing delay \( D_Q(i, p) \) otherwise \( \theta_1(i, p) = 0 \);
(b) If \( t_A(i, p) > t_{p,k} + G_{p,k} \), then \( \theta_2(i, p) = 1 \), buses will not cross within one cycle, and experience a waiting delay \( D_B(i, p) \) otherwise \( \theta_2(i, p) = 0 \);
(c) If \( v_{B}(i, p) > v_{3}^p \), then \( \theta_3(i, p) = 1 \), the bus's speed is higher than the queue clearance speed \( v_{3}^p \), and may experience a moving delay \( D_{sd}(i, p) \), otherwise \( \theta_3(i, p) = 0 \).

On this basis, the total bus delay can be expressed as shown in (3), and bus delay is estimated according to its motion states as follows:

\[ D_B(i, p) = \sum_{N} \left[ \theta_1(i, p) D_Q(i, p) + \theta_2(i, p) D_B(i, p) + \theta_3(i, p) D_{sd}(i, p) \right] \]  

(3)

4.2.1. Delay Estimation for HOVs Stopped. For the HOVs that have stopped, we assumed that they were waiting in the queue, and the \( \theta_1(i, p) \) set to 1. The process that the HOV might experience passing through the intersection was described by a time-space diagram, as shown in Figure 3(b). Based on the shockwave theory, the moment when queue discharge shockwave \( v_{3}^p \) reaches \( d_Q(i, p) \) was calculated as shown in (5). The HOV queuing delay \( D_Q(i, p) \) is the difference between \( t_{v_{Q}}(p, k) \) and \( t_Q(i, p) \), as calculated in (6).

\[ d_Q(i, p) = d(i, p) \]  

(4a)

\[ t_Q(i, p) = t(i, p) \]  

(4b)
To estimate the waiting delay $D_W(i, p)$, we first calculated the moment $t_v\theta_1(i, p) = t_p + \frac{d_Q(i, p)}{v_2}$. 

$$t_v\theta_1(p, k) = t_{p, k} + \frac{d_Q(i, p)}{v_2}. \quad (5)$$

$$D_Q(i, p) = t_v\theta_1(p, k) - t_Q(i, p). \quad (6)$$

$$t_A(i, p) = t_{p, k} + \frac{d_Q(i, p)}{v_2} + \frac{d_Q(i, p)}{v_3}. \quad (7)$$

$$t_R(i, p) = t_{p, k} + G_{p, k}. \quad (8a)$$

$$d_R(i, p) = d_Q(i, p) - v_3 [t_R(i, p) - t_v\theta_1(p, k)]. \quad (8b)$$

$$D_R(i, p) = t_{p, k+1} + \frac{d_R(i, p)}{v_2} - (t_{p, k} + G_{p, k}). \quad (9)$$

The HOV moving delay $D_{sd}(i, p)$ was ignored and set to zero since the HOV had stopped and its speed $v_b(i, p) = 0$, the free speed of the HOV, could not be obtained.

4.2.2. Delay Estimation for HOVs in Motion. A HOV in motion may experience three types of delays. These make up the process that the HOV may experience passing the intersection, described by time-space diagrams as shown in Figure 3(a) and Figure 3(c).

To estimate the waiting delay $D_R(i, p)$, the forecasted maximum queue length $L_Q(p, k)$ and the moment queue discharge shockwave $v_2$ reaches $L_Q(p, k)$ should be calculated first, as shown in (10) and (11). The moment the HOV reaches $L_Q(p, k)$ was calculated as in (12). If $\theta_1(i, p) = 1$, the HOV $n = (i, p)$ will join and wait in the queue. The HOV queuing delay $D_Q(i, p)$ was calculated as shown in (6).

$$L_Q(p, k) = \frac{v_2^2}{v_2^2 - v_1^2} [Q(p, t_Q) + v_1^1(t_{p, k} - t_Q)]. \quad (10)$$

$$t_L(i, p) = t(i, p) + \frac{d(i, p) - L_Q(p, k)}{v_b(i, p)} \quad (11)$$
\[ t_{v_L}(p, k) = t_{p,k} + \frac{L_Q(p,k)}{v_2}. \]  
(12)

\[ t_Q(i, p) = \frac{d(i, p) - Q(p, t_Q) + v_3(i, p) \cdot t(i, p) + v_1^3 t_Q}{v_1^3 + v_4(i, p)}. \]  
(13a)

\[ d_Q(i, p) = v_1^3 \left( t_Q(i, p) - t_Q \right) + Q(p, t_Q). \]  
(13b)

The HOV waiting delay \( D_R(i, p) \) varied under different values of \( \theta_1(i, p) \). If \( \theta_1(i, p) = 1 \), HOV \( n = (i, p) \) may experience \( D_R(i, p) \) as shown in Figure 3(a), calculated as in equation (9). If \( \theta_1(i, p) = 0 \), the HOV \( n = (i, p) \) may experience \( D_R(i, p) \), as shown in Figure 3(c).

