

Signalized Intersection Control in Mixed Autonomous and Regular Vehicles Traffic Environment—A Critical Review Focusing on Future Control

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ABSTRACT The recent advancement in industrial technology has offered new opportunities to overcome different problems of stochastic driving behavior of humans through effective implementation of autonomous vehicles (AVs). Optimum utilization of driving behavior and advanced capabilities of the AVs has enabled researchers to propose autonomous cooperative-based methods for signalized intersection control under an AV traffic environment. In the future, AVs will share road networks with regular vehicles (RVs), representing a dynamic mixed traffic environment of two groups of vehicles with different characteristics. Without compromising the safety and level of service, traffic operation and control of such a complex environment is a challenging task. The current study includes a comprehensive review focused on the signalized intersection control methods under a mixed traffic environment. The different proposed methods in the literature are based on certain assumptions, requirements, and constraints mainly associated with traffic composition, connectivity, road infrastructures, intersection, and functional network design. Therefore, these methods should be evaluated with appropriate consideration of the underlying assumptions and limitations. This study concludes that the application of adaptive traffic signal control can effectively optimize traffic signal plans for variations of AV traffic environments. However, artificial intelligence approaches primarily focusing on reinforcement learning should be considered to better utilization of the improved AV characteristics.

INDEX TERMS Autonomous intersection control, autonomous vehicle (AV), hybrid methods, mixed traffic environment, regular vehicle (RV), signalized intersection control, traffic signal optimization.

I. INTRODUCTION

Different researches have indicated that signalized intersections are more prone to traffic problems due to complex traffic management. For example, around 22% of traffic delays occur at signalized intersections [1]. The contributing factors of such problems may include: human driving behavior, increased traffic demands [2], and inefficient traffic control methods [3]–[5]. Many studies have shown that human driving performance plays a critical role in different traffic problems. Many psychological, environmental, and vehicle design factors influence human driving, such as driver

perception and reaction time, driver age, and design speed. The interaction of these factors leads to significant variance in driving behavior and response to traffic control methods.

Artificial Intelligence (AI) applications and communication technologies have created new opportunities to improve the driving environment through the concept of autonomous driving. The conventional concept of human operating vehicles is revolutionized by introducing computers to take over some or all of the driving tasks. With the full automation level of autonomous vehicles (AVs), human behavior does not play any role in making the decisions related to driving actions or in response to traffic control systems. Compared to the RVs, the implementation of AVs in the traffic networks can potentially change our mobility quality leading to different

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positive impacts on the traffic system [6]. For example, it may increase road capacity, increase the efficiency of traffic control methods and improve traffic stability and safety [7]–[9]. These impacts result primarily from AI's efficient driving and response behavior. Utilizing these capabilities helps AVs to improve car following and lane changing behavior in the traffic flow [10]–[13] and also can lead to faster reaction times [10], [12]–[15]. Moreover, AVs are systemic and behave accurately by assigned algorithms and rules, unlike RVs that behave stochastically due to the nature of human driving behavior [14], [16].

The implementation of AVs may affect the design and operation of traffic control methods such as signalized intersection control methods [9]. Most of the significant positive impacts of AVs occur in a full AV traffic environment. As a result, different methods have been proposed to control the AVs at intersections under full AV environment [17], [18]. Namazi *et al.* [2] included detailed literature on signalized intersection control under full AV environment.

However, it is expected that the full AV will be introduced gradually. The 90% penetration rate of connected autonomous vehicles (CAV) would not occur before 2045 [19]. By the year 2040, 75% of total vehicles would be AVs [20]. Therefore, in the coming transition period, AVs will share the same road network with RVs under different penetration rates representing a dynamic mixed traffic environment. Compared to the full implementation of the AVs, partial implementation will cause different impacts on the traffic flow characteristics [6], [9], [21]–[23].

The effective operation and control of mixed traffic of AVs and RVs are considered as a complex challenge [15]. One of the critical challenges is designing and managing the traffic at signalized intersections under a mixed environment during the transition period [16]. A few researchers reviewed the proposed methods that considered the signalized intersection control under a mixed traffic environment [24], [25]. Chen and Englund [17] discussed different cooperative-based methods. However, most studies considered a fully connected environment with more focus on controlling the non-signalized intersections. Namazi *et al.* [2] discussed the performance of different methods in terms of efficiency, safety, ecology, and passenger comfort. They included seven related studies, but two of these studies [26], [27] did not consider the mixed environment conditions. Guo *et al.* [18], part of their review on the CAV implementation, discussed the signalized intersection control methods that were proposed to optimize traffic signal plans. However, most of the included studies in their review considered the complete connected vehicle (CV) environment rather than AV environment. The main contribution of this study is to conduct a critical review of proposed methods for the signalized intersection control under mixed AV traffic environment, mainly when AVs are sharing the same intersections with RVs without the application of dedicated AV lanes. In addition, based on the review findings, different limitations of the proposed methods are discussed.

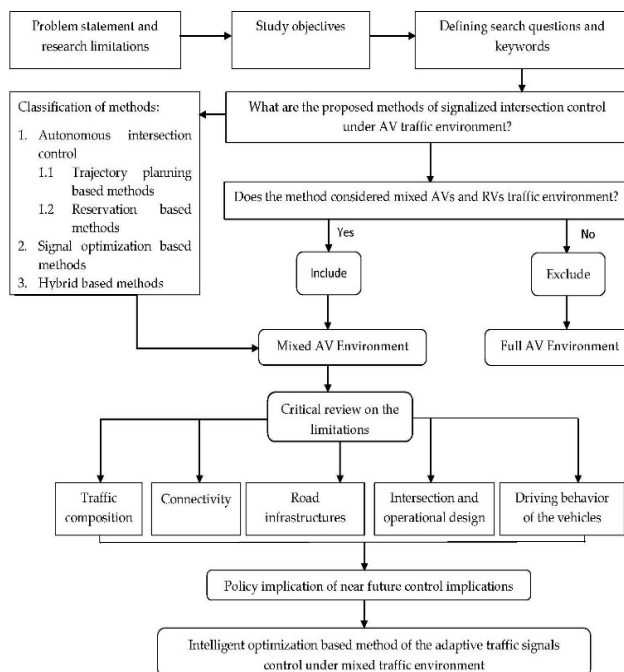


FIGURE 1. General flow chart of the study.

