Received October 30, 2020, accepted November 15, 2020, date of publication November 19, 2020,
date of current version December 9, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.3039263

A Coordination Algorithm for Signalized Multi-Intersection to Maximize Green Wave Band in V2X Network

YANJUN SHI[1], (Senior Member, IEEE), JIAJIAN LI[1], QIAOMEI HAN[2], (Senior Member, IEEE), AND LINGLING LV[1]

[1]School of Mechanical Engineering, Dalian University of Technology, Dalian 116024, China
[2]School of Electrical and Computing Engineering, Western University, London, ON N6A 3K7, Canada

Corresponding author: Yanjun Shi (syj@ieee.org)

This work was supported by the National Key Research and Development Program of China under Grant 2018YFE0197700.

ABSTRACT The signal control system for multi-intersection traffic management is an extensive complex nonlinear and non-equilibrium system and usually leads to a weak control strategy. Existing studies of traffic dynamics mainly focus on the applications to the single network, whereas how the structure of multiple intersections affects the dynamical behaviors is unclear. Connected vehicles in recent studies have shown the potential to eliminate traffic communication barriers and balance the traffic load. For this consideration, we propose a new multi-intersection model based on Vehicle-to-Everything (V2X) network to capture the features of traffic flow, which employs vehicular communication to obtain real-time traffic information and share it among the adjacent intersections. Focus on smoothing traffic flow without stop-and-go driving and improving the coordination of multiple traffic lights, we develop a multi-intersection coordination algorithm based on V2X (MICA-V for short) to maximize the green waveband in the arterial road. Due to the establishment of registration list yielding the average saturated headway time, our method is of high efficiency—the distributed process of data makes the convergence to be very fast with nearly linear time. Simulation results via MATLAB with Simulation of Urban Mobility (SUMO) showed the effectiveness of the proposed MICA-V in improving traffic capacity, reducing the number of stop behaviors, and improve the average speed of vehicles moving on the arterial road.

INDEX TERMS Multi-intersection, traffic signal control, coordination, vehicle-to-everything(V2X), SUMO.

I. INTRODUCTION

With the boost population living in metropolitan areas due to industrialization and immigration, an increase in the number of vehicles hinders the urban traffic and causes severe issues to the economy (e.g., waste of infrastructure costs due to traffic congestion), to the living climate (increase in pollution due to more fuel consumption), and to the human being (e.g., physiological stress due to more delay time wasted).

Specifically, one of the main problems related to urbanization is the traffic congestion in the Traffic Management System (TMS), since this bottleneck results in disorganization in traffic flow and wasted time. According to a study released in 2013, the UK Centre for Economics and Business Research (CEBR) evaluated the direct and indirect cost of congestion of British, French, German, and American scenarios. It showed that the cumulative cost between 2013 and 2030 reached the amount of US$4.4 trillion [1]. To solve the congestion in urban areas, there are many completed and ongoing studies on traffic signaling, which is the essential sub-module of traffic management. In this context, traffic signal optimization, a more feasible solution to balance the traffic load and decrease the waiting time, will play an essential role in effective and dynamic management [2].

An important method to infer the correlations between topology and function is the detection of network structure [3]. Since the traffic management should consider the following tasks [4]: traffic monitoring, congestion detection, and routing suggestion, monitoring the real-time data is a prerequisite for subsequent operations, especially under

The associate editor coordinating the review of this manuscript and approving it for publication was Yichuan Jiang.

variable traffic loads scenarios. A traditional management system using different sensing solutions (such as a sensor network, induction loops, and cameras) to obtain real-time traffic information has many drawbacks due to its intermittent connectivity and coarse-grained data affected by environmental conditions. Meanwhile, many traffic signal systems take improved fixed-time mechanisms whose control inputs, such as green times and cycle times, are calculated according to the beforehand traffic conditions. However, the rigid phase structures are nonvalid to react to the fluctuation of traffic flows. Thus, the next generation TMS needs an improved approach to collect traffic information and a dynamic structure that can adapt to real-time and heavy traffic conditions [5].

The other problem of existing traffic management systems is inadequate to coordinate the multiple agents (e.g., connected vehicles and roadside units). Although the existing TMS becomes a complex network structure that consists of many interconnected devices and different traffic data, it seems that such road participants are insufficient on network scalability, intersection management, multi-standard data fusion, and efficient green waveband usage. Particularly, for many real complex systems, such as social ties that link different people and transportation networks, the time-varying characteristics of agents will produce distortion/interference [6]. In addition, an isolated intersection (only one) management is far from meeting the requirements of large-scale and high-efficiency traffic.

Motivated by these challenges, in this article, we develop a new multi-intersection framework based on V2X, which can gather and exchange fine-grain/real-time data instantaneously using wireless communication technology. Particularly, we focus on maximizing the green waveband of arterial traffic lights between a series of intersections. Generally, the contributions of the proposed method are as follows:

- Motivated by the existing methods, we compare classical fixed-time control and state-of-the-art adaptive control. A new cooperative control system is then provided to capture the features of vehicles and make use of them in the signal time assignment. The establishment of registration list is based on the real-time information exchanged between vehicles and infrastructures.
- We focus on the problem of data cycle in traffic signal optimization. In detail, based on the dynamical optimization of average headway using in the system, the proposed coordination algorithm (MICA-V) realizes the closed-loop control of signaling time and coordinates multiple intersections into a whole system. Meanwhile, due to the precomputed headway parameter, the proposed algorithm is of great efficiency, especially for the multi-intersection traffic network. The computational complexity is nearly linear with the scale of intersections.
- We performed extensive experiments on various traffic conditions showing that our approach substantially smooths the traffic flow without stop-and-go driving and improves the coordination of multiple traffic lights in different load conditions.

In the following sections of the study, at first, it is given the necessary information about signaling studies in literature in Section 2. Then a multi-intersection model based on V2X was introduced in Section 3. Section 4 will give detailed information about the proposed MICA-V algorithm to formulate traffic signal optimization. Simulation results and discussions are provided in Section 5. Finally, conclusions are given in Section 6.

II. RELATED WORK

Traffic lights, first used in 1928 [7], are still the most extensive application of traffic management systems by now [8]–[11]. One of the ways to manage traffic flow at urban intersections is to provide traffic light signal optimization. In [9], C Costa *et al.* proposes a bi-objective optimization of fixed-time traffic signals using an improved genetic algorithm to improve the performance of vehicle speed. Kohler and Strehler [8], [10] have developed a model that optimizes the fixed-time signal plan in a cyclically expanded network. They considered the coordination of multiple traffic signals and presented a corresponding mixed-integer linear programming formulation for simultaneously optimizing both the coordination of traffic signals and the traffic assignment. Thunig *et al.* [11] extended the previous studies [8], [10] and combined the Kohler's analytical model with the coevolutionary transport simulation MATSim to evaluate the optimization performance for practical applications. Although the improved fixed-time control methods in these studies coordinated the adjacent intersections using evolutionary algorithm and graph theory, the signal control parameters such as cycle, green ratio, and offset are determined by historical data.

Traditional fixed-time traffic control cannot dynamically meet current traffic demand, whereas traffic-adaptive signals usually result in less travel time for real-world applications than fixed-time signal control. At present, the widely used traffic signal control systems in the world include Australia's SCATS system and Britain's SCOOT system, etc [12]. SCATS is the scheme-selective control system, whose timing scheme of each intersection is selected by the global objective. SCOOT belongs to the scheme-generating real-time adaptive control system but may be difficult to control large areas by a centralized control structure. Moreover, induction loops installed under the surface of roads can detect only the presence or absence of vehicles.