In the case where \( \theta_1(i, p) = 0 \), it was necessary to determine whether the HOV was affected by the queue dissipating. The moment that the queue dissipates and the HOV arrived at the stop line with the speed of \( v_3(i, p) \) without slowing down or stopping was calculated by (14) and (15), respectively. If \( t_y(i, p) > t_v(p, k) \), then the HOV would not be affected by the queue clearance. The moment the HOV \( n = (i, p) \) reached the stop line without a second stop was calculated by (16).

\[ t_v(i, p) = t_{v_L}(p, k) + \frac{L_Q(p,k)}{v_3}. \]  
(14)

\[ t_y(i, p) = t_L(i, p) + \frac{L_Q(p, k)}{v_3}. \]  
(15)

\[ t_A(i, p) = \begin{cases} 
    t_{p,k} + \frac{d_Q(i, p)}{v_2} + \frac{d_Q(i, p)}{v_3} \cdot \theta_1(i, p) = 1, & \\
    \max(t_y(i, p), t_y(i, p)) \cdot \theta_1(i, p) = 0.
  \end{cases} \]  
(16)

If \( t_A(i, p) > t_{p,k} + G_{p,k} \), then \( \theta_2(i, p) = 1 \), the HOV \( n = (i, p) \) could not pass the intersection within the cycle \( k \). The HOV waiting delay \( D_R(i, p) \) is the difference between \( t_A(i, p) \) and when the discharge shockwave \( v_3^p \) reached \( d_R(i, p) \), as calculated in equation (18). The HOV moving delay \( D_{ad}(i, p) \) varied under different values of \( \theta_1(i, p) \) and \( \theta_2(i, p) \), and was calculated by equation (19).

4.3. Macroscopic Delay Model (MacroDM) for Car Passengers.
We built the macroscopic delay model (MacroDM) based on the Fixed Number Theory. Utilizing the vehicle arrival rate \( \lambda_p \) and queue \( Q(p, t) \) estimated in the previous section, we estimated the travel demands of passengers in CV and non-CV using this model.
To build the delay model, we first discuss the process of queue dissipation, which was divided into two cases: the queue would dissipate in a cycle, and the queue failed to dissipate in a cycle, as shown in Figure 4. To determine whether the queue can dissipate in the green interval, two flag parameters $\gamma_1(p, k)$ and $\gamma_2(p, k)$ were introduced. If $t_{\text{dis}}(p, k) \leq t_{p,k} + G_{p,k}$, the queue could dissipate in a cycle, set $\gamma_1(p, k) = 1$ and $\gamma_2(p, k) = 0$. Otherwise, the queue could not dissipate in the cycle, set $\gamma_1(p, k) = 0$ and $\gamma_2(p, k) = 1$. In the case $\gamma_1(p, k) = 1$ and $\gamma_2(p, k) = 0$, the value of car delay is equal to the area of region A as shown in Figure 4(a) and was calculated in equation (22). In the case $\gamma_1(p, k) = 0$ and $\gamma_2(p, k) = 1$, the value of car delay is equal to the area of regions A and B as shown in Figure 4(b) and was calculated in equation (24). To sum up, the total car delay at phase $p$ during cycle $k$ is expressed in equation (25).

\[
D_{\text{car}}^2(p, k) = \frac{m_1(p, k)}{2}(2t_{p,k} + G_{p,k} - 2t_{p,j} - 2G_{p,j}) + \frac{2M(p, k) - m_1(p, k)}{\lambda_p} + \frac{m_2(p, k)}{2}(2t_{p,k+1} - 2t_{p,k} - 2G_{p,k}) + \frac{m_2(p, k)}{s_p} + \frac{m_2(p, k)}{\lambda_p}, \tag{24}
\]

\[
D_{\text{car}} = \sum_{p=1}^{8} [\gamma_1(p, k)D_{\text{car}}^1(p, k) + \gamma_2(p, k)D_{\text{car}}^2(p, k)]. \tag{25}
\]

