V2X Empowered Non-Signalized Intersection Management in the AI Era: Opportunities and Solutions

Yunting Xu, Haibo Zhou, Jiacheng Chen, Bo Qian, Weihua Zhuang, and Sherman (Xuemin) Shen

Abstract

With significant advancements of vehicle-to-everything (V2X) communication technologies in recent years, intelligent collaboration between connected vehicles and roadside units provides new opportunities for better road safety and vehicle traffic management via innovative non-signalized intersections. In this article, to deal with sophisticated traffic information brought about by a dynamic non-signalized intersection environment, artificial intelligence (AI) solutions together with V2X communication technologies are proposed to provide data-driven intersection management strategies. We first present the emerging technologies and key challenges toward V2X empowered non-signalized intersection management. By introducing the applications of typical AI technologies, we pinpoint three main research issues on V2X empowered non-signalized intersection management, leveraging various AI approaches. Finally, we present a case study where a multi-agent learning approach is applied for intelligent multiple intersection management to demonstrate the effectiveness of our non-signalized intersection solution.

Introduction

With the ever increasing number of private vehicles in urban areas, long-standing road traffic congestion in modern cities has become progressively common and needs to be solved urgently. Recent advancements in vehicular communication technologies have attracted lots of research attention to innovative road intersection management for optimizing traffic regulation efficiency and improving transport system intelligence [1]. Although intersections represent only a comparatively small part of an entire transportation system, they are the bottleneck of traffic flow and account for a significant portion of traffic congestion situations. Traffic lights play the role of an intersection traffic regulator, giving vehicles from different directions pre-fixed time periods for red, yellow, and green lights to pass through the intersection. However, as urban traffic becomes more and more heavy on the roads, regular traffic light scheduling no longer satisfies the demands for efficient intersection management, and the unnecessary waiting at stops caused by red lights often leads to enormous waste of energy and travel time [2]. Therefore, to further enhance the performance of traffic light scheduling, various solutions and strategies have been applied to change the conventional signal control mechanism in intersection management for a more comfortable and economical driving experience.

The evolution of intersection management is a journey from simple regulation with constant traffic light periods to increasingly real-time, intelligent, and high-precision scheduling of vehicle passing. In order to make full utilization of current deployment for traffic light control, with various cameras and sensors in place, adaptive signal regulation is brought in for real-time intersection traffic management. However, further research is required to reduce negative impact of traffic lights, and non-signalized intersection management has gradually come into sight. Non-signalized intersection management means that instead of exploiting traffic lights for vehicle scheduling, more fine-grained vehicle crossing schemes are customized for collision avoidance and throughput enhancement in intersection management. As vehicle-to-everything (V2X) communication technologies have significantly advanced in recent years, the collaboration between intelligent vehicles and an intersection traffic regulation system can potentially bring new opportunities for innovative non-signalized intersection management solutions [3]. In addition, the introduction of connected and automated vehicles (CAVs) equipped with integrated perception, communication, and control functions can enhance the connectivity and reliability of non-signalized intersection management [4].

Artificial intelligence (AI) technologies have been gaining more and more popularity for innovative and high-performance data-driven strategies in intelligent transportation systems (ITS) [5]. When it comes to dealing with sophisticated traffic information in a dynamic intersection environment, creative AI approaches can be leveraged to take responsibility for multi-dimensional data processing and computing tasks. Recent AI technologies that have been applied for vehicle traffic scheduling include reinforcement learning (RL), artificial neural networks (ANNs), and multi-agent systems (MASs) [6]. The diverse algorithms in RL, ANNs, and