A systematic review approach was adopted for conducting this study (Figure 1). At the beginning of this work, the research questions, search keywords, and the inclusion and exclusion criteria of the collected studies were determined. In this study, four main research questions were identified. First, what are the proposed methods of signalized intersection control under an AV traffic environment? Second, whether these methods have considered the case of mixed traffic environment of AVs and RVs? Third, what are the limitations of the actual application of the proposed methods? Fourth, what are the alternatives that may overcome these limitations? The search keywords included the following: autonomous (automated) vehicles, regular (human-driven) vehicles, AV environment, mixed (heterogeneous) traffic, signalized intersection control, autonomous (cooperative-intelligence-smart) intersection control, and signal optimization. However, this review excluded any study which considered the application of dedicated lane(s) for AVs. The contents of the collected studies were reviewed to conduct thematic analysis and achieve the objectives of this study. The remaining sections of this study are organized as follows. Section 2 begins with the classification of signalized intersection control methods under AV environment and then includes a literature review of the proposed methods under mixed AV traffic environment. In section 3, the different obtained limitations of signalized intersection control under mixed AV traffic environments are discussed in detail. Section 4 is the policy implications pertinent to the alternatives of signalized intersection control under a mixed traffic environment. Finally, section 5 includes a summary of the study along with main conclusions and recommendations.

II. SIGNALIZED INTERSECTION CONTROL UNDER MIXED AV TRAFFIC ENVIRONMENT

Signalized intersection control is essential to enhance the traffic flow by optimizing intersections in different aspects [28]. It manages the order and right-of-way of vehicles to cross intersections effectively. The main objectives of these methods are to utilize and optimize the space within an intersection more efficiently to increase the flow, decrease delays and fuel consumption, and improve safety [17], [29]. In the case of a full RV environment, the literature has indicated that different methods have been used for signalized intersection control. These methods are divided into three main systems groups: fixed, actuated, and adaptive systems [30].

Under the AV traffic environment, different methods have been proposed to control the AVs for crossing the signalized intersections. However, these methods differ in their control architectures and logic, the distribution of computations, or they may vary in their required infrastructures for the real applications and targeted objectives. The control methods of the signalized intersections under AV environment may be classified into three main classes: autonomous intersection control, signal optimization-based methods, and hybrid-based methods. The following parts will include a brief description of each class.

A. AUTONOMOUS INTERSECTION CONTROL

This class of methods includes those intelligent or cooperative-based methods that eliminate the traffic signal. It uses different algorithms to optimize the vehicle's crossing of the intersection. Some papers referred to these methods as autonomous intersection management (AIM) [2], [31]. From its control architectures aspects, these methods can be divided into two categories of centralized and distributed-based methods [5].

The centralized-based methods include a central coordination unit that communicates with vehicles, receives real-time information about vehicles, and gives instructions to guide the vehicles to cross an intersection safely [5]. This central agent makes the control decisions globally for all vehicles [25]. The second important aspect of the centralized methods is the vehicle agent within each vehicle, which controls the crossing of AVs [31]. So, it only requires communications between the centralized units and the vehicles without the requirement of vehicle-to-vehicle (V-V) communications. However, the different complex computations rely on the single intersection control agent. Therefore, the high computational requirement is considered a critical concern and needs great efforts to ensure system reliability and robustness [17], [32]. Different meta-heuristics and mathematical methods, such as linear and dynamic programming, have been widely applied to many autonomous intersection-based methods [5]. In contrast, the distributed-based methods are based on the communications between the vehicles to negotiate and agree on vehicle priorities to safely and effectively cross the intersection [5]. Most of these methods are applied in agents based manner where

different agents (such as an AV) interact and coordinate their behaviors to achieve specific objectives. In other words, the vehicles collect the required information and make the control decisions by themselves. Compared to the centralized-based method, the advantage of distributed-based methods is that it requires less infrastructure support since it needs only V-V communications. In addition, it has fewer computational problems since the crossing decisions are made locally, and the computations are distributed among vehicles [17]. However, it relies entirely on the performance of the communication channel and the negotiation protocol between the vehicles [5]. [17] and [29] classified the autonomous intersection-based methods for fully AV environments into two main classes, including: reservation-based and trajectory planning-based methods. These classes are generally described in the following parts.

1) TRAJECTORY PLANNING BASED METHODS

The intersection crossing with the application of these methods is considered as a passing sequence optimization problem aiming at maximizing certain utilities with constraints to ensure intersection safety and vehicle maneuvering limits [17]. It is based on different vehicle trajectories, such as the location and speed of the vehicles. The main objective is to find the optimal sequence, such as optimal departure at the intersection, for each vehicle considering the connectivity and programmability of AVs. With these methods, space tiles are planned and allocated consecutively as travel routes. AVs are controlled along the planned trajectories to safely cross the intersection, with unimpeded movement, strategically guiding AVs to adjust their approaching trajectories. These methods can be improved by exploiting the optimization of vehicle control parameters. Most of the trajectory planning-based methods are based on the application of centralized-based methods. The role of the central unit is to optimize the feasible motion plans for AVs based on different information, then, it assigns specific crossing instructions to AVs.

2) RESERVATION BASED METHODS

It considers the intersection crossing as a discrete resource allocation or scheduling problem. Some of the studies referred to this class as suitable resource reservation-based methods [17] or signal scheduling-based methods [29]. It aims mainly to reserve exclusive time slots and intersection space for each vehicle to cross the intersection safely. It focuses on finding the optimal sequence of serving lanes by sorting incoming requests from the vehicles and allocating the right of way of the intersection based on a set of predefined rules [29].

B. SIGNAL OPTIMIZATION-BASED METHODS

The signal optimization-based methods require traffic signals. These methods are applied to generate optimal traffic signal timing plans using different methods such as classical optimization methods, heuristics optimization algorithms, and machine learning-based optimization methods.

TABLE 1. Proposed signalized intersection control methods for mixed traffic environment.

Authors	Class of Method	Traffic Environment	Method Name
Dresner and Stone [21]	Time slot reservation	AV and RV	First come, first served (FCFS) light Legacy early method
Bento et al. [34]	Spatial-temporal reservation	AV and RV	intelligent traffic management (LEMITM)
Qian et al. [35]	Reservation	AV and RV	Priority-preserving order based method
Yang et al. [36]	Trajectory planning	AV,CV and RV	Optimal departure sequence using a branch and bound technique
Sharon and Stone [31]	Reservation	CAV and RV	Hybrid autonomous intersection management (H-AIM)
Lin et al. [37]	Trajectory planning	CAV and RV	Buffer-assignment based coordinated method
Li and Zhou [38]	Hybrid	CAV and RV	Intersection automation policy (IAP) optimization method
Zhao et al. [39]	Trajectory planning	AV and RV	Real-time distributed cooperative eco-driving strategy-based method
Liang et al. [33]	Hybrid	AV,CV and RV	Rolling-horizon optimization framework
Liu et al. [16]	Trajectory planning	CAV and RV	Permission assignment policy with a coordination protocol
Barthauer and Friedrich [40]	Autonomous intersection control	AV and RV	Pre-sorting and pre-signaling based method
Reddy et al. [24]	Reservation	AV and RV	Synchronous intersection management protocol (SIMP)
Pourmehrab et al. [29]	Hybrid	AV and RV	Intelligent intersection control system (IICS)
Bashiri [5]	Signal optimization	CAV and RV	Real-time Data-driven adaptive signal control
Baz et al. [15]	Trajectory planning	AV and RV	Game-theory-based priority control
Qi et al. [14]	Signal optimization	AV and RV	Particle swarm optimization (PSO) method
Yao and Li [25]	Trajectory planning	CAV and RV	A decentralized based method
Chen et al. [41]	Trajectory planning	CAV and RV	Platoon-based optimal control framework
Tajalli and Hajbabaie [23]	Hybrid	CAV and RV	Mixed-integer non-linear program