4.4. Occupancy-based Adaptive Signal Control System Modeling. The object of the proposed Occupancy-Based ASC strategy is to deal with signal timing optimization for a congested signalized intersection, finding the optimal solution for minimizing total passenger delay. For this purpose, the objective function was expressed as shown in (26). The HOV delay $D_B(i, p)$ and the car delay $D_{\text{car}}$ were calculated above, and $\alpha$ and $\beta$ were the average passenger occupancy of HOV and car, respectively.

\[
\text{MIN} \left( \sum_{N} \alpha D_B(i, p) + \beta D_{\text{car}} \right). \tag{26}
\]

The standard dual-ring, eight-phase structure was applied in our study for the signal phase and timing constraints, and the ring-and-barrier diagram is illustrated in Figure 5. The following constraints are considered here:

- (a) The signal cycle length was set to a fixed value of $C$.
- (b) The phase sequence was also fixed since the phase rotation may have caused confusion to the driver and led to coordination loss at intersections.
(c) We adopted red truncation, green extension, and phase skip for the signal control strategy. In particular, the phase skip was utilized to skip some low-demand phases to lower the total passenger delay.

(d) The range of green interval was between minimal green time $G_{\text{min}}(p,k)$ and maximal green time $G_{\text{max}}(p,k)$, or equal to 0 if the phase was skipped. Meanwhile, the yellow interval was also set to 0 if $G_{p,k} = 0$.

(e) To avoid a phase being continuously jumped due to low vehicle numbers or no priority vehicles passing, we stipulated that a phase cannot be continuously jumped.

\[
\begin{align*}
\text{MIN} & \quad \sum_{i} a D_B(i,p) + \beta D_{\text{car}} \\
C &= \sum_{i=1}^{4} (G_{p,k} + Y_{p,k}), \\
t_{1,k+1} &= t_{1,k} + C, \\
t_{p+1,k} &= t_{p,k} + G_{p,k} + Y_{p,k}, \quad p \in \{1, 2, 3\} \{5, 6, 7\}, \\
s.t. & \quad G_{p,k} = 0 \text{ or } G_{\text{min}}(p,k) \leq G_{p,k} \leq G_{\text{max}}(p,k), \\
Y_{p,k} &= \begin{cases} 
3, & \text{if } G_{p,k} \neq 0, \\
0, & \text{if } G_{p,k} = 0,
\end{cases} \\
t_{p,j} &= \begin{cases} 
\text{if } G_{p,k-1} \neq 0, \\
\text{if } G_{p,k-1} = 0,
\end{cases}
\end{align*}
\]

To sum up, the Occupancy-Based ASC control strategy proposed aimed to find the optimal solution to minimizing total passenger delay by transforming the complex signal control into a mixed-integer linear programming problem. The optimization problem was formulated as shown in equation (27). In equation (27), the HOV delay $D_B(i,p)$ was calculated using equations (3) through (19), and the car delay $D_{\text{car}}$ was calculated using equations (20) through (25). Statistics determined the average passenger occupancy of HOVs and cars. The output was a passenger-based signal timing scheme that included all the phase timings of the current cycle, which was updated at a particular frequency.

5. Simulation Study

This section evaluates the performance of the proposed Occupancy-Based ASC strategy. To make the simulation realistic, the modeling was carried out according to the actual intersection located at Guanggu 3rd Rd, in Hongshan District, Wuhan, Hubei province, China, described in the Problem definition section. We set the basic parameters of the intersection according to the traffic data collected at the Guanggu 3rd Rd location.

5.1. Simulation Setup. The basic parameters of the intersection are outlined in Table 1.

For the intersection discussed, the main roads are northwest (NW) and southeast (SE) bound, the minor roads are northeast (NE) and southwest (SW) bound, and the speed limit is 60 km/h. We set the initial signal timing according to the collected actual phase and timing data of the real-world location. The V2X communication range was set to 500 meters as default. To simulate the change in traffic during the morning and afternoon rush hours, the input vehicle volume was changed from under-saturation to over-saturation and then decreased accordingly. The evaluation below consists of two steps: the arrival estimation results of the MLE model were analyzed first, followed by several case studies used to illustrate the effectiveness of the proposed OBASC model.