Digital Object Identifier:
10.1109/MCOMSTD.001.2000020

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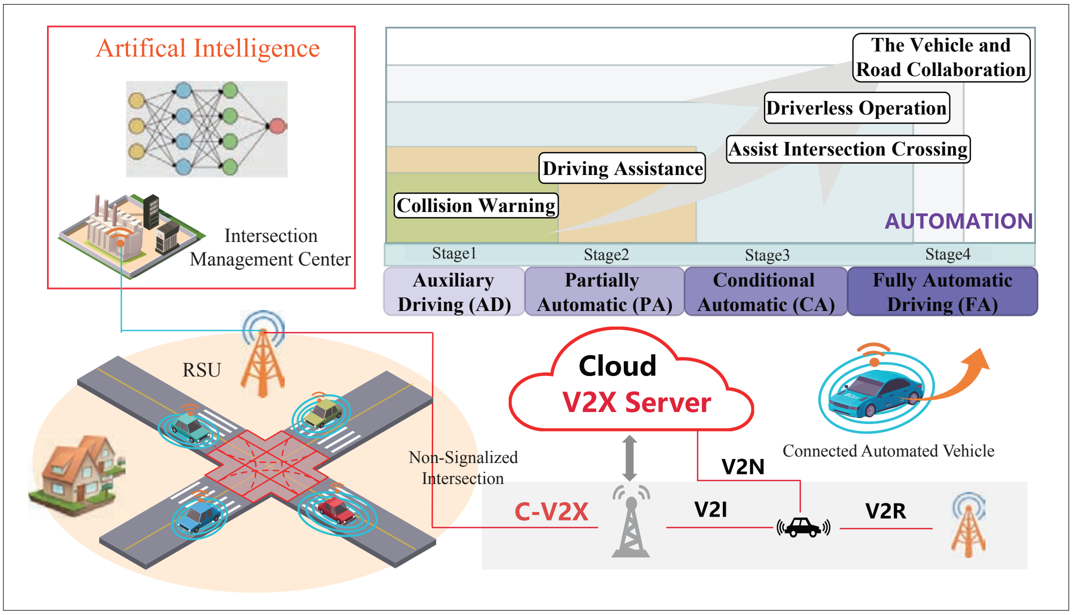

FIGURE 1. V2X empowered non-signalized intersection management: architecture and development.

By leveraging advanced V2X communication and innovative AI technologies, non-signalized intersection management aims for efficient traffic management with proper allocation of urban transportation system resources, for sustainable development of environmental protection, and for intelligent and automated transportation.

MASs can be employed separately or jointly, depending on the particular problem and solution. In the case of non-signalized intersection management, the intersection manager and vehicles are normally looked upon as intelligent agents. Via a virtual traffic model projected in the real world or directly using a practical traffic environment, agents are capable of obtaining an optimal scheduling strategy based on the received feedback under different situations. Non-signalized intersection management mechanisms can potentially leverage various AI technologies to achieve road safety and enhance traffic management efficiency.

By leveraging advanced V2X communication and innovative AI technologies, non-signalized intersection management aims for efficient traffic management with proper allocation of urban transportation system resources, for sustainable development of environmental protection, and for intelligent and automated transportation [7]. The specific objective is to ensure road safety, increase transportation efficiency, enhance travel experience, and achieve environment-friendly driving, as elaborated in the following:

- *Road safety* — Through vehicle communication connectivity, a non-signalized intersection is expected to provide collision avoidance service and reduce fatal crashes to the upmost extent.
- *Transportation efficiency* — Relieving traffic congestion is one of the most fundamental objectives for achieving traffic mobility, enhancing vehicle throughput, and improving management efficiency.
- *Travel experience* — Compared to traffic light control, the non-signalized intersection has the potential for a more comfortable travel experience including less intersection waiting time.
- *Environment-friendly driving* — Sustainable eco-driving means less fuel consumption, less CO_2 emission, and more economic regulation.

The remainder of this article is organized as follows. We provide an overview of emerging technologies and challenges for V2X-based non-signalized intersection management. We present AI-based approaches for non-signalized intersections. We investigate research issues on V2X empowered non-signalized intersection management, leveraging various AI approaches. A case study of multiple non-signalized intersection management is introduced. Finally, we provide some concluding remarks.

