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Intelligent Intersection Management Systems Considering Autonomous Vehicles: A Systematic Literature Review

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ABSTRACT Over the past several decades, the development of technologies and the production of autonomous vehicles have enhanced the need for intelligent intersection management systems. Subsequently, growing interest in studying the traffic management of autonomous vehicles at intersections has been evident, which indicates a critical need to conduct a systematic literature review on this topic. This paper offers a systematic review of the proposed methodologies for intelligent intersection management systems and presents the remaining research gaps and possible future research approaches. We consider both pure autonomous vehicle traffic and mixed traffic at four-way signalized and unsignalized intersection(s). We searched for articles published from 2008 to 2019, and identified 105 primary studies. We applied the thematic analysis method to analyze the extracted data, which led to the identification of four main classes of methodologies, namely rule-based, optimization, hybrid, and machine learning methods. We also compared how well the methods satisfy their goals, namely efficiency, safety, ecology, and passenger comfort. This analysis allowed us to determine the primary challenges of the presented methodologies and propose new approaches in this area.

INDEX TERMS Autonomous vehicle, intelligent intersection management system, mixed traffic, vehicle-to-infrastructure (V2I) communication, vehicle-to-vehicle (V2V) communication.

I. INTRODUCTION

The rapid population growth and the attendant increase in vehicle numbers over the last few decades have caused traffic congestion worldwide, with traffic congestion forecast to increase by 60% by 2030 [1]. Because intersections significantly impact the efficiency of traffic management systems in urban areas, this study focuses on intelligent traffic management systems at intersections.

It has previously been observed that traditional traffic lights are inefficient when traffic volumes are high [2]. Moreover, research has shown that intersections play a critical role in collision numbers and traffic delays in urban areas [3]. For instance, Franke *et al.et al.* mentioned that more than 33% of traffic accidents resulting in injury occur at urban intersections [4]. Likewise, in the United States and Europe, more than 40% of reported traffic accidents occur at intersections [5]. Traffic delays, which affect congestion costs, is another critical matter in traffic management systems. By analyzing the traffic data of 101 urban areas from 1982 to 2014, we found that traffic delays have tended to increase, which has led to rising congestion costs.

In addition, accidents and traffic delays at intersections lead to an enormous waste of human and natural resources [5]. In the United States, accidents at intersections cost $97 billion in 2000 [6], and national congestion costs increased from $42 billion in 1982 to $160 billion in 2014 [7]. Forecasts show that if this trend continues, the national cost of congestion will increase to $192 billion by 2020 [7]. Based on the 2011 Urban Mobility Report, U.S. commuters experienced annual delays of 34 hours—at a cost of more than $100 billion [8].

Data from several studies prove that human error plays a crucial role in traffic congestion and accidents. Recent studies indicate that driver error contributes to up to 75% of all roadway crashes [9]. However, developments in computer science, sensing technology, artificial intelligence (AI), and communication technology have highlighted the possibility

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of introducing autonomous vehicles (AVs). The major concepts that must be improved by the development of AVs, namely sensing environments, data collection and analysis, planning, decision making, and vehicle control, have the potential to solve current problems with traffic management systems. Additionally, Moody's Investors Service predicts that the vast majority of vehicles will change to autonomous versions after 2045 and that AVs will become close to universal by 2055 [10].

Although several studies (e.g., [11]–[17]) have focused on various aspects of AVs and others (e.g., [18]–[20]) on intersection management related to AVs, our study differs from those in methodology, scope, and research focuses.

- In our study, we applied the systematic literature review (SLR) approach. We began with a keyword-based search and identified 105 primary studies systematically from 2952 search results, whereas other studies mostly used survey or review approaches.
- Our study covers traffic management studies at signalized intersections when AVs and mixed traffic are considered, and at unsignalized intersections when only AVs are considered. Studies [18]–[20] focused on different types of traffic flows and/or different types of intersections.
- Unlike studies [18]–[20], which focus on summarizing the approaches of traffic management systems, our study concentrates on investigating and comparing how well the approaches are evaluated and on the results of the evaluation. We first identified and categorized the goals, for example, improving efficiency, of the approaches. Then, we compared how well different approaches meet a certain goal. In addition, we identified and summarized the data collected from AVs and/or infrastructure for intelligent traffic management at intersections.