5.2. Traffic State Estimation Result Analysis. We were able to validate the traffic state estimation result using the simulation data. The idea was to estimate the vehicle arrival and shockwave speed by the CV trajectories data and the SPaT data. Since the shockwave speed was calculated by the arrival rate and could not be observed, we restricted our analysis here to the results of the arrival rate estimation.
The simulation ran for 23400 seconds (6.5 hours) in total, with the input vehicle volume changed every 300 seconds, from under-saturation to over-saturation and then decreased accordingly. The intersection flow ratios varied from 0.57 to 1.0 to simulate traffic volume changes during morning and afternoon rush hours. It composed of cars (with low CV penetration rate) and HOVs (with 100% CV penetration rate) and were randomly distributed in traffic streams. We chose the trajectory data of the main road as an example because of its large volume and characteristic variation. Since the penetration rate, sampling length, and time were key factors affecting the estimation result, we took

<table>
<thead>
<tr>
<th>Direction</th>
<th>Phase number</th>
<th>Green interval (s)</th>
<th>Yellow interval (s)</th>
<th>Minimum green (s)</th>
<th>Throughput (pcu·h⁻¹)</th>
<th>Saturation flow rate (pcu·h⁻¹)</th>
</tr>
</thead>
<tbody>
<tr>
<td>NW</td>
<td>Left turn</td>
<td>1</td>
<td>20</td>
<td></td>
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<td></td>
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<tr>
<td></td>
<td>Through</td>
<td>6</td>
<td>45</td>
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<td></td>
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<tr>
<td>SE</td>
<td>Left turn</td>
<td>5</td>
<td>20</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>Through</td>
<td>2</td>
<td>45</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>NE</td>
<td>Left turn</td>
<td>3</td>
<td>15</td>
<td>3</td>
<td>10</td>
<td></td>
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<tr>
<td></td>
<td>Through</td>
<td>8</td>
<td>12</td>
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<tr>
<td>SW</td>
<td>Left turn</td>
<td>7</td>
<td>15</td>
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<tr>
<td></td>
<td>Through</td>
<td>4</td>
<td>12</td>
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Figure 6: Arrival rate estimation results (a) Arrival rate estimation results in different sampling lengths (b) Arrival rate estimation results in different sampling times (c) Arrival rate estimation results in different CV penetration rates.
them into account in the analysis. To be clear, the sampling length in this paper refers to the minimum vehicle interval $x_{pi}$, and the sampling time is $T_p$ as defined in section Traffic State Estimation.

First, we analyzed the estimation results under different sampling lengths. The penetration rate and sampling time were fixed at 50% and 30-min, respectively. Considering the actual traffic conditions and the limited red interval in a signal cycle, we selected the following sampling lengths for analysis: 3 vehicles, 5 vehicles, and 10 vehicles. The estimation results are reproduced in Figure 6(a), where the blue polyline represents the actual input vehicle volume, and the arrival rate estimation results are illustrated from the bottom orange polyline to the top green polyline. The sample length of each curve is marked in the figure. The estimation results show that when the sampling length was longer, the estimation result was closer to the actual flow and was less volatile: the estimation error varies from 1.15% to 32.80% under the sampling length of 10 vehicles, from 5.00% to 44.08% under the sampling length of 5 vehicles, and from 17.00% to 58.00% under the sampling length of 3 vehicles. And the standard deviation of the estimated result was 228.41, 320.66, and 511.80 under the sampling length of 3, 5, and 10 vehicles, respectively.

Then, we analyzed the estimation results under different sampling times. The penetration rate and sampling length were fixed at 50% and 10-vehicle, respectively. To capture more details of the changing traffic demands, we favored a shorter sampling time for this study on the premise of sufficient trajectory data collection. On this basis, we selected the following sampling times for analysis: 15 minutes, 30 minutes, and 60 minutes. The estimation results under different sampling times are compared in the polyline diagram illustrated in Figure 6(b). The estimation results show that the MLE model can respond to volume changes faster with a shorter sampling time. The disadvantage is that the shorter sampling time results in more volatility. The estimation error varies from $-4.93\%$ to $35.88\%$ under the sampling time of 15 minutes, from $1.15\%$ to $32.80\%$ under the sampling time of 30 minutes, and from $1.00\%$ to $50.00\%$ under the sampling time of 60 minutes. The standard deviation of the estimated result was 200.70, 228.41, and 287.07 under the sampling time of 15, 30, and 60 minutes, respectively.