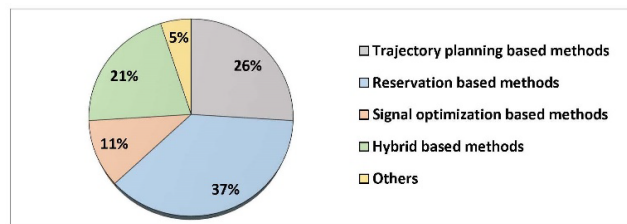


FIGURE 2. Distribution of methods of signalized intersection control under mixed traffic environment.

CAVs data, can optimize the signal plan based on current traffic states and do not apply prediction. The platoon-based methods, using CAVs coordination, can optimize the signal plan by grouping incoming vehicles into platoons thought predicting their traffic flow status. The planning-based methods, also using CAVs coordination, treat each vehicle individually by considering its detailed trajectories and optimizing the signal plan in a forward time horizon by adopting more accurate and complex models.

C. HYBRID BASED METHODS

These methods combine autonomous intersection control-based methods (Class 1) and signal optimization-based methods (Class 2). These methods jointly optimize AV trajectories and signal timing at the same time. This combination can significantly improve signalized intersection performance. For example, optimizing the arrival time of the vehicles to the intersection may result in better utilization of green durations [23]. Another example, when the signal plans are identified, the desired speed of the AVs can be optimized to ensure that they can cross the intersection without stopping [33].

The literature included in this study indicated that most of the proposed methods of signalized intersection control focused on the full AV traffic environment. However, a limited number of studies have focused on solving the problems of signalized intersection control under a mixed traffic environment of AVs and RVs sharing the same network. Namazi *et al.* [2], in their review, found that out of 103 reviewed studies, 94% of these studies considered full AV environment, while only around 6% considered the mixed traffic environment. This finding regarding the research limitations is also confirmed in this current review. In addition to the reviewed studies by [2], we found 14 additional related studies until September 2021. Figure 2 shows the distribution of different methods under a mixed traffic environment. About 68% of the proposed methods are autonomous intersection control-based methods, 11% are signal optimization-based methods, and 21% are hybrid-based methods. Table 1 summarizes the collected studies, including study variables: class of the proposed method, traffic environment, and method name.

III. LIMITATIONS OF SIGNALIZED INTERSECTION CONTROL UNDER MIXED AV TRAFFIC ENVIRONMENT

In general, the conducted review indicated that the autonomous intersection control-based methods are expected

Guo *et al.* [18] classified the CAV-based signalized intersection control methods into three main classes, including adaptive traffic signals control, platoon-based control and planning-based control. The adaptive-based methods, using

to improve the efficiency of the signalized intersections under the AV environment [2], [25]. Unlike the trajectory planning-based methods, the main drawback of Reservation based methods in minimizing delay at a signalized intersection is that they do not consider the added benefit of optimizing AV trajectories [29]. The main problem of applying such autonomous-based methods in a mixed traffic environment is that each control policy requires a traffic signal model so that the RVs understand the crossing instructions. Compared to the autonomous-based methods, the hybrid-based methods may lead to significantly different performance [2]. However, some studies indicated that the effective combination of both methods is complex and requires significant efforts to develop methods that can balance computational complexity and control performance. For example, it is not likely that a centralized unit can handle all the required computations to cooperate between the signal controller and approaching vehicles [23].

The findings from this review indicated that the applications of both autonomous or hybrid-based methods are built on some different assumptions, requirements, and constraints. Those are related to the network environment, including the traffic composition, connectivity, road infrastructures, intersection and functional network design, in addition to the driving behavior. Those will lead to different limitations of their possible practicability and reliability of controlling signalized intersections under different conditions of mixed traffic environment of AVs and RVs. In the following parts, we will discuss some of these limitations supported with examples.

A. TRAFFIC COMPOSITION

The traffic composition of a mixed environment may include different penetrations rates of AVs and RVs. Some of the proposed methods have assumed a specific traffic composition for the application of their methods. For example, some methods were proposed to be applied only at under-saturated traffic flow conditions [29]. The trajectories-based methods may not be effective with scenarios of high traffic volume since that the trajectories of all involved vehicles need to be optimized for each signal cycle. Other methods have shown improvement only at specific conditions of the traffic composition. For example, different proposed reservation based methods showed improved performance only at lower penetration rates of RVs (less than 10%) [21], [34]. Other methods showed improvement when the penetration rate of CAVs is more than 10% [31]. Some trajectory planning based methods showed improvement only when the penetration rate of AVs is more than 50% [36]. In contrast, other methods showed improvement only when the penetration rate of CAV was less than 21% [37]. The above findings indicated that most of the proposed methods would not be applicable at any traffic composition or traffic flow conditions that may occur in the transition period of the expected mixed traffic environment.

B. CONNECTIVITY

The autonomous or hybrid-based methods assumed different required levels of connectivity of the traffic environment. The connectivity enables other communications to exchange the required information, including crossing requests or crossing instructions, between the vehicles or with intersection control units. For example, the centralized-based methods can be applied only under a fully connected environment where the involved vehicles and the intersection units must be connected. On the other hand, in terms of vehicles capabilities, all of these methods assumed that the involved vehicles have vehicle to vehicle (V-V), vehicle-to-infrastructure (V-I), and infrastructure-to-vehicle (I-V) communications. The proposed method by [41] assumed that the RVs are connected to the central unit and can exchange the required information. In their proposed method, [24] assumed that the RVs have the same sensing capabilities as AVs. In the case of a mixed traffic environment, unlike the CAVs, most of the existing RVs do not include these required connectivity capabilities. Therefore, RVs will not be able to exchange or receive the required information on how to cross the intersections with cooperative methods safely. The availability of connectivity is not the only concern. Indeed, the performance of the cooperative-based methods will be built on the quality and performance of the different involved communications. That brought up concerns about its accurate performance and safety guarantee for real-world conditions under a mixed traffic environment [5], [17]. For example, some studies have shown different constraints related to communication ranges.