The urban traffic network is composed of hundreds of intersections, some of which are adjacent. The vehicle clusters are highlighted, especially when going through the multiplex traffic network. Hui-jia Li *et al.* developed a new dynamical network approach where a general index is provided to capture the critical leader identification problem [13]. Based on the optimization of quality function using the dynamical system, nodes are assigned to the clusters led by precomputed leaders. To solve the multi-intersection issue dynamically, Hu *et al.* [14]

proposed a novel multi-intersection model based on cellular automata and a multi-intersection signal timing plan algorithm. Xun Li *et al.* presented an improved cell transmission model implemented with an improved genetic algorithm (GA) [15]. Biao Yin, Mahjoub Dridi *et al.* proposed an online learning method for adaptive traffic signal control in a multi-intersection system [16]. But these works ignore the information sharing between the intersection for traffic coordination. EI-Tantasy *et al.* [17] put forward an integrated control method of regional traffic signal based on multiagent reinforcement learning. Ge *et al.* [18] proposed a cooperative deep Q-network with Q-value transfer (QT-CDQN) for adaptive multi-intersection signal control. To extract the intersection state information effectively, an estimation model based on a convolutional neural network is developed to automatically extract the features from the original traffic state. However, some problems are needed to be solved, such as control parameters analysis, phase structure scheme fixed, and traffic flow adjust mechanism.

Recently, the V2X has been employed for collecting fine-grained information on the vehicle and designing the adaptive signal about coordinated intersections. Li and Shimamoto [19] proposed a branch-and-bound-based traffic control algorithm to enable vehicles to travel smoothly with phase exchanges as few as possible. The proposed algorithm attempts to schedule a passing order that requires the least amount of time for vehicles and the fewest green duration for waiting vehicles, and the fewest number of green light exchanges between two road segments of an intersection.

Zhou *et al.* [20] designed an adaptive traffic light control scheme to determine both the green light layouts and lengths based on detected traffic information. However, only the local traffic condition was considered in computing the weight, and the neighboring intersection conditions were considered only when the next signal phase was determined. In other words, [20] merely used the traffic information on neighboring intersections to extend the green light duration for the green-wave purpose. In contrast, our works considered both local and adjacent traffic flow before the next signal phase was assigned.

Cai *et al.* [21] presented an intersection signal control mechanism assisted by far vehicle information. According to the estimated waiting time of each traffic flow, a real-time information scheme using a VANET to determine the intersection traffic condition at a specific time was proposed. The proposed scheme reduced the average waiting time of vehicles and the ratio of the long-waiting vehicles. However, [21] could not coordinate the traffic signaling of multiple intersections to allow vehicles on arterial roads to move as few stops as possible.

III. COOPERATIVE SYSTEM MODEL

The intersections in this study are assumed to be regular signal intersections, without considering the influence of pedestrians and non-motor vehicles. We also assume that each vehicle participating in the coordinated control is equipped with OBUs (On Broad Units) to collect vehicular data and wireless transmission facilities. In other words, the proposed method is based on the V2X network. Our focus herein is balancing the traffic load to reduce the average travel time, so wireless channels are assumed to be error-free and with a tiny delay.

RSU (Road-Side Unit) refers to a computing device located on the roadside that provides connectivity support to passing vehicles. Therefore, we assume that RSUs have been installed at intersections to obtain vehicle information (such as identification index, vehicle speed, turning information, etc.) via V2X.

Fig. 1 shows an intersection based on V2X and vehicle statuses (approaching, stopping, crossing, and unregistered) at different locations near the intersection. Each intersection has a network interface to communicate with vehicles and traffic controllers and has a traffic microprocessor to control its traffic light. Both the network interface and microprocessor are integrated into a RSU. Each vehicle has a network interface, a GPS receiver, and an OBU interface. The OBU interface can obtain the absolute timestamp, speed, acceleration, and turning intention of a vehicle. So we can track the dynamic information of vehicles.

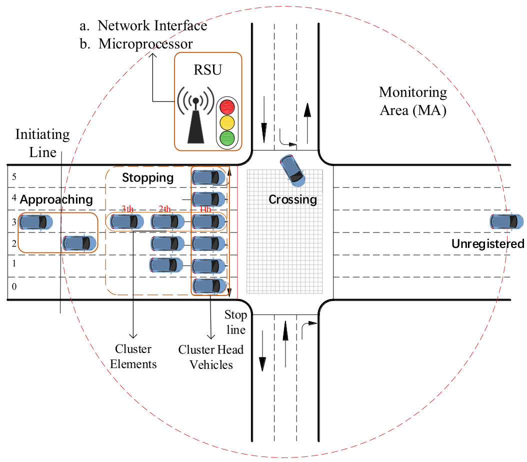

FIGURE 1. A schematic diagram of the intersection framework based on V2X and the monitoring mechanism. The RSU consisted of a network interface and a microprocessor, provides connectivity support to passing vehicles. The goal of our framework is to collect traffic information and establish a registration list that contains the cluster features.

Fig. 1 also shows a mechanism of traffic monitoring. The distance between the initiating detection line and the stop line is the radius of the Monitoring Area (MA). Firstly, when a vehicle enters the monitoring area, its wireless transmission facilities will broadcast the onboard traffic data (such as acceleration, position, and turning intention) to the RSU, using Vehicle-to-Infrastructure (V2I) communication. Then, the vehicle is prohibited from changing lanes until it goes out of the MA. Here, we classify traffic flow for registered and unregistered vehicles to estimate the optimal green duration accurately. When the first vehicle arrives and stops in front of the stop line because of the red light, it registers itself as a

Cluster Elements					Cluster Index
0	0	0	0	5h	
0	0	0	0	4h	
0	0	3.2	3.1	3h	
0	0	2.2	2.1	2h	
0	0	0	1.1	1h	
0	0	0	0	0h	

FIGURE 2. Registration list in the intersection.

cluster head to RSU. When the following vehicles stop behind the cluster head, they will also register to RSU and be grouped into the cluster. Namely, each lane has its cluster head. Note that the moving vehicles merely share the traffic information with RSU, whereas only the vehicles stopped in the lane can be grouped into the cluster. Then, as shown in Fig 2, the RSU establishes a registration list dynamically in terms of cluster head and following vehicles. When the phase turns to green, the registration list of current signal cycle will be expired after the microprocessor calculates traffic parameters (such as average headway time, green duration, and offset).

The main information needed for traffic signal control is the vehicle status information: the timestamp and the vehicle speed on each lane entering the intersection. In this study, L donates the register list and $CV(VehID) \in L$ donates a vehicle traffic data set containing the status information. As soon as a vehicle enters into MA, its OBU collects the data set $CV(VehID) = [dir, t_a, t_d, v_t]$ and transmits data to the nearest RSU in real time. The *VehID* refers to the vehicle identification index, *dir* represents the turning intention, t_a represents the timestamp when the vehicle stops because of red light, t_d represents the timestamp when the front bumper of the vehicle departs from the stop line, and v_t represents the time-varying speed of the vehicle. Here, let $\dot{Q}_n$ be the total number of one cluster elements, where n is the lane index. In Fig. 2, the value of $\dot{Q}_3$ for cluster *3h* is 3, because three vehicles stop in front of the stop line. After a vehicle registers as a cluster head, the RSU will sort out each vehicle according to different clusters. The cluster head denotes a column index, and the subsequent element denotes a row index, where 0 denotes no vehicle. Then the microprocessor of RSU can establish a vehicle information list L for its intersection. The dynamic list can record and update each data set *CV(VehID)* in real-time.

For the convenience of describing the problem of multi-intersection signal coordination, here we take a two-intersection road network as an example. The traffic network structure is given in Fig. 3, which gives a corridor network with an upstream intersection *I* and downstream intersection *II*. Each intersection consists of four road segments. Each road segment has different traffic flows consist of right-turn, left-turn, and go-straight. The west-east segments, called arterial roads, are only for one-way traffic flow. Moreover, the north-east segments, called branch roads, are for two-way traffic flow.

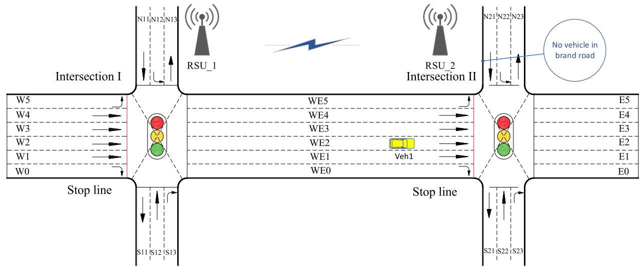

FIGURE 3. The vehicle is crossing two continuous intersections, which can share the traffic info via RSU. The downstream microprocessor (such as II) takes incoming traffic flow from neighboring intersections into considerations. The microprocessor aims to schedule traffic offsets over the continuous intersections of an arterial road so that their traffic lights can be coordinated to likely form a green waveband.