V2X-Based Non-Signalized Intersection Management

The Connected Automated Vehicle

The connected automated vehicle refers to a vehicle that can utilize V2X communications to make precise, intelligent, and automatic driving decisions [8]. It is generally recognized that the construction of a vehicular communication environment will have a significant impact on the intersection management. From the perspective of developmental progression as illustrated in Fig. 1, the practical applications of vehicular technologies currently remain in the partially automatic (PA) and conditional automatic (CA) stages. Equipped with line-of-sight in-vehicle devices such as high-end cameras and sensors, vehicles are capable of sensing the environment and gaining sufficient time for collision reaction and prevention. However, their semi-automatic features cannot meet the requirements for stable and reliable connectivity in non-signalized intersection management. As vehicular ad hoc networks (VANETs) have progressively evolved in recent years, dedicated short-range communication (DSRC) and cellular V2X (C-V2X) technologies are becoming mature to provide reliable connectivity, such as in vehicle-to-vehicle (V2V), vehicle-to-roadside unit (RSU, V2R), vehicle-to-infrastructure (V2I), and vehicle-to-network (V2N) communications [9]. To pass through an intersection, vehicles equipped with an onboard unit

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(OBU) can communicate with a nearby RSU or directly interact with other vehicles in proximity. The connectivity-driven V2X communication is certainly a powerful mechanism that will help to facilitate conditional automatic driving and eventually reach fully automatic (FA) driving. Therefore, CAVs will support the collaboration between the vehicles and intelligent transportation infrastructure, which is essential to non-signalized intersection management.

Advanced Technologies for Perception, Processing, and Computation

Traffic information perception, vehicle data processing, and computation are essential for decision making in crossing a dynamic non-signalized intersection. For vehicle perception, Internet of Things (IoT) technologies based on massive machine communications enable CAVs to detect and collect a wide range of external vehicle information, while Global Positioning System (GPS) devices enrich the way to obtain accurate location-related data. Other self-driving vehicular data, including real-time movement direction and velocity, will also be utilized by corresponding integrated units [10]. With regard to the processing of vehicular data, information aggregation and data storage are two fundamental procedures that need to be taken into consideration. For intersection regulation, raw vehicular information should be gathered and preprocessed by CAVs to extract valuable data for scheduling. Subsequently, cloud or edge servers should be established to process and store data for further computation. Cloud computing can balance network load and provide powerful network services. In terms of edge computing for vehicle scheduling, each lane can deploy a computational unit for its own control tasks, and intelligent CAVs can potentially act as computing nodes for collaborative work requirements [11]. Modern technologies for perception, processing, and computation offer a great potential of intersection management without traffic lights.

Challenges for V2X Empowered Non-Signalized Intersection Management

Although remarkable features of emerging vehicular technologies can promote the application of non-signalized intersection management, how to enhance traffic efficiency while guaranteeing vehicle safety poses significant technical challenges for developing crossing solutions [12]. The main difficulties include the following aspects:

1. How to realize the cooperative system scheduling: Effective cooperation among vehicles and the other intelligent agents is required for road safety with appropriate traffic regulation.
2. How to provide the real-time fault detection in an accidental situation: Timely and accurate fault detection followed by proper control is essential to avoid system breakdown, reduce failure percentage of AI mechanisms, and ensure normal operation.
3. How to achieve reliable V2X communications under stringent delay requirements: The dependence of cross scheduling on V2X communications needs to be carefully evaluated, and minimizing communication overhead should also be taken into consideration.
4. How to reduce computation complexity for cross scheduling: As non-signalized intersection management requires solving data-intensive problems in real time, it is necessary to develop simplified computational methods for fast computation, especially in a traffic congestion scenario.

Artificial Intelligence for Non-Signalized Intersection Management

In this section, we introduce AI approaches that have been studied for intersection management, including RL, ANN, and MAS.

Reinforcement Learning Method

Reinforcement learning has shown great potential in coping with sophisticated and dynamic traffic related problems. In RL, the decision maker is usually seen as an intelligent agent, which is able to constantly interact with the environment for exploring an optimal strategy. A complete RL task is modeled as a Markov decision process (MDP), and the agent learns the policy for achieving its goal based on the cumulative reward. Q-learning is one classical value-based optimization approach, which relies on updating the value of state-action pairs to measure importance of actions for a specific state. Q-learning can work well if the problem has small state and action spaces, but suffers from the curse of dimensionality otherwise. Combined with deep learning methodology, the algorithm of deep reinforcement learning (DRL) is often applied to approximate corresponding Q-values. In addition to the value-based RL approach, policy-based optimization approaches such as policy gradient (PG) and actor-critic (AC) are widely used in intersection management [13]. Policy-based RL algorithms can generate the probability for each action, which is suitable for circumstances with a large action set or a continuous action space.