C. ROAD INFRASTRUCTURES

Some of the proposed methods of signalized intersection control under a mixed traffic environment have required different modifications of the existing road infrastructures. To provide the required V-V and V-I communications, the central-based method's main problem is that it requires establishing and installing centralized units at each intersection [37]. Also, to collect the required information, different supported roadside units at each intersection must be installed. For example, most proposed autonomous or hybrid-based methods require various sensors to detect traffic information [23]. Other methods have used different prediction models, such as kinematic wave theory and Newell's car-following model, to predict the information of the RVs, such as their arrival sequence and trajectories. These road infrastructures must be provided at each intersection of the existing network, which is considered highly costly [5], [17]. As a result, the most proposed methods may face difficulties in their real application because of the additional constraints regarding the required infrastructure. To overcome that, some of the proposed methods assumed that the information of the RVs can be provided by the AVs or the CVs [33], [36]. However, the RV information level and accuracy will depend on its penetration rate in the mixed

traffic environment. With low penetration rates, the performance of these methods may not be effective.

D. INTERSECTION AND FUNCTIONAL NETWORK DESIGN

The findings indicated that the autonomous-based methods' performance could be sensitive to different turning options at the intersection, considering different involved vehicle types. To solve the related issues, some of the proposed methods have assumed specific operational configurations. A method is applied when left-turn movements operate exclusively [23]. Another method assumed only one-way traffic without turning movements [15]. Some of these special configurations, mainly in the case of a mixed environment, may lead to increased delays for the AVs [35]. On the other hand, other proposed methods have assumed specific intersection designs. For example, some methods were applied only for intersections with single-lane roads [24], [25], [38]. Some studies have indicated that the hybrid control-based methods may improve the performance of the signalized intersection; however, it may lead to negative impacts on the intersection capacity. Barthauer and Friedrich [40] concluded that the application of the pre-sorting and pre-signaling decrease the capacity of the intersection by 50% compared to a conventional method. Most of these modifications in terms of operation and intersection designs were considered to include collision-free features to ensure the safety of the vehicles crossing. However, applying these modifications to each existing intersection is complex due to different related aspects. Alternative intersection designs, such as the tandem intersection concept, require more space than a traditional four-leg intersection [40]. In addition to that, these modifications may improve safety, however, they may cause negative impacts on the intersection operational performance, such as increased delays [40].

E. DRIVING BEHAVIOR

Another common assumption of the autonomous and hybrid-based methods is related to the driving behavior of the involved vehicles. There are sets of constraints in terms of vehicle operational characteristics related to the design or application of the method or related to the safety requirements. Examples include safe headway, speed limits, acceleration, deceleration limits, and lane-changing capabilities [17]. Some autonomous-based methods assumed that all of the involved vehicles are highly automated that have similar operational settings [17]. Some reservation based methods assumed that RVs could keep a safe distance from their leading vehicles [42]. However, the RVs have stochastic driving behavior that may vary based on different factors. The main difference that should be realized is that the RVs have complete freedom to change a control input at any time, while the AVs can only adjust control input at periodic discrete times [16]. With the application of such autonomous-based methods, all of the involved vehicles are assumed to follow exact assigned instructions of crossing the intersection, given by the control system, without any unplanned maneu-

vers such as overtaking or lane-changing [17]. For example, some proposed methods assumed that the RVs strictly follow the path and will not perform undesired or illegal maneuvers [35], [41]. However, in case of a mixed traffic environment, the critical concern is that whether the RVs with human control are able to respond to the crossing instructions completely and cope with the AV driving behavior [35], [43]. Unlike the AVs, we have to realize that the driving actions of the RVs cannot be identified by the control system [44]. So, it may be concluded that the reliability of the RV driving behavior should be highly considered while designing or evaluating the performance of different proposed methods.

IV. POLICY IMPLICATIONS

The existing traffic environment of road networks mainly includes RVs and different types of semi-autonomous vehicles. However, in the coming near future, it is expected that full AV will gradually be introduced into the traffic networks of many cities. Therefore, full AV will share networks, including intersections, with the RVs. The proposed autonomous and hybrid-based methods of signalized intersection control, in the literature, can be applied in the case of a mixed traffic environment. However, the effective implementation of such methods will be based on specific requirements and assumptions of the AV traffic environment. As discussed in the previous section, these requirements and assumptions will lead to different types of limitations which may affect the generalization of applying such methods to control any existing signalized intersection in a mixed traffic environment of urban networks in the actual practice. Examples of the limitations may include required communication protocols, computational power, and other required modifications in addition to the different assumptions related to the traffic composition and driving behavior of the RVs. Moreover, one of the main drawbacks of most proposed autonomous and hybrid-based methods is that it have focused on the vehicle's movements and ignored the other users such as pedestrians and bicycles at the intersections [45]. However, in the case of an urban signalized intersection, the movement of such users should be considered. On the other hand, another important aspect that should also be considered and evaluated carefully is the duration of the execution time of such cooperative-based control methods that may induce extra delay due to the required computations and communications. As an example of extra expected delay, one of the reservation-based methods limitations is that the frequent switches of right-of-way may disrupt platoons resulting in increased traffic delays [29].

In a mixed traffic environment, the control methods should be applicable at different conditions of traffic compositions. The traffic signal may be applied effectively regardless of the penetrations rates of AVs and RVs without any constraint or assumption of traffic compositions or saturation traffic flow conditions. In terms of connectivity, unlike the autonomous or hybrid-based methods, traffic signals do not require any level of V-V or V-I communications within the traffic environment. Based on the collected data of the different detectors, the

signal agents need to send the required phase information to the AVs. So, the traffic signal-based methods can be applied even when the involved vehicles, including RVs, are not connected to each other or to the infrastructure. Moreover, with an application of the traffic signals, the requirements of the extra modifications of the existing road infrastructures can be eliminated. It may only require simple traffic detectors to detect specific information, such as traffic volume and vehicle type, as the case of the existing adaptive traffic signals in the RV traffic environment. The application of the traffic signal-based methods is considered an effective solution to the existing road network since it can be applied without the need for extra costly modifications of the operational designs and intersection layouts. It can be applied under different features of the road, intersection and operational designs such as highway class, number of lanes and signal phasing. The driving and traffic signal response behavior of the involved vehicles, mainly the RVs, in mixed traffic environment are different and cannot be assumed to be fully controlled or predicted. To overcome the human driving behavioral issues of the control response, we need to apply control methods that are quite familiar to them, such as traffic signals which can be also easily formulated and controlled to be totally understood and accurately followed by the AVs. In terms of road safety, the traffic signals can provide safety measures inherent, as in the case of the full RV traffic, where there will not be any conflicting trajectories between the involved vehicles during crossing intersections. The traffic signal-based methods are suitable and reliable for both involved vehicle types considering their expected driving behavior and capabilities.