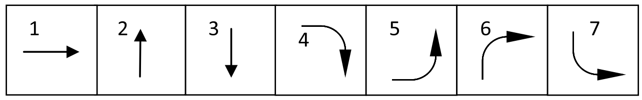

FIGURE 4. Turning intention diagram.

The intersection's information and turning intentions are shown in Fig. 4. Each RSU of the intersection merges the received vehicle information and processes the data by a specific algorithm. Then it sends the optimal timing plan to the traffic microprocessor for the assignment of green duration, which schedules the signal timing according to the queue length of the straight-through vehicle cluster. Simultaneously, the RSU will record the speed and timestamp when the straight-through vehicle departs from the stop line. Vehicles heading from the north to south orientation also send information to RSU through V2X to obtain a right of the way.

The cooperative traffic control problem is defined as follows. As the model is based on the one-way multi-intersection scenario, we focus on calculating an effective signal timing plan of WE5-WE0 to realize the green wave concept for the arterial road. As shown in Fig. 3, the connected vehicles need to pass through the intersection *I* to the adjacent *II* continuously. We might as well assume that though no vehicle on the south or north is approaching, a vehicle (*veh*1 in Fig. 3) passed the intersection *I* will arrive at the stop line of *II* with the red phase. This rigid timing structure will result in the green light gap problem of branch road (green time for no vehicle passing) and serious stop delay time in the arterial road.

Our goal is to calculate the most appropriate signal parameter from data list L yielding the highest pass rate considering adjacent intersections and to decide respective green signal duration by addressing the following issues:

- *Green Duration Determination:* How much time should be assigned to the green phase in each intersection based on the number of vehicles waiting for the red light and the vehicles approaching from the upstream.
- *Green Wave Coordination:* How to schedule traffic offsets over the continuous intersections of an arterial road

so that their traffic lights can be coordinated to likely form a green waveband.

IV. MULTI-INTERSECTION COORDINATION ALGORITHM BASED ON V2X (MICA-V)

In the proposed signal coordination algorithm, we take the influence of traffic flows from upstream into consideration. The controller requests the real-time traffic information of adjacent controllers before its signal scheduling (i.e., decide the next phase and green duration). Based on that information, we develop an algorithm of green time estimation for each intersection to adapt the current number of vehicles over a road network instead of only considering a single intersection. Our coordination algorithm also provides demands for branch roads and realizes the green wave concept for the arterial road.

A. AVERAGE SATURATED HEADWAY ESTIMATION

The average saturated headway $\bar{h}_a$ at signalized intersections refers to the corresponding time interval when queuing vehicles pass the stop line at stable time intervals continuously. It is crucial for analyzing traffic flow states and providing critical data for improving the signal timing strategy. The proposed method is based on the technology of V2X, where the data interacted between RSU and vehicles can apply to the analysis of the intersection decision.

The headway time of each vehicle can be obtained by the timestamp when the front bumper of the vehicle departs from the stop line. In this method, we let the green phase in a signal cycle as the logical control period. When the traffic light turns to the green phase, we let t_d^1 be the timestamp when the front bumper of the first vehicle departs from the stop line and t_1 represents the start-up time of the green light at intersection I. Then, the headway of the first vehicle can be expressed as: $h_1 = t_d^1 - t_1$. Furthermore, the following vehicles headway can be calculated as:

$$h_i = t_d^i - t_d^{i-1} \quad (i \geq 2) \tag{1}$$

In practical research, there is no definite conclusion that the number of vehicles in the queue is appropriate for the starting element for calculating the saturated headway, due to the number of vehicles from 4th to 7th are all used to estimate the headway [22], [23]. In this study, we consider that the initial 2∼4th vehicles in the queue have a start-up delay, so we consider the 4th vehicle as the starting point vehicle for saturated headway calculation, which is more in line with the actual situation. The vehicle clusters capable of extracting headway must satisfy that the number of vehicles in the queue is not less than 7veh and the number of vehicles in saturated flow is not less than 4veh. Let p denotes the total element number of one cluster. Then, the average headway $\bar{h}^c$ of one cluster can be written as:

$$\bar{h}^c = \frac{1}{p-3}\sum\nolimits_{i=4}^{p} h_i \quad (p \geq 7) \tag{2}$$

where i is the cluster element index, c is the cluster head index. To obtain the overall average saturated headway $\bar{h}_a$, let m be the number of clusters that satisfy the above conditions. Thus, $\bar{h}_a$ can be defined as:

$$\bar{h}_a = \frac{1}{m}\sum\nolimits_{j=1}^{m} \bar{h}_j^c \tag{3}$$

If all the clusters are not satisfied with the extraction rule, it will fail to obtain an appropriate average saturated headway time in a signal cycle. In this case, we set 2.5 s derived from comprehensive experiments as the initial headway time for the current signal cycle according to [24].

So far, the saturated headway of the current cycle has been obtained. However, due to the influence of traffic conditions, such as the sudden increase of large vehicles, the saturated headway used in signal timing design will change sharply and lead to a large deviation. To address this problem, we use an exponential smoothing method to smooth the current headway, let $\bar{h}_m$ be the revised saturated headway, which is described as:

$$\bar{h}_m = 0.25\bar{h}_a + 0.75H \tag{4}$$

where $\bar{h}_a$ is average headway in the current smoothing cycle, whereas H is the historical average headway. Here we take H as the result of the last cycle.

The following Algorithm 1 gives the pseudocode for the proposed approach.

B. MAXIMUM GREEN WAVE BAND ALGORITHM

The green wave traffic means that vehicles can get the green light and another continuously to smoothly pass all intersections when traffic flow moves along a long artery corridor that includes a series of intersections. As mentioned earlier, the traditional intersection is incapable of meeting the specific traffic demand in traffic corridor. The corridor

Algorithm 1 Extracting the Average Saturated Headway Dynamically

Input: t_a, t_d, L
Result: $\bar{h}_a$
Initialize network parameters and a list L
Initialize the simulation *step* and a historical headway for $\bar{h}_a$ as default
begin:
  for $i = 0$ **to** $i = step$ **do**
    initialize the first intersection states t_1 and T_1
    /*control logic*/
    if the first intersection turns to green phase, **then**
      the list L elements in this green phase cycle will get no change
      firstly, calculate the first vehicle headway
      $h_1 = t_d^1 - t_1$
      update the average saturated headway $\bar{h}_a$ by (3)
      smooth current headway
      end if
  end for
return $\bar{h}_a$

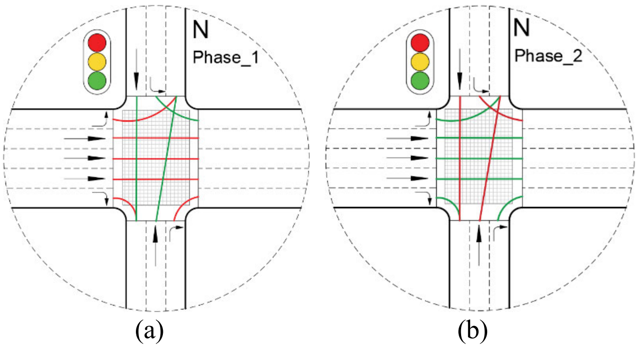

FIGURE 5. Phase plan for the intersections.

in the cooperative vehicle infrastructure system refers to the specific highway or advanced road set up of the roadside unit on the wayside. Based on the traffic data collected by V2X, this article proposed an algorithm to adjust the timing scheme of traffic lights in real-time to meet the random and dynamic traffic flow demand. The upstream signal controller cooperates with the downstream controllers to maximize the green-wave band of arterial road WE5-0 in the one-way road scenario. The following will describe the dynamic scheme of signal timing.

The signal timing phases of intersection I and intersection II are divided into 1 and 2. As shown in Fig. 5, the green line represents the right of way, and the red line indicates the impassable status of the way in the current phase. To highlight the switching between the green light and red phase, the yellow-light phase is omitted.

Phase 1 represents the green light for the N-S direction and the red light for the W-E direction. And phase 2 represents the red light for the N-S direction and the green light for the W-E direction.