Artificial Neural Network Method

The original concept of a neural network is the biological brain neural system in which cells connect sensors and reflectors for coordination operation. The modern ANN is a mathematical model that can be processed and optimized by computers. A trainable neural system employs forward or backward propagation to update its neurons so as to compute the expected outcome and solution. The simplest ANN structure consists of an input layer, hidden layers, and an output layer. For the application of ANN in intersection management, the input can be a specific characteristic expression of traffic state. According to different numbers and functions of the hidden layers, diverse network construction can be built, such as convolutional neural network (CNN), recurrent neural network (RNN), and long-short term memory (LSTM). Of all these neural networks, CNN is regularly used for dynamic traffic regulation as it can extract relevant traffic features using the convolution layer and pooling layer for a complex environment. The ANN is also broadly incorporated

Non-signalized scheduling mechanisms	Description	Advantage/limitation
Centralized isolated intersection mechanism	• N-IMC is modeled as the only agent. Goal: collision avoidance, efficiency improvement RL algorithm: Q-learning, deep Q-network, policy gradient, actor-critic, etc.	• Global optimal decision • Large computation overhead
Distributed isolated intersection mechanism	• All vehicles are modeled as agents. Goal: collision avoidance, reduce personal time MAS algorithm: MA-DDPG, CommNet, etc.	• Personal optimal decision • Enable computation offloading • Large communication overhead
Multiple non-signalized intersections	• Independent intersection scheduling • Centralized MIS agent control • Multiple vehicle agent mechanism • Cooperative distributed scheduling	• Without intersection interaction • Powerless against large-scale MIS • Only improve personal navigation • Enhance global traffic efficiency

Table 1. An overview of different non-signalized intersection solutions.

When the multi-agent system is applied to non-signalized intersection management, vehicles and intersections can be modeled as intelligent agents, and AI algorithms can be employed to facilitate vehicle-road and vehicle-vehicle collaboration for high transportation efficiency.

into RL for nonlinear function approximation or generating required system output [14].

Multi-Agent System Method

A multi-agent system comprises a number of entities: intelligent agents that are appointed in a specified environment [15]. Each agent obtains feedback by interacting with the environment so as to learn and improve the optimal policy under the joint action space with all other agents. The multi-agent system can be used to deal with problems that are difficult for a single agent to solve. The process of one agent interacting with the environment includes obtaining an environment state, independently executing an optional decision, and receiving the influence of corresponding action. The initial multi-agent system is extended from the analysis of behaviors for a single agent, in which all agents are separated from each other and maintain their own strategies. To make connections among the agents, the reward function is designed to create a cooperation or competition environment for independent agents. In a communication-enabled multi-agent system, agents can also share their domain knowledge and required information with each other for enhancing performance in achieving their goals. CommNet and bidirectional-coordinated nets are two up-to-date communication-based multi-agent training models. In multi-agent learning, agents can either leverage distributed networks such as MA-DDPG to train their own strategies or use a centralized training decentralized execution framework for global computing. When the multi-agent system is applied to non-signalized intersection management, vehicles and intersections can be modeled as intelligent agents, and AI algorithms can be employed to facilitate vehicle-road and vehicle-vehicle collaboration for high transportation efficiency.

Research Issues on V2X Empowered Non-Signalized Intersection Management

In this section, as shown in Fig. 2, we pinpoint three research issues on V2X empowered non-signalized intersection management according to different scenarios, leveraging various AI approaches. We summarize the technical features, along with their advantages and limitations, in Table 1.