The optimization of existing traffic networks by the effective application of the current artificial intelligent-based methods is becoming an increasingly important aspect for solving different traffic problems. The application of the signal optimization-based methods can easily handle single or multiple objectives and complex traffic conditions [2]. Under the RV traffic environment, the literature indicated that different optimization methods had been applied to optimize the performance of signalized intersection systems. These methods range basically from mathematically based methods to artificial intelligence-based methods [4], [46]–[51]. For example, several heuristics algorithms, such as genetic algorithms (GA) and differential evolution (DE), have been applied to optimize signal plans in order to minimize the delays, number of stops, and queue length [49]. To improve the learning ability of the adaptive control systems, advanced machine learning methods were applied and showed superior performance compared to other shallow learning methods such as the artificial intelligent networks (ANNs) [52].

Most of the related studies of traffic signal optimization, under the RV environment, have considered and assumed stochastic behavior of human driving and have focused on the solution quality for the traffic volumes. With the implementation of AVs, to improve the performance of the traffic signals, we have to consider the expected positive impacts of the AVs without compromising the reliability of control

systems for the RVs in a mixed traffic environment. The deterministic driving behavior [14] and improved operational and connectivity characteristics of the AVs, in addition to its expected impacts on the traffic flow characteristics, should be significantly utilized for better improvement of the traffic signal optimization [15]. For example, in terms of its advanced capabilities, the shorter perception and reaction time of the AVs may help to minimize the yellow interval or to optimize the duration of green times. Also, the shorter start-up times may decrease the total lost times. In terms of its operational characteristics, the shorter headways may help to minimize the maximum green durations as a result to the improved saturation flow rates. All of that may effectively assist the signal to optimize its main control parameters, such as signal timing parameters, which will result in decreased delays and, therefore, better utilization of the intersection capacities [9].

Basic optimization methods, such as mathematical or dynamic programming, are based on analytical relationships. These cannot be applied for the mixed AV traffic environment due to absence of real existing data or the high computational complexity of the optimization. For example, it is not possible to establish the exact, reliable mathematical models that can represent the traffic conditions or select the optimum control policy in the case of a mixed traffic environment [3]. We need defined functions or equations to relate the inputs and the outputs of this unique environment. This step requires the reformulation of some essential traffic flow functions as a result of the adjusted AVs characteristics and its impacts on the traffic flow characteristics. However, with the application of the machine learning (ML) optimization-based methods, we need only big data for the learning process of the different hidden relationships of the mixed traffic environment. These methods may be used to overcome the different issues of the basic optimization methods and also may improve the optimization performance due to its intelligent learning.

The findings of the current review have indicated that few efforts have considered the traffic signal optimization for the AV traffic environment. Our review found only two studies that aimed to optimize the traffic signal under a mixed AV environment [5], [14]. Moreover, the literature indicated that the application of the ML-based methods is still limited and needs more efforts of investigations under a mixed AV traffic environment. Namazi *et al.* [2] found that out of 103 published studies in the area of signalized intersection control of AV environment, only about 4% of the studies have applied machine learning-based methods.

Nowadays, due to the recent explosion in the development and availability of different information and communications technologies, in addition to the advancement in computing capabilities, there are significant improvements in ML approaches that should be considered in solving the mentioned challenges of signalized intersection control under mixed AV traffic environment. Examples of advanced ML-based methods may include deep learning (DL) and reinforcement learning (RL). Using different concepts, these methods can learn and extract the inherent

complex relationships of the system's behavior of the mixed traffic environment without any predefined models or underlying processes. The deep architecture can improve the learning process and produce better results compared to the most of the common shallow networks that usually have only one hidden layer. For example, some studies applied reinforcement learning to improve the performance of adaptive traffic signals under RV traffic environment [3], [53]–[60]. Most of these studies indicated that the reinforcement learning-based method is much superior compared to the common traffic signal control methods.

V. CONCLUSION AND RECOMMENDATIONS

The industrial revolution creates new opportunities to improve traffic control systems through autonomous driving. The intelligent incorporation of the AV implementation can increase the efficiency of signalized intersection control. Most of the expected positive impacts of the AV implementation that may be utilized to propose autonomous-based methods may assume to happen in case of full traffic of the AVs. This paper included a comprehensive literature review about the different proposed signalized intersection control methods under mixed AV traffic environments.

With the existence of AVs, many methods with different control architectures and logic were proposed to control AVs at signalized intersections. According to previous studies, the aforementioned methods can be categorized into three categories, namely: autonomous intersection control, signal optimization-based methods, and hybrid-based methods. Although these methods are expected to improve traffic operation and efficiency at the signalized intersections with AV environments, the effective application of such methods is complex due to the significant efforts, which are needed to balance computational complexity and control performance.

Different limitations of the proposed methods in the literature were discussed to provide a policy implications discussion. The review findings conclude that the real application of most proposed methods will be based on different assumptions, requirements, and constraints related to the network environment, including the traffic composition, connectivity, road infrastructures, intersection, and functional design, and the driving behavior of the vehicles. Most of the proposed methods can be applied effectively only for a fully connected traffic environment, mainly where the required connectivity is achievable along with full behavioral control of the involved vehicles. That may occur when we reach a 100% penetration rate of the CAVs in our traffic network, which is not feasible in the near future. Therefore, the proposed methods should be evaluated considering the underlying assumptions and limitations for appropriate generalization and implementation of controlling existing signalized intersections in a mixed traffic environment of urban networks. The control methods should be applicable for both AVs and RVs, considering their different penetration rates and capabilities, under different scenarios in the future. Any proposed method should be designed

and operated with minor modifications or requirements of the existing infrastructure.

Based on the significant improvements in ML approaches, this study proposed an alternative reliable solution that can help to control the signalized intersection control under mixed AV traffic environment. It is proposed to develop a novel machine learning-based optimization method for the design of intelligent adaptive traffic signal controller under mixed traffic environment of AVs and RVs. The proposed system can respond effectively to mixed traffic's dynamic and complex environment using its intelligent continuing learning and adaptation. It can optimize signal plans by smarter utilizing the AV characteristics and their potential impacts. Such systems are recommended to control signalized intersections in the transition period to the full AV environment. The expected resulted improvement of the proposed alternative will increase gradually with an increase in the AV penetration rate till our traffic network reaches full AV environment where the autonomous or hybrid-based methods may be easily and effectually applied. The development of such intelligent optimization-based methods of adaptive traffic signals control is still limited and needs more investigation under mixed traffic environments of AVs and RVs. Finally, the different obtained outcomes of this review are valuable for future control of the signalized intersection under an AV traffic environment.