Thirdly, the performances of the MLE model with different penetration rates were investigated, and the results are shown in Figure 6(c). The sampling time and length were fixed at 30-minute and 10-vehicle, respectively. Different typical penetration rates were predefined during simulations, drawn from rates ranging from 50% and decreasing to 45%, 40%, 35%, 30%, and 25%. The estimation results showed that the MLE model could respond to volume changes under different penetration rates. However, as the penetration rate decreased, the accuracy deteriorates. The estimated errors for penetration rate at 50%, 45%, 40%, 35%, 30%, and 25% are $1.15\%$ to $32.80\%$, $-1.33\%$ to $33.40\%$, $-0.48\%$ to $34.94\%$, $-1.17\%$ to $35.28\%$, $1.89\%$ to $37.06\%$, and $3.31\%$ to $38.40\%$, respectively.

To sum up, the vehicle arrival rate was estimated by the proposed MLE model using trajectories data and SpAT data acquired in the V2X environment, although some error exists. By analyzing the factors affecting the estimation result, we found that the estimation result was closer to the actual traffic demand when the sampling length was longer. Besides, higher penetration rate also contributed to improving estimation accuracy. To meet the actual traffic conditions and the real-time requirements, a 10-vehicle sampling length and a 30-minute sampling time were chosen.

<table>
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<th>Table 2: HOV entering time and directions in three test scenario.</th>
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<td>Test scenario</td>
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<td>Scenario A</td>
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<tr>
<td>Scenario B</td>
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<td>Scenario C</td>
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<table>
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<th>Table 3: Results of phase timing variation.</th>
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<tbody>
<tr>
<td>Test scenario</td>
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<tr>
<td>---------------</td>
</tr>
<tr>
<td>Scenario A</td>
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<td>Scenario C</td>
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for this study. The arrival rates estimated by the MLE model were higher compared with the actual value. Based on this, we adjusted our estimates to make them closer to the actual volume and applied them as input for the delay estimation.

5.3. Occupancy-Based ASC Strategy Optimization Result Analysis. To further discuss the performance of the proposed Occupancy-Based ASC strategy, we conducted case studies by numerical simulation. The basic parameters of the intersection were set in the Simulation Setup section. The average passenger occupancy of HOVs and cars was set to 30 and 1.5, respectively, determined by statistics. We then evaluated the proposed Occupancy-Based ASC strategy under different volumes (from under-saturation to over-saturation) and different HOVs entry time and directions. The evaluation was carried out in three one-cycle case studies and a continuous multi-cycles simulation. The results of passenger delay, maximum queue, and phase timing variation were discussed to qualify the performance of the proposed ASC strategy.

5.3.1. One-Cycle Case Studies. For the one-cycle case study, we set three test scenarios, as outlined in Table 2. Each test scenario experienced three traffic states: the intersection flow ratios were set to 0.78, 0.89, and 1.00, respectively, and the difference is that the HOV entered at different times and lanes, as specified in Table 2. Firstly, we tested the function and performance of the ASC strategy under different traffic demands. The CV penetration rate was set at 50% for cars and 100% for HOVs. The optimized phase timing is outlined in Table 3, and the results of reduced passenger delays and the max queue are laid out in Figures 7–9.

In scenario A, only one HOV entered the V2X communication range at time $t_1 + 20\text{s}$, from the NW to the SE. The HOV could not pass the intersection in cycle $k$ under the

![Figure 7: ASC optimization results in scenario A](image-url)
fixed timing plan; each HOV passenger would experience delays of 57.30, 59.80, and 66.40 seconds under the different flow ratios. Optimized by the ASC time plan, the green intervals of phases 2 and 6 were extended since the traffic demands of HOVs and cars in these two directions were higher. The green intervals of the other low-demand phases were reduced responsively. Especially during the high flow ratio cycle, phases 4 and 8 were skipped, allowing more green intervals to be allocated to phases with higher traffic demands. HOV passenger delays were reduced to zero in the tests, and the HOV passed through the intersection without any slowing down and stops. The changes of passenger delay in cars were weak by comparison. Instead of decreasing as the flow ratio increased, car passenger delays increased when the flow ratio was set to 1.00. It might be due to the high occupancy vehicle had been allocated more rights of way. Overall, total passenger delays decreased at different traffic ratios. However, the results showed that the higher the intersection flow ratio, the lower the benefit for all passengers traveling through the intersection. The optimized max queue at the intersection decreased by 2 vehicles, 4 vehicles, and 2 vehicles in total under the three flow ratios, respectively. To sum up, the ASC strategy performed stable and efficient in scenario A.