Centralized Isolated Intersection Mechanism

For an isolated intersection, there are both centralized and distributed mechanisms to realize non-signalized intersection management. As shown in Fig. 2, in a centralized isolated intersection mechanism, a non-signalized intersection management coordinator (N-IMC) is deployed to take the place of traffic lights for vehicle communication and crossing strategy computation. Vehicles can establish a direct communication link with N-IMC to upload their traffic information or by means of multihop V2V relay. In the context of RL for centralized intersection management, the N-IMC is viewed as an intelligent agent that is required to collect global traffic information for an optimal scheduling solution. There are various multi-objectives in non-signalized intersection management, such as collision avoidance, waiting time reduction, and queue length shortening. In order to obtain accurate real-time knowledge of the dynamic environment, vehicle motion related information is a primary requirement. The most important variables include vehicle position, movement velocity, driving direction, and current traveling lane. As for optional actions that vehicles will take when passing through the intersection, different crossing priority, and movement accelerating and decelerating should be taken into consideration. Finally, a reward function should properly measure the effect of corresponding actions, which can be quantified by the intersection passing delay, traffic throughput, or occurrence of a vehicle collision.

After defining specific state space, action space, and reward function, the simplest solution is to use Q-learning to evaluate the effects of actions on each state. Since a non-signalized intersection is a dynamically changing environment, it is difficult to make the training process converge merely using the Q-table method. Therefore, the ANN can be introduced for Q-value approximation. The vector expression of traffic state can be taken as the input of the ANN to generate a measurable value for each

While isolated non-signalized intersection management aims at maximizing traffic throughput at the intersection, there is room for regulation efficiency improvement by jointly managing multiple- intersection system (MIS) in a neighborhood.

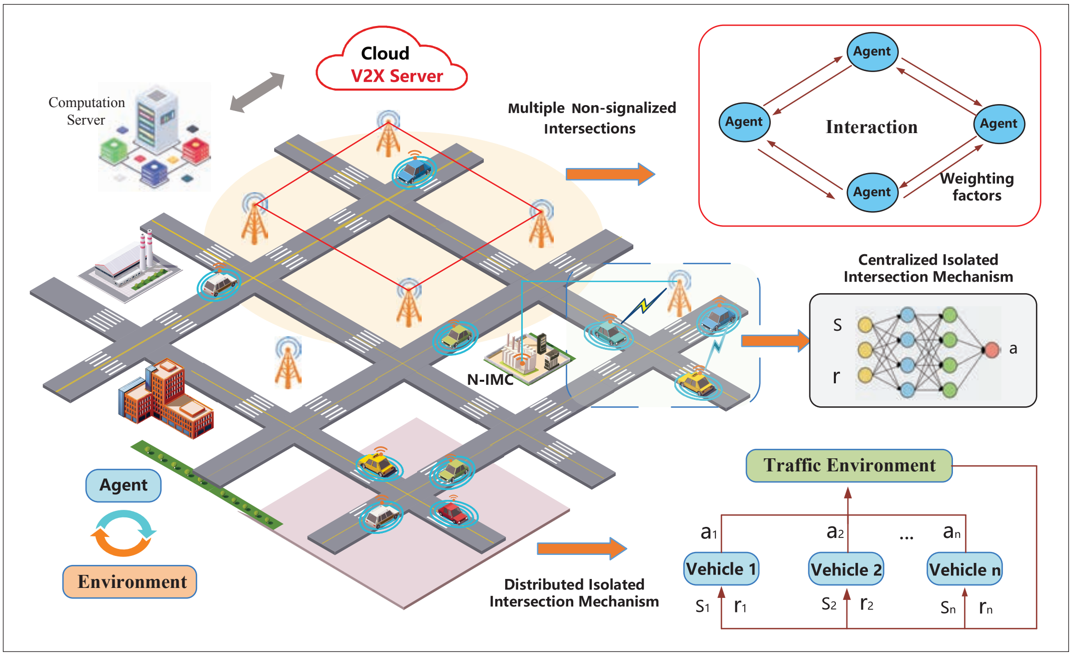

Figure 2. Example scenarios of non-signalized intersection management.

action. In a complex scenario, a CNN or other functional ANN can be exploited for better perceiving and processing the characteristics of traffic information. The ANN can also be used to generate the probability distribution, which is capable of solving a continuous action problem such as selecting a specific velocity or time to pass the intersection. Policy-based RL optimization such as PG and AC is another approach for centralized non-signalized intersection management, of which the agent emphasizes the effect of transferred state. For instance, the state of collision appearance or queue length increase will result in unfavorable feedback from the environment.