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REFERENCES

- [1] Y. Bichiou and H. A. Rakha, "Real-time optimal intersection control system for automated/cooperative vehicles," *Int. J. Transp. Sci. Technol.*, vol. 8, no. 1, pp. 1–12, Mar. 2019, doi: [10.1016/j.ijst.2018.04.003](https://doi.org/10.1016/j.ijst.2018.04.003).
- [2] E. Namazi, J. Li, and C. Lu, "Intelligent intersection management systems considering autonomous vehicles: A systematic literature review," *IEEE Access*, vol. 7, pp. 91946–91965, 2019, doi: [10.1109/ACCESS.2019.2927412](https://doi.org/10.1109/ACCESS.2019.2927412).
- [3] Y. Wang, X. Yang, H. Liang, and Y. Liu, "A review of the self-adaptive traffic signal control system based on future traffic environment," *J. Adv. Transp.*, vol. 2018, pp. 1–12, Jun. 2018, doi: [10.1155/2018/1096123](https://doi.org/10.1155/2018/1096123).
- [4] M. Al-Turki, A. Jamal, H. M. Al-Ahmadi, M. A. Al-Sughaiyer, and M. Zahid, "On the potential impacts of smart traffic control for delay, fuel energy consumption, and emissions: An NSGA-II-based optimization case study from Dhahran, Saudi Arabia," *Sustainability*, vol. 12, pp. 1–22, Jan. 2020.
- [5] M. Bashiri, "Data-driven intersection management solutions for mixed traffic of human-driven and connected and automated vehicles," 2020, *arXiv:2012.05402*. [Online]. Available: <https://arxiv.org/abs/2012.05402>
- [6] M. Al-Turki, N. T. Ratrouf, S. M. Rahman, and I. Reza, "Impacts of autonomous vehicles on traffic flow characteristics under mixed traffic environment: Future perspectives," *Sustainability*, vol. 13, no. 19, pp. 1–22, 2021, doi: [10.3390/su131911052](https://doi.org/10.3390/su131911052).
- [7] F. Bohm and K. Häger. (2015). *Introduction of Autonomous Vehicles in the Swedish Traffic System Effects and Changes Due to the New Self-Driving Car Technology*. [Online]. Available: <http://uu.diva-portal.org/smash/get/diva2:816899/FULLTEXT01.pdf>
- [8] N. Jiang, "Optimal signal design for mixed equilibrium networks with autonomous and regular vehicles," *J. Adv. Transp.*, vol. 2017, pp. 1–13, Jan. 2017, doi: [10.1155/2017/5649823](https://doi.org/10.1155/2017/5649823).