In our study, to maximize the green-wave band of an arterial road in the adjacent intersections, priority will be given to the arterial demand. So, the proposed algorithm focuses on the phase 2 timing scheme. Both green light duration and start-up time refer to the parameter of phase 2 in the following description.

The upstream intersection I is the starting point of the whole control logic. According to the upstream information, we can optimize the green light duration and the start-up time of the downstream intersection. One of the microprocessor missions is to adjust the own timing scheme in terms of the queue length of stopping vehicles. In our coordination algorithm, we denote T_i as the green light duration of i th intersection and t_i as the green light start-up time of i th intersection. Note that the green light duration T_i is a period, whereas the t_i is an absolute time representing the timestamp with the origin of the time axis as reference. Then the first intersection green light duration T_1 based on real-time traffic queue length be calculated as:

$$T_1 = \left(Q_{\max}^{up} - 1\right) \times \bar{h}_a + t_{loss} \tag{5}$$

where $\bar{h}_a$ is the average saturated headway of clusters according to Algorithm 1. t_{loss} is the start loss time, which is defined as:

$$t_{loss} = t_s - t_c \tag{6}$$

where t_s is the time required for a saturated fleet to accelerate through the stop line after the green light started, and t_c is the time for the saturated fleet to pass the stop line at a constant speed. The start loss time t_{loss} is a historical parameter obtained by the observation of real traffic flow. The t_{loss} setting can be determined according to the real traffic flow and simulation environment.

In (5), $Q_{\max}^{up}$ is the maximum vehicle number in all lanes of the upstream intersection, it can be gained by:

$$Q_{\max}^{up} = \max_{n}\left(\dot{Q}_n\right) \tag{7}$$

where n is the number of lanes at this intersection.

The above is the programming of the green light duration of the upstream intersection I. Furthermore, according to (5), the green light duration of the downstream intersection will be discussed in different situations. The assignment of downstream signal time is not only for the vehicles coming from the upstream arterial road but also for the vehicles coming from the upstream branch road.

To adapt different conditions and demands of downstream intersections, we first denote two decision variables obtained by RSU as q_{upb}^i and q_{dstop}^i. q_{upb}^i refers to the number of vehicles coming from the upstream branch road. q_{dstop}^i refers to the number of vehicles stopping in front of the stop line at i th intersection. The decision variables can be transformed into Boolean variables because we separate the condition according to whether the decision variables are equal to zero. Thus, four situations have been summarized in the following section.

- *Case of* $q_{upb}^i = 0$ *and* $q_{dstop}^i = 0$:

In this case, the RSU has no information about the upstream branch road or the stopping area of the intersection. There are only vehicles passed the upstream moving to the downstream. Therefore, the green phase duration of the downstream intersection only needs to consider the number of vehicles passing through the upstream intersection. The green light duration of the downstream intersection is defined as:

$$T_i = \left(Q_{\max}^{up} - 1\right) \times h \tag{8}$$

- *Case of* $q_{upb}^i > 0$ *and* $q_{dstop}^i > 0$:

In this case, the downstream RSU receives messages from the branch road or the stopping area of the intersection. It is necessary to consider the passing time of the upstream through vehicles and the time of the left turning and right turning vehicles from the upstream branch road passing through the intersection and the stopped vehicles in front of the stop line.

However, it should be noted here that vehicles from upstream branch roads should also be filtered. For global throughput maximization, it is inappropriate to set a long green duration for all vehicles from the upstream branches due to an interval between the upstream and downstream intersections. So here we have to bound the green duration T_i in a range $[T_{\min}, T_{\max}]$ to avoid T_i being too long or too short. Based on the above considerations, the green light duration is calculated as:

$$T_i = \left(Q^{up}_{\max} + q^i_{dstop} + q^i_{upb} - 1\right) \times h + t_{loss} \quad s.t.\ T_{\min} \leq T_i \leq T_{\max} \tag{9}$$

- *Case of* $q^i_{upb} = 0$ *and* $q^i_{dstop} > 0$:

In this case, only the downstream vehicles stopped in front of the stop line need to be considered to obtain the green duration, referring to (5).

- *Case of* $q^i_{upb} > 0$ *and* $q^i_{dstop} = 0$:

In this case, only the vehicles approaching from the upstream branch road need to be considered, so the green light duration can be calculated as:

$$T_i = \left(Q^{up}_{\max} + q^i_{upb} - 1\right) \times h + t_{loss} \tag{10}$$

C. SOLUTION OF THE OFFSET TIME

To assign the start-up time of the adjacent intersections dynamically and realize the maximum green-wave band of the arterial road, the phase offset time between the intersections needs to be solved. Fig. 6 describes the relationship between the time and distance of vehicles moving from intersection I to intersection II. The red bar represents the red phase, the green bar represents the green light phase, and the curve represents the relationship between vehicle time and distance. In Fig. 6(a), we can find that when the vehicle arrives at intersection II, the signal light is in the red-light phase that results in unnecessary stop time. If the starting time of the green phase of intersection II can be advanced, as shown in Fig. 6(b), there is no stop behavior the driver has to take. Therefore, the delay time can be roughly used as the offset time of intersection II.

The above is a brief description of the concept of signal offset time. To obtain the specific offset time accurately for the downstream intersection, it needs to be calculated according to the vehicles' information from upstream and branch roads. Based on the above conditions, the offset time O^i_f can be obtained as follows:

$$O^i_f = \frac{L_i}{V_i} \tag{11}$$

where O^i_f represents the offset time of intersection i, L_i is the distance between the two intersections of upstream and downstream; V_i is the average speed of the clusters from upstream toward downstream.

However, some vehicles might miss the current green light phase because of the vehicles at the cluster's tail. Moreover, there might be vehicles waiting in front of the stop line at the downstream intersection, so (11) is adjusted to obtain optimal offset O^i_{of} as follows:

$$O^i_{of} = \frac{L_i}{V_i} - \left(\left(Q^i_{\max} - 1\right) \times h + t^i_{loss}\right) \tag{12}$$

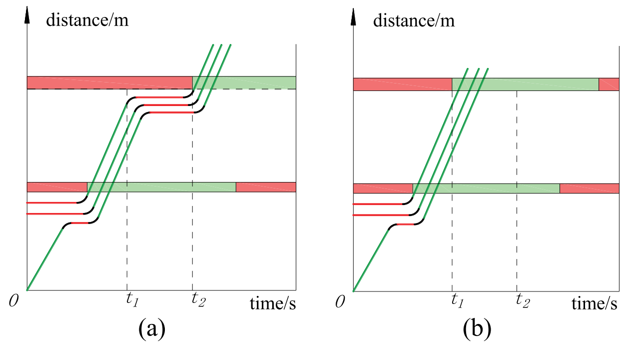

FIGURE 6. **Schematic of offset time: (a) without coordination control; (b) coordination control effect after adjustment. For example, $O_f = t_2$-t_1 is offset time, eliminating the stop delay when vehicles arrive at the second intersection.**

where the $Q^i_{\max}$ is the maximum vehicle number in all lanes of the downstream intersection i, and t^i_{loss} is the start loss time of the intersection i.

We first initialize the start time of the green light of the intersection I as t_1, and then we denote the start time of the green light of the intersection i as t_i. Based on these works, we can control and program the intersection signal controller to assign the green light start time as the following formula:

$$t_i = t_1 + \sum_{j=2}^{i} O^j_{of} \quad (i = 2, 3, \cdots) \tag{13}$$

To perform the intersections coordination practically, we design the algorithm, and the detailed description of the algorithm is shown in Algorithm 2, which gives the pseudocode for the proposed approach.

In the proposed algorithm, calculation of T_i, $t_i O^i_{of}$ occurs at the end of the red phase takes $O(mn)$, where m represents the number of the clusters, and n represents the number of intersections in the networks. Due to the establishment of dynamic registration list L, the microprocessor can obtain the precomputed headway h_a before signal timing calculation. Thus the number of the clusters n and timing parameters can be processed in the distributed period. Practically, the computational complexity of Algorithm 2 can be regarded as linear in m, i.e., $O(m)$. It is one of the advantages of the proposed algorithm.