Distributed Isolated Intersection Mechanism

In a distributed isolated intersection mechanism, all vehicles are modeled as intelligent agents so as to form a multi-agent system. Each vehicle in the multi-agent system typically obtains partial environment information for reaching its goals. The specific structure of multiple vehicle agents interacting with the traffic environment is shown in Fig. 2. In a non-signalized intersection, the primary objective of all vehicle agents is to avoid collision with each other. Here, each agent should keep interacting with other vehicle agents that are within its communication range. However, once the driving paths are determined, not all the agents have chances to meet one another at the intersection. Consequently, the unnecessary connection can result in a large amount of additional communication overhead. An alternative way to reduce communication overhead, while ensuring scalability, is to have the N-IMC as a mediator agent. When a vehicle is going to pass through the intersection, its trajectory-related information is sent to the N-IMC, and the N-IMC will respond to this agent with identified vehicles that may collide with each other based on the predefined crossing routes. Thus, the agent can decide to directly communicate with these vehicles or use the N-IMC to relay its messages.

At an intersection, the partially perceived observation by each vehicle agent should include the position, velocity, and driving path information from neighboring vehicles. Each agent independently executes the decision making process and takes appropriate actions. In each time interval of the decision process, the agent has two possible actions: to move forward or brake when crossing the intersection without change movement direction, which is the simplest situation. The action set can be further extended to include movement speed with a continuous value range of velocity. The feedback from the environment emphasizes that agents are desired to be in collision-free status and should complete its own route as soon as possible. Therefore, the reward function depends on the total cost for collision occurrence and total time consumption for vehicles to cross the intersection. If a collision happens, the affected routes are captured via a failure policy by the agents. Each vehicle agent computes its own strategies with mixed cooperation or competition and can share a common reward value with other agents in proximity. In comparison to centralized intersection management, the distributed mechanism demands more V2V connections and higher communication overhead. However, from the viewpoint of computations, the overall large scheduling task of global N-IMC can be offloaded to the vehicle agents, which can potentially enhance the computation capacity and elevate the robustness of the intersection management.

Multiple Non-Signalized Intersections

While isolated non-signalized intersection management aims at maximizing traffic throughput at the intersection, there is room for regulation efficiency improvement by jointly managing a multiple-intersection system (MIS) in a neighborhood. Correlation of vehicle traffic in both time and space domains suggests joint collaboration among adjacent intersections. The basic scheduling solution is to separately apply isolated intersection mechanisms in a connected multi-intersection environment. Each intersection independently performs its regulation strategy without interacting with others. To promote cooperation in managing nearby intersections, we can consider both centralized and distributed approaches. In centralized management with only one agent in charge, traffic information of the entire neighborhood is required to make global management decisions for all the intersections. However, as the number of traffic states and scheduling actions increases exponentially with the number of intersections, it is infeasible or extremely complex to obtain an optimal scheduling policy in real time for a large-scale MIS.

In an extreme scenario of a multiple-vehicle-agent mechanism, each vehicle navigates over the road system according to its destination, to avoid collision and minimize the total personal travel time. With the individual agents focusing on their own objectives, the management of MIS can hardly strive for maximum efficiency. Another distributed approach is to model the intersections as intelligent agents, and they are able to realize cooperative scheduling, which can be seen in Fig. 2. Each intersection adopts a scheduling policy based on its perception and the information received from neighboring intersections, such as specific control actions or Q-values in the latest time interval. Weighting factors can be introduced for various components of the neighborhood information about vehicles and intersections, based on the vehicle density, distances, and traffic flow correlation among the intersections. This distributed approach accounts for impact of traffic flows in neighboring intersections along with other vehicles in this intersection to enhance traffic throughput efficiency.

Multi-Agent Learning-Based Non-Signalized Intersection Management: A Case Study

In this section, as shown in Fig. 3, we present a case study where an RL-based centralized isolated intersection mechanism and scheduling four connected non-signalized intersection systems are jointly considered to evaluate the effectiveness of non-signalized intersection management.