In scenario B, two conflicting HOVs entered the intersection. The HOV with ID 2 could not pass through the intersection in cycle $k$ under the fixed timing plan. Optimized by the ASC time plan, the green intervals of phases 2 and 6 were extended, and phases 4 and 8 were skipped in the cycles with traffic ratios of 0.89 and 1.0. The extended green interval in phase 2 allowed the HOV with ID 2 to pass the intersection in cycle $k$, but the passenger delay of the HOV with ID 1 was prolonged. This was because the start time of phase 7 was delayed, and the HOV with ID 1 experienced a longer waiting delay. Taken together, the average HOV passenger delays were reduced in the tests, and the two HOVs all passed through the intersection in cycle $k$. The passenger delay in cars decreased at the flow ratios of 0.78 and 0.89 and still increased when the flow ratio was set to 1.00. Overall, total passenger delays all decreased at different traffic ratios, and the higher the intersection flow ratio, the lower the benefit for all
passengers traveling through the intersection. The optimized max queue at the intersection decreased by 2 vehicles, 3 vehicles, and 2 vehicles in total under the three flow ratios, respectively. To sum up, the ASC strategy was also stable and efficient in scenario B.

In scenario C, four HOVs entered the intersection. The HOVs with IDs 3 and 4 could not pass the intersection in cycle $k$ under the fixed timing plan. Optimized by the ASC time plan, phases 4 and 8 were skipped, allocating more green intervals to phases with higher traffic demands. The extended green interval in phases 6 and 7 allowed the HOVs with IDs 3 and 4 to pass the intersection in cycle $k$, and average HOV passenger delays were reduced in the tests. The passenger delay in cars increased and even more when the flow ratio was higher. It might be due to the four HOVs entered in this scenario: these HOVs preempted the right of way of cars, extending the cars’ travel time. Overall, total passenger delays still all decreased in the tests. The max queue at the intersection increased by 1 vehicle, 3 vehicles, and 3 vehicles in total for the three different flow ratios, respectively. To sum up, the ASC strategy reduced the total passenger delays, but the queue at the intersection increased in scenario C.

Then, the performances of the Occupancy-Based ASC strategy with different penetration rates were investigated, and the results are shown in Tables 4 and 5. Different typical CV penetration rates of cars were predefined during simulations, drawn from rates ranging from 50% and decreasing to 40%, 30%, and 20%. The result showed that when the penetration rate decreases from 50% to 20%, the actual delays increase in some scenarios. Since the amount of true CV data available diminished, it leaded to lower accuracy of vehicle arrival estimation. It is larger than the actual volume as the penetration rate is lower, according to the test results in the previous section. Cars were allocated more right of way than they actually needed in this case. Therefore, we could see lower performance in the reduction in HOV delay in the scenarios B and C. Although the performance of the
Figure 10: Changes of passenger delays and the maximum queue. (a) Reduced passenger delays. (b) Changes of Max Queue.
ASC strategy deteriorated with lower penetration rate, the passenger delays were still effectively reduced in most cases.

5.3.2. Multi-Cycle Case Studies. In addition to the one-cycle case study, we conducted a multi-cycle case study to analyze the performance of the ASC strategy in a long run. The simulation ran 22 cycles, with the input volume changed from under-saturation to over-saturation and the intersection flow ratios varying from 0.75 to 1.00: the input volume reached saturation in the 7th cycle and continued to increase to the flow ratio of 1.00 at the 10th cycle. The intersection was at over-saturation from the 7th to the 14th cycle and then decreased accordingly. The optimized results and analysis are explained below:

(a) The HOV passenger delay was decreased in every cycle by different amounts. We compared the results of each cycle with the input HOV data and found that the fewer HOVs in a cycle, the more significant the reduction in delay. For example, there were only one or two HOVs in the 6th, 11th, 12th, and 18th cycles. The reduction of HOV passenger delay was significant in these cycles and is consistent with the optimization results in scenarios A and B.