V. EXPERIMENTAL STUDIES

In this section, the experiments are conducted to evaluate the performance of the MICA-V. Firstly, we presented the simulation setup and parameters. Then we had completed the simulation on TraCI4MATLAB and validated the performance of the MICA-V in terms of improving traffic capacity. The specifications of system used for simulation are: Processor - Intel®CoreTM i5-9300HF CPU @ 2.40 GHz, 16GB RAM, Hard Disk - 1 TB (951GB free), and OS - Windows 10 Home 64-bit. SUMO is an open-source framework for running traffic network simulations.

Algorithm 2 Multi-Intersection Coordination Control Algorithm (MICA-V) Based on V2X

Input: t_a, t_d, L, t_1, T_1
Result: T_i, t_i, O_f^i
Initialize network parameters and a list L
Initialize simulation *step* and the average default speed for V_i
begin
 for $i = 0$ to $i = step$ **do**
  initialize the first intersection states t_1 and T_1
  if the first intersection is the red phase, **then**
   reset the headway time $\bar{h}_a$ <- **Algorithm 1**
   trigger the CVC control state and establish the list then the list members get no change until the end of the red phase
   if the current time is the last second of red phase, **then**
    calculate the offset O_{of}^i of downstream intersection
    allocate the green light start time of downstream intersection t_i
    calculate T_i of downstream intersection respectively, according to the values q_{upb}^i, q_{dstop}^i
   end if
  end if and return T_i, t_i, O_{of}^i
 end for
end

A. EXPERIMENTAL SETTINGS

This simulation was implemented by the open-source simulator SUMO (version 1.3.1 in this article) and MATLAB (version 2017a) for joint simulation. The software integration had been realized by taking MATLAB as the main control program, and SUMO served as the server, which directly called the SUMO program through the TraCI interface. Thus, it is also called TraCI4MATLAB [25]. The simulation process had been shown in Fig. 7. In the co-simulation process, the SUMO objects were defined and produced by DUAROUTER tool. Then, SUMO traffic state information was obtained after running the SUMO and MATLAB program. The traffic information was transmitted to MATLAB for processing the data. MATLAB provided an optimized control scheme by a specific algorithm to support the signal control of SUMO. Finally, an integrated simulation platform was built, which could process the simulation cycle with setting parameters.

As shown in Fig. 3, each intersection is composed of four roads. The incoming artery road has six lanes, where the right-most lane(W0) is for right-turn traffic flow, four middle lanes (W4-1) allow vehicles to go straight only, and the left lane (W5) allows vehicles to turn left. The route of each car is generated by the path generator randomly.

The method by which vehicles are generated and departed into the network significantly impacts any traffic simulation quality [26]. The most popular vehicle production method is to randomly sample from probability distribution numbers that respect to the time interval between vehicles. However, we struggled to implement a more stochastic version that

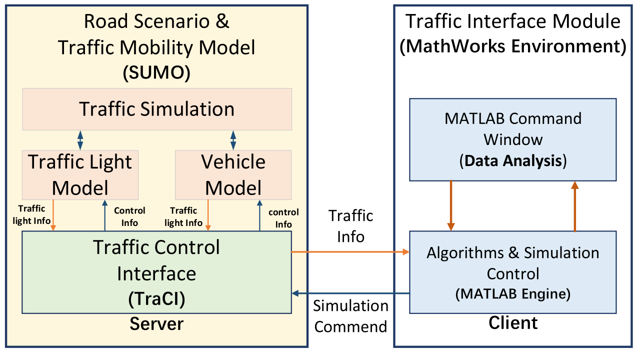

FIGURE 7. The process of the co-simulation with MATLAB and SUMO.

TABLE 1. Traffic information on the one-way road model

Index	W4-1	W5	W0	N11	N12	N13	S11	S12	S13
Intention	1	5	4	3	7	2	3	2	6
Possibility	0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1
Target lane	WE4-1	N13	S11	S11	W5	\	\	N13	W0

batters attached to realistic scenarios. We construct vehicle routes based on various turning probability of the main road WE5-0 (shown in Table.1) by using the JTRROUTER tool. Besides, previous research had demonstrated that different vehicle rates are suitably approximated by different probability distributions [27]. In this experiment, the vehicle production rate followed the Bernoulli process (which approximates a Poisson distribution for small probabilities). Our goal is to address the efficiency of arterial lanes in this circumstance, so we focused on maximizing the green waveband for straight-forward lanes WE4-1 and omitted the branch's production effect. The traffic volume of the branch road was set as 100 pcu/h per lane.

In vehicular longitudinal dynamics modeling, namely the car-following control model, the common ones are Krauss [28], IDM [29], PWagner, BKerner, etc. Jufu *et al.* [30] proposed that the Krauss model possesses the best performance under the SUMO platform. Based on the consideration that the realization of the proposed algorithm is needed to make use of SUMO (a traffic simulation platform), so we adopted the Krauss model to conduct vehicles in this simulation.

To simulate the intersection traffic flow, it is significant to set appropriate traffic environment parameters. In this work, the distribution of the four intersections is shown as Fig. 8. Each monitoring area radius was 75 m. In the SUMO simulation environment, the vehicle parameter setting is shown in Table 2, and each simulation time was set as 1000 s. Note that the phase time is a time-varying parameter which will be changed with iteration. After the initial experiment, the four intersections' initial phase 1 was set as 12 s, and phase 2 was 24 s. The probabilities of turning were shown in Table 1. To ensure the simulation randomness, we carried out ten simulation experiments with setting the random SEED from 1 to 10. To avoid long green duration waiting for all vehicles from the upstream branches, we set $T_{\min} = 15$ s

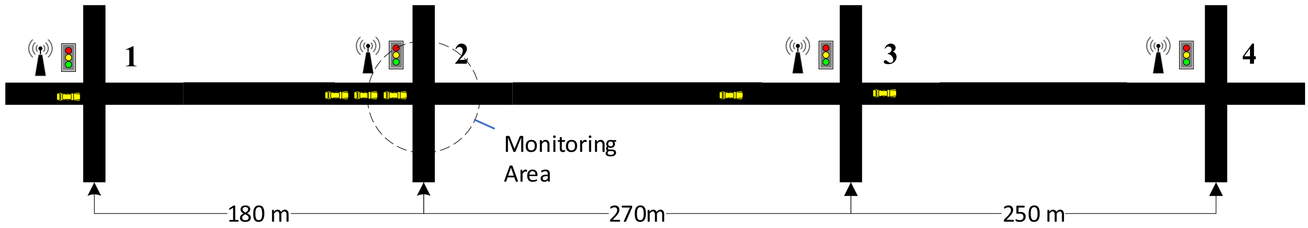

FIGURE 8. The distribution of four intersections in simulation.

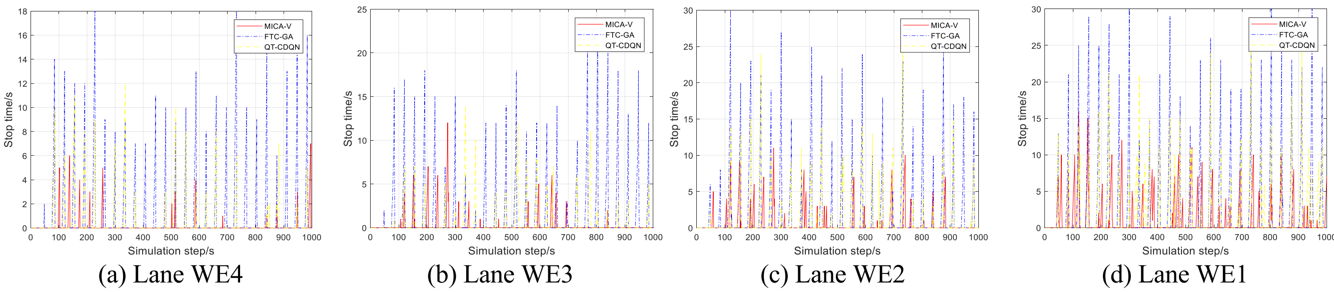

FIGURE 9. The stop time of the vehicles in four artery lanes. The number of peaks represents the red phase frequency, and the peak values are the vehicle stop times in a specific phase.