In isolated intersection management, the N-IMC is normally modeled as a global agent to take the role of a central controller. Instead of employing traffic lights for intersection scheduling of vehicle passing, the central controller determines a fine-grained crossing schedule that specifies the time for each vehicle to enter the intersection. To do so, the controller obtains the motion trajectory information of all vehicles at the intersection through constant V2X communications. By ensuring no simultaneous overlap at the intersection among trajectories of all the vehicles, vehicle collision is avoided. Without traffic accidents, the goal of intersection management is to maximize traffic throughput, and RL is leveraged for an optimal solution. The traffic state, scheduling action, and reward function in the RL framework are discussed as follows:

- Traffic state: Locations of vehicles at the intersection are used to obtain traffic status. For mathematical expression, lanes of the intersection are partitioned into sections of equal length to record vehicle positions, and there are 10 sections for each lane, as shown in Fig. 3.
- Scheduling action: For all vehicles to cross the intersection in a time interval, the scheduling action specifies the intersection entering sequence of the vehicles.
- Reward function: The reward function captures intersection traveling time, which is the crossing time difference between non-signalized scheduling and navigating with a preset maximal velocity. A smaller traveling time on average corresponds to higher scheduling efficiency.

For a large dimension of traffic states due to a complex traffic environment in the low-tier management at each intersection, two ANNs with the same four-layer structure are used to approximate the corresponding Q-value for each action (i.e., target network and evaluation network). During each scheduling time interval, the central controller collects current traffic state as the input of the ANNs. Subsequently, according to the Q-value generated by the evaluation network, the controller makes an appropriate decision based on the state. The optimizer of gradient descent is used for training loss function, which is calculated based on the target Q-value and evaluated Q-value. For the high-tier management of multiple intersections, we consider cooperative scheduling among four connected adjacent intersections. The isolated centralized management in the low tier is extended to all intersections to determine an optimal strategy. The decision process at one intersection also depends on the latest Q-value of scheduling actions at the adjacent intersections via timely information sharing. The impact of neighboring intersections is weighted based on the traffic density over joint lanes with the intersections. The more vehicles over the joint lanes,

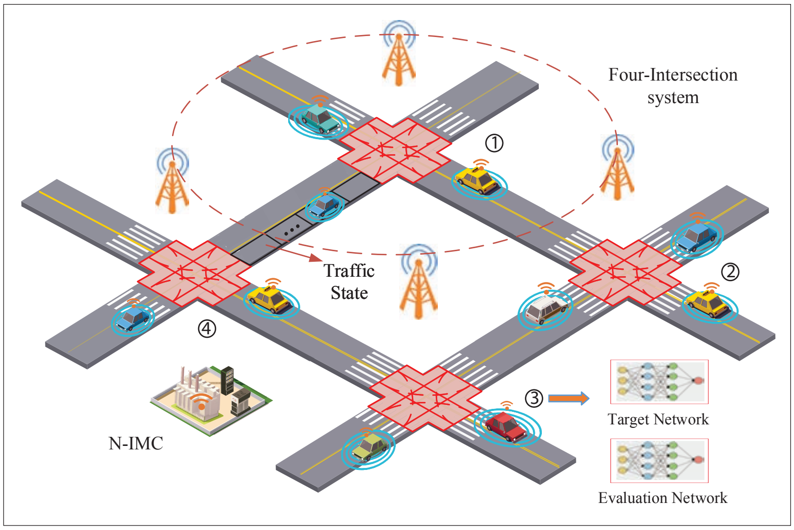

Figure 3. Four connected non-signalized intersections in the case study.

The cooperative approach has higher throughput than the independent training scheme, as expected. This simple case study demonstrates that non-signalized intersection management enabled by V2X communication and artificial intelligence is a promising approach to intelligent transportation for achieving road safety and enhancing transport management efficiency.

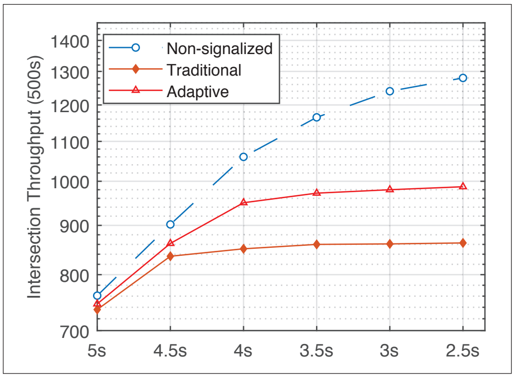

FIGURE 4. Intersection throughput performance under heavy traffic density.