(b) The car passenger delay increased in almost every cycle. Possible reasons are: firstly, too many HOVs entered the intersection in some cycles, e.g., there were no less than four HOVs in the 3rd, 5th, and 8th cycle. These HOVs preempted the right of way of cars, leading to increased car passenger delay, which is consistent with the results in scenario C. Alternatively, estimation errors of the delay model may have caused the delays. As the simulation time ran longer, the calculation error of the model may have accumulated, leading to poor performance.

(c) For the total passenger delay and the max queue at the intersection, they were generally decreasing. The total passenger delay had a slight increase in the 13th cycle, while the max queue increased in the 4th, 13th, and 18th cycles. In general, while the ASC strategy could improve the traffic efficiency at the intersection within a certain range, it demonstrated a stable and efficient performance in this multi-cycle test.

In summation, when the intersection is oversaturated, the traffic demand has exceeded the capacity, and the ASC strategy could not solve the issue. Once the intersection desaturates, the ASC strategy can reduce the queue and restore efficiency quicker, even during peak traffic volume, as shown in Figure 10. We have shown that the proposed ASC strategy can effectively balance the demands of HOVs and cars during peak volume periods by reasonably allocating green time to each. In addition, the strategy allows for passengers on HOVs to pass through the intersection faster, thus reducing total passenger delays.

6. Conclusion

In this study, an Occupancy-Based ASC control strategy was developed for a congested signalized intersection to optimize signal timing and reduce total passenger delay in the low CV penetration environment. To achieve this goal, we addressed two difficulties. One was the issue of the incomplete traffic information caused by the existing non-CVs, and the other was to model the mixed traffic flow and estimate passenger delay.
delay. To estimate the arrival of CVs and non-CVs and obtain the changing traffic demands at the intersection in real-time, we proposed a Maximum Likelihood Estimation (MLE) model for vehicle arrival estimation based on CV trajectories data, critical parameters for delay estimation. To model the mixed traffic flow and estimate the passenger delay, which included both HOV and car passenger, we developed the shockwave-based Microscopic Delay Model (MicroDM) for HOVs with 100% CV penetration, and the Fixed Number Theory-based Macroscopic Delay Model (MacroDM) for car with low CV penetration. We introduced total passenger delay as a control variable to balance traffic demands with fair treatment for passengers approaching the intersection. The complex signal control problem was transformed into a mixed-integer linear programming problem to find the optimal solution for minimum total passenger delay. A occupancy-based signal timing scheme that included all the phases of the current cycle was outputted and was updated at a particular frequency to reach the optimal solution.

To evaluate the proposed Occupancy-Based ASC strategy, we conducted simulation case studies. The results of the MLE model evaluation confirmed that, based on CV trajectories data and SpAT data acquired in the V2X environment, vehicle arrival could be estimated with a small degree of error, even when the CV penetration was low. Although a shorter sampling time was preferable since it could help capture more detail of the changing traffic demands, the estimation result was closer to the actual traffic conditions when the sampling length and time were longer. Therefore, it was essential to choose the sampling length and time according to the actual traffic conditions and the real-time requirements. The result of the Occupancy-Based ASC strategy evaluation confirmed that, with the TSP control strategy, the HOVs could pass through the intersection faster, and the total passenger delay and maximum queue length significantly decreased in the low CV penetration environment. Most noteworthy is that the proposed ASC strategy could effectively balance the demands of HOVs and cars during peak volume periods by reasonably allocating green time between cars and HOVs.

As to the limitations of this paper, we conducted the proposed Occupancy-Based ASC strategy evaluation using numerical simulation due to limited experiment conditions, and therefore the results lack field testing. Secondly, the MLE model proposed could be improved by introducing other observational data, both historical and real-time, to improve the accuracy and stability of the estimates. Further discussion is required on choosing the sampling length and time to achieve greater accuracy in the estimation results. Furthermore, the calculation error of the delay estimation models in the multi-cycle case study accumulated as the simulation time ran longer, leading to poor performance. The proposed MicroDM and MacroDM should be further developed to improve the estimation accuracy. Finally, the proposed Occupancy-Based ASC strategy was only tested at a single intersection; the intersections of upstream and downstream were not considered, which may have a significant bearing on its efficacy. These issues will be explored in the future studies.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

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