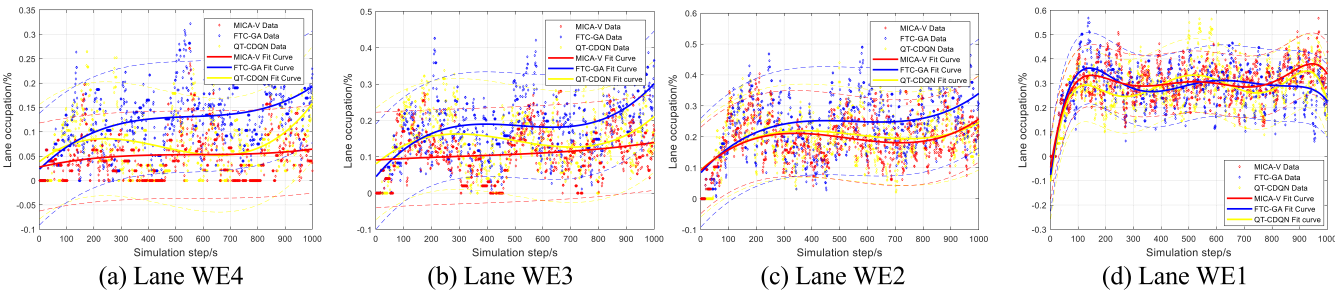

FIGURE 10. The occupation percentage of four arterial lanes: (a) performance of lane WE4; (b) performance of lane WE3; (c) performance of lane WE2; (d) performance of lane WE1; The solid lines show the curve obtained by discrete data fitting, the areas surrounded by two dotted lines show the confidence interval with $\alpha = 0.05$ and the thicken curves show the mean.

TABLE 2. Vehicle parameter in SUMO simulation

Parameter	Car	Bus
Length	5 m	10 m
Maximum speed	12 m/s	8 m/s
Acceleration	0.8 m/s^2	0.4 m/s^2
Deceleration	4 m/s^2	2 m/s^2
Minimum safety distance	1.5 m	2 m
Production rate	0.30	0.1
Call-following model	Krauss	
Lane change model	SL2015	
Start loss time t_{loss}	2.0 s	

and $T_{\max} = 35$ s. With the initial experiments on traffic flow, we found the t_{loss} was different due to the different vehicle types and set t_{loss} as 2.0s for the simulation.

B. EXPERIMENTAL RESULTS AND ANALYSIS

To assess the performance of the proposed MICA-V, we made comparisons with the fixed-time control based on the genetic algorithm (FTC-GA) [9] and a cooperative deep Q-network (QT-CDQN) for multi-intersections signal control [18].

According to simulation circumstances, we adopted the following metrics to evaluate the performance of the mechanism. Simulation results have been summarized in Fig. 9–13.

- Stop time refers to the time of the vehicles waiting in front of the stop line. The average value characterized the whole performance of the stopping phenomenon.
- Lane occupancy refers to the density of vehicles in the last simulation step.
- The waiting count refers to the account of vehicles whose velocity was under 0.1m/s due to the red phase.
- Average speed refers to the mean speed of the whole traffic flow.

Focusing on the efficiency of the artery lanes, we omitted the results of the brand road. Instead, we presented the performance of the lanes WE4-1, which allowed the vehicles straight forward only. The intersection was the starting point of coordinated control and was not considered in analyzing simulation results [31].

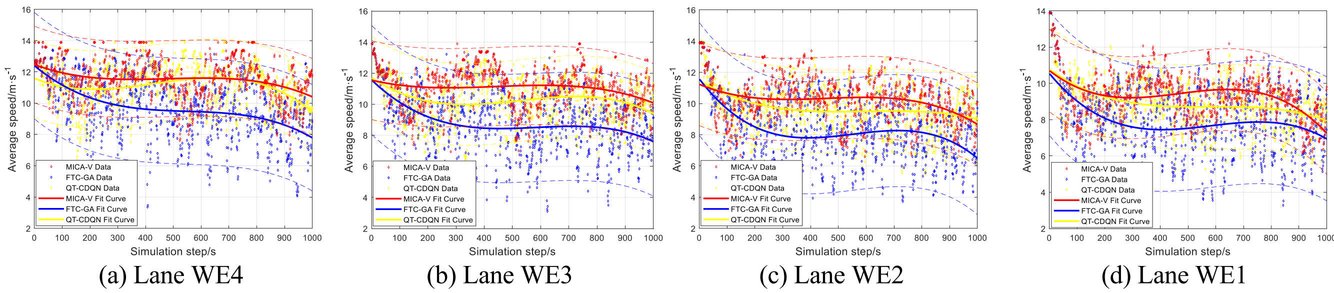

FIGURE 11. **The average speed of vehicles driving on arterial lanes: (a) performance of lane WE4; (b) performance of lane WE3; (c) performance of lane WE2; (d) performance of lane WE1.**

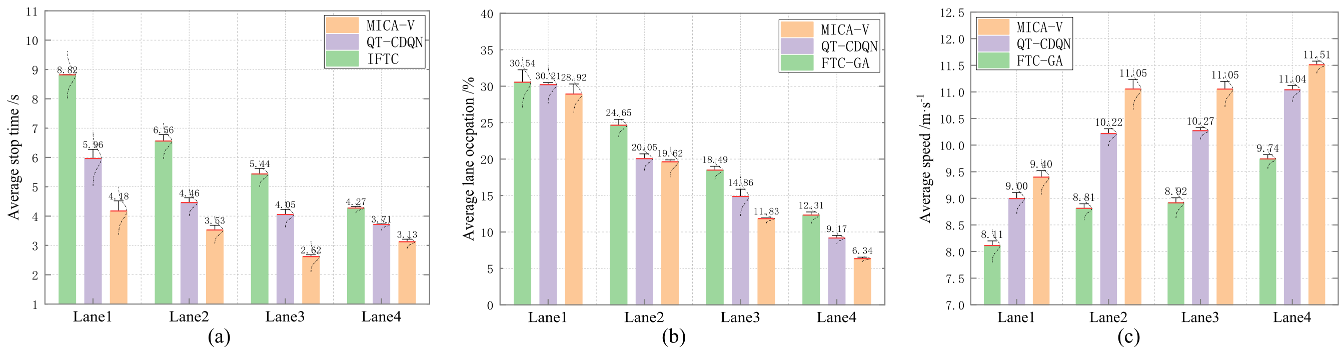

FIGURE 12. **Statistical analysis chart of the four lanes: (a) average stop time; (b) average lane occupation; (c) average speed.**

Fig. 9 shows the stopping behaviors of the vehicles in the macroscope. The vehicles are only stopped due to the red traffic phase. Thus, the number of peaks in Fig. 9 are represented as the red phase frequency, and the peak values are the vehicle stop times in a specific phase. Fig. 10, 11 show the occupation percentage of four arterial lanes and the average speed of vehicles driving on arterial lanes. The solid lines show the curve obtained by discrete data fitting, and the two dotted-line areas show the confidence interval with $\alpha = 0.05$ and the thicken curves show the mean. Furthermore, to facilitate quantitative analysis, we provided the boxplot-bar chart for simulation data, as shown in Fig. 12.

From Fig. 9-11, we observed that the FTC-GA has the worst adaptability to recurring congestion. Compared with the other two algorithms, the proposed MICA-V has the best adaptability to form a green waveband in the arterial road and produces more stable results for the three metrics. Note that SUMO is based on right-side driving rules at the intersection, which resulted in uneven distribution of the performance of the four lanes. In the illustrated figures, the three metrics had been greatly improved. According to Fig. 12, compared with FTC-GA, MICA-V reduced the average stop time by 45.63% and the lane occupation by 22.42% and improved the average speed by 17.27% totally in four lanes. Similarly, compared with QT-CDQN, MICA-V reduced the average stop time by 24.97% and the lane occupation by 10.20% and increased average speed by 12.21%. Since the travel time is the sum of delay and moving time, the less stop time leads to less travel time, and it had been provided in the following discussion.