- [9] E. Ş. Berktaş and S. Tanyel, "Effect of autonomous vehicles on performance of signalized intersections," *J. Transp. Eng., A, Syst.*, vol. 146, no. 2, Feb. 2020, Art. no. 04019061, doi: [10.1061/jtepbs.0000297](https://doi.org/10.1061/jtepbs.0000297).
- [10] R. Hoogendoorn, B. van Arerm, and S. Hoogendoorn, "Automated driving, traffic flow efficiency, and human factors," *Transp. Res. Rec., J. Transp. Res. Board*, vol. 2422, no. 1, pp. 113–120, Jan. 2014, doi: [10.3141/2422-13](https://doi.org/10.3141/2422-13).
- [11] Y. Liu, J. Guo, J. Taplin, and Y. Wang, "Characteristic analysis of mixed traffic flow of regular and autonomous vehicles using cellular automata," *J. Adv. Transp.*, vol. 2017, pp. 1–10, Oct. 2017, doi: [10.1155/2017/8142074](https://doi.org/10.1155/2017/8142074).
- [12] S. C. Calvert, W. J. Schakel, and J. W. C. van Lint, "Will automated vehicles negatively impact traffic flow?" *J. Adv. Transp.*, vol. 2017, pp. 1–17, Sep. 2017, doi: [10.1155/2017/3082781](https://doi.org/10.1155/2017/3082781).
- [13] Q. Lu, T. Tettamanti, D. Hörcher, and I. Varga, "The impact of autonomous vehicles on urban traffic network capacity: An experimental analysis by microscopic traffic simulation," *Transp. Lett.*, vol. 12, no. 8, pp. 540–549, Sep. 2020, doi: [10.1080/19427867.2019.1662561](https://doi.org/10.1080/19427867.2019.1662561).
- [14] H. Qi, R. Dai, Q. Tang, and X. Hu, "Coordinated intersection signal design for mixed traffic flow of human-driven and connected and autonomous vehicles," *IEEE Access*, vol. 8, pp. 26067–26084, 2020, doi: [10.1109/ACCESS.2020.2970115](https://doi.org/10.1109/ACCESS.2020.2970115).
- [15] A. Baz, P. Yi, and A. Qurashi, "Intersection control and delay optimization for autonomous vehicles flows only as well as mixed flows with ordinary vehicles," *Vehicles*, vol. 2, no. 3, pp. 523–541, Aug. 2020, doi: [10.3390/vehicles2030029](https://doi.org/10.3390/vehicles2030029).
- [16] X. Liu, P.-C. Hsieh, and P. R. Kumar, "Safe intersection management for mixed transportation systems with human-driven and autonomous vehicles," in *Proc. 56th Annu. Allerton Conf. Commun., Control, Comput. (Allerton)*, Oct. 2018, pp. 834–841, doi: [10.1109/ALLERTON.2018.8635849](https://doi.org/10.1109/ALLERTON.2018.8635849).
- [17] L. Chen and C. Englund, "Cooperative intersection management: A survey," *IEEE Trans. Intell. Transp. Syst.*, vol. 17, no. 2, pp. 570–586, Sep. 2016.
- [18] Q. Guo, L. Li, and X. J. Ban, "Urban traffic signal control with connected and automated vehicles: A survey," *Transp. Res. C, Emerg. Technol.*, vol. 101, pp. 313–334, Apr. 2019, doi: [10.1016/j.trc.2019.01.026](https://doi.org/10.1016/j.trc.2019.01.026).
- [19] P. Bansal and K. M. Kockelman, "Forecasting Americans' long-term adoption of connected and autonomous vehicle technologies," *Transp. Res. A, Policy Pract.*, vol. 95, pp. 49–63, Jan. 2017, doi: [10.1016/j.tra.2016.10.013](https://doi.org/10.1016/j.tra.2016.10.013).
- [20] T. Litman, "Autonomous vehicle implementation predictions: Implications for transport planning," 2020.
- [21] K. Dresner and P. Stone, "Multiagent traffic management: A reservation-based intersection control mechanism," in *Proc. Int. Joint Conf. Auton. Agents Multiagent Syst.* Washington, DC, USA: IEEE Computer Society, vol. 3, 2004, pp. 530–537.
- [22] N. K. Bailey, "Simulation and queueing network model formulation of mixed automated and non-automated traffic in urban settings," Ph.D. dissertation, Massachusetts Inst. Technol., Cambridge, MA, USA, 2016.
- [23] M. Tajalli and A. Hajbabaie, "Traffic signal timing and trajectory optimization in a mixed autonomy traffic stream," *IEEE Trans. Intell. Transp. Syst.*, early access, Feb. 18, 2021, doi: [10.1109/TITS.2021.3058193](https://doi.org/10.1109/TITS.2021.3058193).
- [24] R. Reddy, L. Almeida, and E. Tovar, "Work-in-progress: Synchronous intersection management protocol for mixed traffic flows," in *Proc. Real-Time Syst. Symp.*, Dec. 2019, pp. 576–579, 2019, doi: [10.1109/RTSS46320.2019.00068](https://doi.org/10.1109/RTSS46320.2019.00068).
- [25] H. Yao and X. Li, "Decentralized control of connected automated vehicle trajectories in mixed traffic at an isolated signalized intersection," *Transp. Res. C, Emerg. Technol.*, vol. 121, Dec. 2020, Art. no. 102846, doi: [10.1016/j.trc.2020.102846](https://doi.org/10.1016/j.trc.2020.102846).
- [26] S. A. Fayazi, A. Vahidi, and A. Luckow, "Optimal scheduling of autonomous vehicle arrivals at intelligent intersections via MILP," in *Proc. Amer. Control Conf. (ACC)*, May 2017, pp. 4920–4925, doi: [10.23919/ACC.2017.7963717](https://doi.org/10.23919/ACC.2017.7963717).
- [27] M. O. Sayin, C.-W. Lin, S. Shiraishi, J. Shen, and T. Basar, "Information-driven autonomous intersection control via incentive compatible mechanisms," *IEEE Trans. Intell. Transp. Syst.*, vol. 20, no. 3, pp. 912–924, Mar. 2019, doi: [10.1109/TITS.2018.2838049](https://doi.org/10.1109/TITS.2018.2838049).
- [28] S. Wang, X. Xie, K. Huang, J. Zeng, and Z. Cai, "Deep reinforcement learning-based traffic signal control using high-resolution event-based data," *Entropy*, vol. 21, no. 8, pp. 1–16, 2019, doi: [10.3390/e21080744](https://doi.org/10.3390/e21080744).
- [29] M. Pourmehrhab, L. Elefteriadou, S. Ranka, and M. Martin-Gasulla, "Optimizing signalized intersections performance under conventional and automated vehicles traffic," *IEEE Trans. Intell. Transp. Syst.*, vol. 21, no. 7, pp. 2864–2873, Jul. 2020, doi: [10.1109/TITS.2019.2921025](https://doi.org/10.1109/TITS.2019.2921025).
- [30] X. Liang, S. I. Guler, and V. V. Gayah, "A heuristic method to optimize generic signal phasing and timing plans at signalized intersections using connected vehicle technology," *Transp. Res. C, Emerg. Technol.*, vol. 111, pp. 156–170, Feb. 2020, doi: [10.1016/j.trc.2019.11.008](https://doi.org/10.1016/j.trc.2019.11.008).
- [31] G. Sharon and P. Stone, "A protocol for mixed autonomous and human-operated vehicles at intersections," in *Proc. Int. Conf. Auton. Agents Multiagent Syst.* Cham, Switzerland: Springer, 2017, pp. 151–167.
- [32] H. Ahn, A. Colombo, and D. Del Vecchio, "Supervisory control for intersection collision avoidance in the presence of uncontrolled vehicles," in *Proc. Amer. Control Conf.*, Jun. 2014, pp. 867–873, doi: [10.1109/ACC.2014.6859163](https://doi.org/10.1109/ACC.2014.6859163).
- [33] X. Liang, S. I. Guler, and V. V. Gayah, "Joint optimization of signal phasing and timing and vehicle speed guidance in a connected and autonomous vehicle environment," *Transp. Res. Rec., J. Transp. Res. Board*, vol. 2673, no. 4, pp. 70–83, Apr. 2019, doi: [10.1177/0361198119841285](https://doi.org/10.1177/0361198119841285).
- [34] L. C. Bento, R. Parafita, S. Santos, and U. Nunes, "Intelligent traffic management at intersections: Legacy mode for vehicles not equipped with V2V and V2I communications," in *Proc. 16th Int. IEEE Conf. Intell. Transp. Syst. (ITSC)*, Oct. 2013, pp. 726–731, doi: [10.1109/ITSC.2013.6728317](https://doi.org/10.1109/ITSC.2013.6728317).
- [35] X. Qian, J. Gregoire, F. Moutarde, and A. De La Fortelle, "Priority-based coordination of autonomous and legacy vehicles at intersection," in *Proc. 17th Int. IEEE Conf. Intell. Transp. Syst. (ITSC)*, Oct. 2014, pp. 1166–1171, doi: [10.1109/ITSC.2014.6957845](https://doi.org/10.1109/ITSC.2014.6957845).
- [36] K. Yang, S. I. Guler, and M. Menendez, "Isolated intersection control for various levels of vehicle technology: Conventional, connected, and automated vehicles," *Transp. Res. C, Emerg. Technol.*, vol. 72, pp. 109–129, Nov. 2016, doi: [10.1016/j.trc.2016.08.009](https://doi.org/10.1016/j.trc.2016.08.009).
- [37] P. Lin, J. Liu, P. J. Jin, and B. Ran, "Autonomous vehicle-intersection coordination method in a connected vehicle environment," *IEEE Intell. Transp. Syst. Mag.*, vol. 9, no. 4, pp. 37–47, Oct. 2017, doi: [10.1109/MITS.2017.2743167](https://doi.org/10.1109/MITS.2017.2743167).
- [38] P. Li and X. Zhou, "Recasting and optimizing intersection automation as a connected-and-automated-vehicle (CAV) scheduling problem: A sequential branch-and-bound search approach in phase-time-traffic hypernetwork," *Transp. Res. B, Methodol.*, vol. 105, pp. 479–506, Nov. 2017, doi: [10.1016/j.trb.2017.09.020](https://doi.org/10.1016/j.trb.2017.09.020).
- [39] W. Zhao, D. Ngoduy, S. Shepherd, R. Liu, and M. Papageorgiou, "A platoon based cooperative eco-driving model for mixed automated and human-driven vehicles at a signalised intersection," *Transp. Res. C, Emerg. Technol.*, vol. 95, pp. 802–821, Oct. 2018, doi: [10.1016/j.trc.2018.05.025](https://doi.org/10.1016/j.trc.2018.05.025).
- [40] M. Barthauer and B. Friedrich, "Presorting and presignaling: A new intersection operation mode for autonomous and human-operated vehicles," *Transp. Res. Proc.*, vol. 37, pp. 179–186, Jan. 2019, doi: [10.1016/j.trpro.2018.12.181](https://doi.org/10.1016/j.trpro.2018.12.181).
- [41] C. Chen, J. Wang, Q. Xu, J. Wang, and K. Li, "Mixed platoon control of automated and human-driven vehicles at a signalized intersection: Dynamical analysis and optimal control," *Transp. Res. C, Emerg. Technol.*, vol. 127, Jun. 2021, Art. no. 103138, doi: [10.1016/j.trc.2021.103138](https://doi.org/10.1016/j.trc.2021.103138).
- [42] X. Qian, J. Gregoire, F. Moutarde, and A. De La Fortelle, "Priority-based coordination of autonomous and legacy vehicles at intersection," in *Proc. 17th Int. IEEE Conf. Intell. Transp. Syst. (ITSC)*. IEEE, 2014, pp. 1166–1171.
- [43] P. Sukennik, J. Lohmiller, and J. Schlaich, "Simulation-based forecasting the impacts of autonomous driving," *Transp. Res. Proc.*, vol. 3, pp. 1–9, Aug. 2018. [Online]. Available: <https://www.sciencedirect.com/locate/procedia2352-1465>
- [44] E. Onieva, V. Milanés, J. Villagrà, J. Pérez, and J. Godoy, "Genetic optimization of a vehicle fuzzy decision system for intersections," *Expert Syst. Appl.*, vol. 39, no. 18, pp. 13148–13157, Dec. 2012, doi: [10.1016/j.eswa.2012.05.087](https://doi.org/10.1016/j.eswa.2012.05.087).
- [45] B. Xu, X. J. Ban, Y. Bian, W. Li, J. Wang, S. E. Li, and K. Li, "Cooperative method of traffic signal optimization and speed control of connected vehicles at isolated intersections," *IEEE Trans. Intell. Transp. Syst.*, vol. 20, no. 4, pp. 1390–1403, Apr. 2019, doi: [10.1109/TITS.2018.2849029](https://doi.org/10.1109/TITS.2018.2849029).
- [46] A. Stevanovic, P. T. Martin, and J. Stevanovic, "VisSim-based genetic algorithm optimization of signal timings," *Transp. Res. Rec., J. Transp. Res. Board*, vol. 2035, no. 1, pp. 59–68, Jan. 2007, doi: [10.3141/2035-07](https://doi.org/10.3141/2035-07).
- [47] G. N. Purohit, A. M. Sherry, and M. Saraswat, "Time optimization for real time traffic signal control system using genetic algorithm," *Glob. Journal Enterp. Inf. Syst.*, vol. 3, no. 4, pp. 36–40, 2011.
- [48] J. I. Tech, S. Eng, D. Rahbari, and R. TI, "Help the genetic algorithm to minimize the urban traffic on intersections," *J. Inf. Technol. Softw. Eng.*, vol. 4, no. 2, pp. 1–9, 2014, doi: [10.4172/2165-7866.1000135](https://doi.org/10.4172/2165-7866.1000135).
- [49] P. Álvarez and M. A. Hadi, "Evaluating the effectiveness of signal timing optimization based on microscopic simulation," *Obras Projectos*, no. 16, pp. 85–94, Dec. 2014, doi: [10.4067/0718-28132014000200006](https://doi.org/10.4067/0718-28132014000200006).