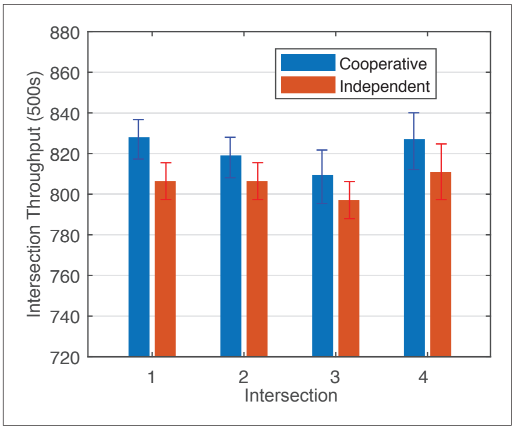

FIGURE 5. Throughput comparison for two different multi-intersection management scenarios.

the greater the weighting factor. Each intersection possesses an independent training network and stores the neighboring information in replay memory buffers. The ANN training process takes account of the overall weighted Q-values of the neighboring intersections in loss function for collaboration in managing the multiple intersections.

To evaluate the performance of the proposed non-signalized intersection management solution, we simulate both the isolated centralized intersection management scheme and distributed multi-intersection scheduling mechanism in a PYTHON environment. The TensorFlow component is exploited to build ANNs, and vehicle arrivals at each intersection are modelled as a Poisson process with various traffic densities. We broadly divide the volume of traffic flow into three levels, including heavy traffic, moderate traffic, and light traffic, which are specified by the average vehicle inter-arrival time of less than 5 s, 5–10 s, and more than 10 s, respectively. Vehicle throughput in every 500 s is recorded to evaluate the efficiency of non-signalized intersection management. The vehicle acceleration ranges from -3 m/s^2 to 4 m/s^2. Based on passing schedule, vehicles travel through the intersection with constant velocity randomly selected from 10 m/s to 15 m/s. Each scheduling time interval is 2 s, and vehicle safety separation time is set to 2 s for collision avoidance between adjacent vehicles in the same lanes.

Figure 4 shows the throughput comparison among the non-signalized scheduling scheme, traditional traffic light regulation, and adaptive signal control. Traditional traffic lights operate on a fixed 30-s time period for each direction of vehicles, while adaptive signal control uses a scheduling time period of 5 s and can change scheduling priority based on real-time traffic. For the traffic density that is less than one vehicle arriving every 5 s (light traffic and moderate traffic), traditional traffic lights and adaptive signal control can cope well with intersection regulation. However, they quickly reach the upper scheduling limitation as the vehicle density increases. In traffic congestion with high vehicle density, a non-signalized intersection has much better throughput performance, indicating its ability to alleviate traffic congestion.

In the multi-intersection scenario, cooperative scheduling management with both Q-value exchanges and independent training are simulated. Independent training refers to the distributed management where each intersection separately determines its optimal scheduling solution without any interaction with other intersections. Figure 5 shows the throughput performance in every 500 s of these two training schemes. The cooperative approach has higher throughput than the independent training scheme, as expected. This simple case study demonstrates that non-signalized intersection management enabled by V2X communication and AI is a promising approach to intelligent transportation for achieving road safety and enhancing transport management efficiency.

CONCLUSION

In this article, we have investigated V2X empowered data-intensive non-signalized intersection management based on advanced AI technologies. We have manifested primary research issues for non-signalized intersection management and discussed essential approaches, leveraging various AI techniques, with the aims of traffic efficiency improvement. A case study applying the multi-agent learning approach has been presented to demonstrate the applicability and potential advantage of non-signalized intersection management over the existing solutions.

ACKNOWLEDGMENTS

This work was supported in part by the National Natural Science Foundation of China under Grant 61871211, the Natural Science Foundation of the Jiangsu Province Youth Project under Grant BK20180329, the Innovation and Entrepreneurship of Jiangsu Province High-Level Talent Program, the Summit of the Six Top Talents Program of Jiangsu Province, and the Natural Sciences and Engineering Research Council of Canada.

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