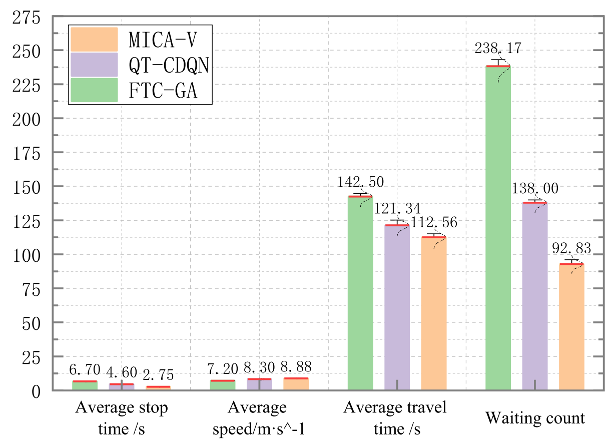

FIGURE 13. **Statistical analysis chart of the four lanes: (a) average stop time; (b) average lane occupation; (c)average speed.**

Furthermore, to evaluate the simulation performance from a microscope, we made a statistic for 164 vehicles traveling in the artery, and the results had been illustrated in Fig. 13. It was feasible to obtain the traffic information of all individual vehicles, respectively, by utilizing the SUMO vehicles statistics file (* tripinfo.xml). From the following bar chart, we observed that the MICA-V reduced the average stop time to 2.75 s, improved average speed by 23.33% compared with FTC-GA, shortened the travel time by 21.01%, and reduced the waiting counts by 61.34%. Similarly, compared with QT-CDQN, MICA-V had improved the average speed by 6.99% and reduced the waiting count by 34.18%. Although the travel time and average speed did not get dramatic improvement,

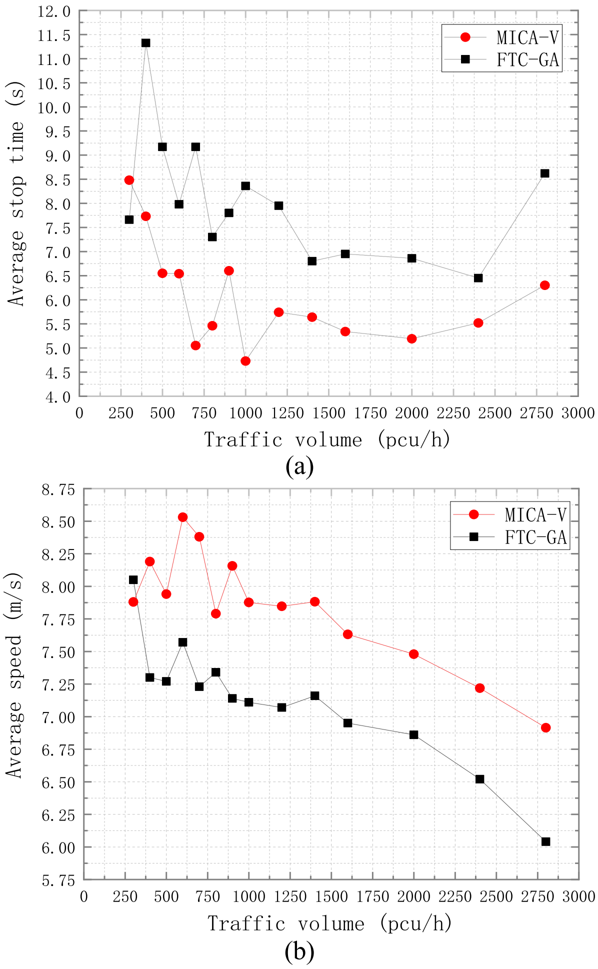

FIGURE 14. Comparison performances in different traffic volumes: (a) average parking delay time; (b) average speed of the traveled vehicles.

the fewer stops demonstrated this coordinated method had given drivers a better experience. As for the other unsatisfactory improvement, there are two possible reasons for this performance. The first reason is that the maximum speed as a calculation parameter; its value contributes to impacting the calculation results. The second one is that the network was simulated in a particular traffic volume, which results in no access to universality.

To validate the expansibility and stability of proposed MICA-V, we made a comparison with our control method and FTC-GA. In the realistic traffic, the control strategy needs to meet traffic fluctuation demands on the whole day, such as daily peaks causing a thorny traffic problem. If a system is rigid and cannot adapt to the real-time fluctuation of traffic flow, it might lead to an inefficient and unsatisfactory reality. So, following the same parameters set as Table 2, but we changed the traffic volume of the arterial lanes WE5-0. Correspondingly, the traffic volume was 300, 400, 500, 600, 700, 800, 900, 1000, 1200, 1400, 1600, 2000, 2400 and 2800 pcu/h respectively. We calculated average values from these experiments, which were illustrated in Fig. 14.

We found that the proposed MICA-V was also available for the high traffic volume and dramatically maintained an outstanding performance. According to Fig. 14(a)-(b), there was no significant gap between the two signal control methods under a sparse traffic volume. With increasing in the traffic flow, the FTC-GA shows its limitations, and the average speed was reduced to half of the maximum speed, whereas the V2X coordinated control could adaptively adjust the signal timing and offset based on real-time flow. On the one hand, with the traffic flow increasing in Fig 14(a), the average stop time decreased under two control strategies, but MICA-V outperformed FTC-GA. On the other hand, the MICA-V could adapt to traffic flow fluctuation and maintain the average speed in 300∼2000 pcu/h.

VI. CONCLUSION

In this study, a multi-intersection coordination algorithm based on V2X (MICA-V) was proposed. The proposed traffic model was composed of upstream and downstream intersections. In our traffic signal control, the upstream RSU obtains the state information of the vehicle group via V2X, which integrates and processes real-time data with a specific algorithm. Moreover, the upstream RSU shares traffic information with the downstream ones. The upstream information conducts the downstream controller to allocate the green light duration through the upstream and downstream traffic flow. Due to the dynamic optimization of the average headway parameter used in the system, the MICA-V algorithm realizes the closed-loop control of signaling time. Besides, the controller adjusts the signal starting time according to the arrival time of the upstream traffic flow. Finally, a one-way multi-intersection scenario was employed to evaluate the performance of our method. The simulation results showed that the vehicles along the green waveband could smoothly pass by the arterial road, and MICA-V reduces the stop time in each intersection. Also, further experiments showed the robustness of our coordination algorithm, even under a high traffic volume condition.

However, some limitations were observed in the present work. We assumed that the error-free V2X communication had been deployed in this scenario, but the communication delay, load, and packet loss cannot be ignored in realistic traffic conditions. Thus, we need to perform comprehensive experiments under the Veins framework, which combines the network simulator and SUMO, to validate the proposed method. Meanwhile, we will conduct comparative experiments based on real data sets to validate the algorithm efficiency with some classical methods in the future.

REFERENCES

[1] *The Future Economic and Environmental Costs of Gridlock in 2030*, Center Econ. Bus. Res., INRIX, Kirkland, WA, USA, 2013.

[2] M. Balta and İ. Özçelik, "A 3-stage fuzzy-decision tree model for traffic signal optimization in urban city via a SDN based VANET architecture," *Future Gener. Comput. Syst.*, vol. 104, pp. 142–158, Mar. 2020.

[3] H.-J. Li, L. Wang, Y. Zhang, and M. Perc, "Optimization of identifiability for efficient community detection," *New J. Phys.*, vol. 22, no. 6, Jun. 2020, Art. no. 063035.

[4] D. L. Guidoni, G. Maia, F. S. H. Souza, L. A. Villas, and A. A. F. Loureiro, ''Vehicular traffic management based on traffic engineering for vehicular ad hoc networks,'' *IEEE Access*, vol. 8, pp. 45167–45183, 2020.

[5] K. Gao, S. Huang, J. Xie, N. N. Xiong, and R. Du, ''A review of research on intersection control based on connected vehicles and data-driven intelligent approaches,'' *Electronics*, vol. 9, no. 6, p. 885, May 2020.

[6] H.-J. Li, Z. Wang, J. Pei, J. Cao, and Y. Shi, ''Optimal estimation of low-rank factors via feature level data fusion of multiplex signal systems,'' *IEEE Trans. Knowl. Data Eng.*, early access, Aug. 13, 2020, doi: 10.1109/TKDE.2020.3015914.