- [50] W. Genders and S. Razavi, "An open-source framework for adaptive traffic signal control," 2019, *arXiv:1909.00395*. [Online]. Available: <https://arxiv.org/abs/1909.00395>
- [51] X. Liang, S. I. Guler, and V. V. Gayah, "An equitable traffic signal control scheme at isolated signalized intersections using connected vehicle technology," *Transp. Res. C, Emerg. Technol.*, vol. 110, pp. 81–97, Jan. 2020, doi: [10.1016/j.trc.2019.11.005](https://doi.org/10.1016/j.trc.2019.11.005).
- [52] Q. Lu and K.-D. Kim, "A mixed integer programming approach for autonomous and connected intersection crossing traffic control," in *Proc. IEEE 88th Veh. Technol. Conf. (VTC-Fall)*, Aug. 2018, pp. 1–6, doi: [10.1109/VTCFall.2018.8690681](https://doi.org/10.1109/VTCFall.2018.8690681).
- [53] B. Abdulhai and G. J. Karakoulas, "Reinforcement learning for true adaptive traffic signal control," *J. Transp. Eng.*, vol. 129, no. 3, pp. 278–285, 2003, doi: [10.1061/\(ASCE\)0733-947X\(2003\)129:3\(278\)](https://doi.org/10.1061/(ASCE)0733-947X(2003)129:3(278)).
- [54] D. Houli, L. Zhiheng, and Z. Yi, "Multiobjective reinforcement learning for traffic signal control using vehicular ad hoc network," *EURASIP J. Adv. Signal Process.*, vol. 2010, no. 1, pp. 1–7, Dec. 2010, doi: [10.1155/2010/724035](https://doi.org/10.1155/2010/724035).
- [55] S. El-Tantawy and B. Abdulhai, "Multi-agent reinforcement learning for integrated network of adaptive traffic signal controllers (MARLIN-ATSC)," in *Proc. 15th Int. IEEE Conf. Intell. Transp. Syst.*, Sep. 2012, pp. 319–326, doi: [10.1109/ITSC.2012.6338707](https://doi.org/10.1109/ITSC.2012.6338707).
- [56] Q. Liu and J. Xu, "Traffic signal timing optimization for isolated intersections based on differential evolution bacteria foraging algorithm," *Proc. Social Behav. Sci.*, vol. 43, pp. 210–215, Jan. 2012, doi: [10.1016/j.sbspro.2012.04.093](https://doi.org/10.1016/j.sbspro.2012.04.093).
- [57] I. Bargegol, M. Nikookar, R. V. Nezafat, J. Lashkani, and A. M. Roshandeh, "Timing optimization of signalized intersections using shockwave theory by genetic algorithm," *Comput. Res. Prog. Appl. Sci. Eng.*, vol. 1, no. 4, pp. 160–167, 2015.
- [58] E. Van Der Pol, "Deep reinforcement learning for coordination in traffic light control," M.S. thesis, Univ. Amsterdam, Amsterdam, The Netherlands, 2016.
- [59] J. Gao, Y. Shen, J. Liu, M. Ito, and N. Shiratori, "Adaptive traffic signal control: Deep reinforcement learning algorithm with experience replay and target network," 2017, *arXiv:1705.02755*.
- [60] Q. Zhao, C. Xu, and S. jin, "Traffic signal timing via parallel reinforcement learning," *Smart Innov. Syst. Technol.*, vol. 149, no. 3, pp. 113–123, 2019, doi: [10.1007/978-981-13-8683-1_12](https://doi.org/10.1007/978-981-13-8683-1_12).



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