[7] M. Alam, J. Ferreira, and J. Fonseca, ''Introduction to intelligent transportation systems,'' in *Intelligent Transportation Systems*, 1st ed, J. Fonseca, Ed. Cham, Switzerland: Springer, 2016, pp. 1–17.

[8] E. Köhler and M. Strehler, ''Traffic signal optimization using cyclically expanded networks,'' *Networks*, vol. 65, no. 3, pp. 244–261, Feb. 2015.

[9] B. C. Costa, S. S. Leal, P. E. Almeida, and E. G. Carrano, ''Fixed-time traffic signal optimization using a multi-objective evolutionary algorithm and microsimulation of urban networks,'' *Trans. Inst. Meas. Control*, vol. 40, no. 4, pp. 1092–1101, Nov. 2016.

[10] E. Köhler and M. Strehler, ''Traffic signal optimization: Combining static and dynamic models,'' *Transp. Sci.*, vol. 53, no. 1, pp. 21–41, Feb. 2019.

[11] T. Thunig, R. Scheffler, M. Strehler, and K. Nagel, ''Optimization and simulation of fixed-time traffic signal control in real-world applications,'' *Procedia Comput. Sci.*, vol. 151, pp. 826–833, May 2019.

[12] L. Chen and C. Englund, ''Cooperative intersection management: A survey,'' *IEEE Trans. Intell. Transp. Syst.*, vol. 17, no. 2, pp. 570–586, Feb. 2016.

[13] H.-J. Li, Z. Bu, Z. Wang, and J. Cao, ''Dynamical clustering in electronic commerce systems via optimization and leadership expansion,'' *IEEE Trans. Ind. Informat.*, vol. 16, no. 8, pp. 5327–5334, Aug. 2020.

[14] W. Hu, H. Wang, B. Du, and L. Yan, ''A multi-intersection model and signal timing plan algorithm for urban traffic signal control,'' *Transport*, vol. 32, no. 4, pp. 368–378, Aug. 2014.

[15] X. Li, Z. Zhao, L. Liu, Y. Liu, and P. Li, ''An optimization model of multi-intersection signal control for trunk road under collaborative information,'' *J. Control Sci. Eng.*, vol. 2017, pp. 1–11, May 2017.

[16] B. Yin, M. Dridi, and A. El Moudni, ''Adaptive traffic signal control for multi-intersection based on microscopic model,'' in *Proc. IEEE 27th Int. Conf. Tools with Artif. Intell. (ICTAI)*, Nov. 2015, pp. 49–55.

[17] S. El-Tantawy, B. Abdulhai, and H. Abdelgawad, ''Multiagent reinforcement learning for integrated network of adaptive traffic signal controllers (MARLIN-ATSC): Methodology and large-scale application on downtown toronto,'' *IEEE Trans. Intell. Transp. Syst.*, vol. 14, no. 3, pp. 1140–1150, Sep. 2013.

[18] H. Ge, Y. Song, C. Wu, J. Ren, and G. Tan, ''Cooperative deep Q-learning with Q-value transfer for multi-intersection signal control,'' *IEEE Access*, vol. 7, pp. 40797–40809, 2019.

[19] C. Li and S. Shimamoto, ''An open traffic light control model for reducing Vehicles' CO_2 emissions based on ETC vehicles,'' *IEEE Trans. Veh. Technol.*, vol. 61, no. 1, pp. 97–110, Jan. 2012.

[20] B. Zhou, J. Cao, and H. Wu, ''Adaptive traffic light control of multiple intersections in WSN-based ITS,'' in *Proc. IEEE 73rd Veh. Technol. Conf. (VTC Spring)*, May 2011, pp. 1–5.

[21] Z. Cai, Z. Deng, J. Li, J. Zhang, and M. Liang, ''An intersection signal control mechanism assisted by vehicular ad hoc networks,'' *Electronics*, vol. 8, no. 12, p. 1402, Nov. 2019.

[22] H. Zhu and H. Nakamura, ''Study on start-up lost time at signalized intersections considering downstream conditions,'' *J. Jpn. Soc. Civil Eng., Ser. D3, Infrastruct. Planning Manage.*, vol. 75, no. 5, pp. I-1121–I-1130, 2019.

[23] Y. Wang, J. Rong, C. Zhou, and Y. Gao, ''Dynamic estimation of saturation flow rate at information-rich signalized intersections,'' *Information*, vol. 11, no. 4, p. 178, Mar. 2020.

[24] Q. Luo, J. Yuan, X. Chen, S. Wu, Z. Qu, and J. Tang, ''Analyzing start-up time headway distribution characteristics at signalized intersections,'' *Phys. A, Stat. Mech. Appl.*, vol. 535, Dec. 2019, Art. no. 122348.

[25] A. F. Acosta, J. E. Espinosa, and J. Espinosa, ''TraCI4MATLAB: Enabling the integration of the SUMO road traffic simulator and MATLAB through a software re-engineering process,'' in *Modeling Mobility With Open Data*. Cham, Switzerland: Springer, Mar. 2015, pp. 155–170.

[26] J. Gu, Y. Fang, Z. Sheng, and P. Wen, ''Double deep Q-Network with a dual-agent for traffic signal control,'' *Appl. Sci.*, vol. 10, no. 5, p. 1622, Feb. 2020.

[27] R. Riccardo and G. Massimiliano, ''An empirical analysis of vehicle time headways on rural two-lane two-way roads,'' *Procedia Social Behav. Sci.*, vol. 54, pp. 865–874, Oct. 2012.

[28] J. Song, Y. Wu, Z. Xu, and X. Lin, ''Research on car-following model based on SUMO,'' in *Proc. 7th IEEE/Int. Conf. Adv. Infocomm Technol.*, Nov. 2014, pp. 47–55.

[29] B. S. Kerner, S. L. Klenov, and A. Brakemeier, ''Testbed for wireless vehicle communication: A simulation approach based on three-phase traffic theory,'' in *Proc. IEEE Intell. Vehicles Symp.*, Jun. 2008, pp. 180–185.

[30] C. Jufu, H. Benxu, X. Hui, C. Fei, and C. Xiangguo, ''Comparative analysis of ismulation of multi-car-following models under SUMO platform,'' *J. Chongqing Univ.*, pp. 1–15, Feb. 2020.

[31] K. Gao, F.-R. Han, M.-F. Wen, R.-H. Du, S. Li, and F. Zhou, ''Coordinated control method of intersection traffic light in one-way road based on V2X,'' *J. Central South Univ.*, vol. 26, no. 9, pp. 2516–2527, Sep. 2019.

YANJUN SHI (Senior Member, IEEE) received the B.S. degree in mechanical engineering from Dalian Ocean University, China, in 1996, the M.S. degree in mechatronic engineering from Beihang University, China, in 1999, and the Ph.D. degree in computer engineering from the Dalian University of Technology, China, in 2005.

He is currently an Associate Professor with the School of Mechanical Engineering, Dalian University of Technology. He has authored or coauthored over 80 articles in scientific journals and international conferences. His research interests include collaborative planning and scheduling, multi-access edge computing, 5G applications, and autonomous vehicles. He is the Vice Chair of the IEEE SMC Dalian Chapter. He is an Associate Editor of the *IET Collaborative Intelligent Manufacturing*.

JIAJIAN LI received the B.S. degree in mechanical engineering from the Dalian University of Technology, Dalian, China, in 2020.

He is currently pursuing the M.S. degree in mechanical and electronic engineering with the Dalian University of Technology, Dalian, China. His research interests include Internet of Vehicles, intersection coordination, and intelligent traffic.

QIAOMEI HAN (Senior Member, IEEE) received the B.S. and M.S. degrees in mechanical engineering from the Dalian University of Technology, Dalian, China, in 2017 and 2020, respectively. She is currently pursuing the Ph.D. degree with the School of Electrical and Computing Mechanical Engineering, Western University, London, Canada. Her research interests include Internet of Vehicles, 5G applications, and device-edge-cloud collaboration.

LINGLING LV received the B.S. degree in industrial engineering from Xinjiang University, China, in 2018. She is currently pursuing the M.S. degree in industrial engineering with the Dalian University of Technology, China. Her research interests include 5G applications, intelligent transport system, and Internet of Vehicles.