The remaining parts of the review have been organized as follows. Section II provides a brief overview of related reviews and surveys, whereas section III defines AVs, intelligent transportation system (ITS), and autonomous intersection management (AIM). Section IV presents the SLR process and our research questions, and illustrates the quantitative analysis of the selected papers and the answers to the research questions. We discuss the findings of our review and potential research directions in section V, and threats to the validity of the study are presented in section VI. The final section contains our conclusions and future work.

II. RELATED WORK

To manage AV-related traffic at an intersection, we need to consider both the traffic flow and the type of intersection. The traffic flow could be pure AV traffic or mixed traffic (i.e., a mixture of human-driven and automated vehicles). The intersection could be signalized or unsignalized and regulated by vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication. To improve researchers' understanding of these and similar factors, several reviews and surveys have investigated different aspects of AVs, such as adaptive cruise control (ACC) systems [11], cooperative adaptive cruise control (CACC) systems [12], decision-making and control approaches [13], the impact of AVs on traffic [14], techniques related to AV localization [15], communication between AVs and road users [16], and vehicular communication for controlling the traffic [17].

TABLE 1. Research scope.

Intersection type	Traffic type	
	Pure AV	Mixed traffic
Signalized	[18], [19], [20], and our study	[18], [19], [20], and our study
Unsignalized	[18], [19], and our study	--

Chen *et al.*and Englund [18] surveyed cooperative intersection management techniques considering V2V and V2I communication at signalized and unsignalized intersections. The cooperative methods were categorized into trajectory planning, time slots and space reservation, and virtual traffic lights. Rios-Torres and Malikopoulos [19] focused on the coordination of connected and autonomous vehicles (CAVs) at intersection crossings and when merging at highway on-ramps. They covered various proposed approaches based on centralized and decentralized coordination, and they classified the approaches as heuristic rules and optimization. Guo *et al.et al.* [20] surveyed urban signalized intersection management considering CAVs. The main focus of [20] was to review the proposed methods for estimating traffic flow and for optimizing traffic signal timing.

In addition to studying the approaches to controlling the traffic at intersections, it is also important to summarize and compare how effectively and efficiently the approaches meet their goals to identify gaps and improve the efficiency and effectiveness of the approaches. This insight drives our main research questions. Moreover, it is essential to cover studies related to mixed traffic, which will likely be prevalent in the next 10 to 20 years, and to unsignalized intersections. However, mixed traffic at unsignalized intersections may not be relevant, because human-driven vehicles cannot intelligently communicate and coordinate with other road users. These observations helped us to define the scope of the papers we wanted to review, as shown in Table 1.

III. INTRODUCTION TO AV AND INTELLIGENT TRAFFIC MANAGEMENT

In this section, we present a brief description of AVs, intelligent transportation systems, and autonomous intersection management.

A. AUTONOMOUS VEHICLES

The Defense Advanced Research Projects Agency's (DARPA) Grand Challenge was launched in 2004 to

TABLE 2. SAE J3016^{TM} automation levels.

Level 0	Level 1	Level 2	Level 3	Level 4	Level 5
Users are driving even when driver support features are engaged.			Users are not driving if automated driving features are engaged.		
Drivers supervise the support features.			Drivers must drive if features request them to drive.	Automated driving features do not require users to drive.	
Driver support features			Automated driving features		
Warning Momentary assistance	Steering OR brake/acceleration support	Steering AND brake/acceleration support	Automated driving features can drive the vehicle under limited conditions		Automated driving features can drive the vehicle in all conditions

demonstrate the technical feasibility of AVs [21]. Since then, numerous companies, such as Tesla, Audi, GM, and Google, have begun to develop and test AV technologies. As shown in Table 2, SAE International has classified the automation of vehicles according to six different levels [22].

AVs can gather information about the surrounding environment by using the camera, radar, LiDAR, laser, ultrasonic sensors, and GPS. Therefore, from a transportation engineering perspective, AVs are expected to enhance the safety, efficiency, ecology, and passenger comfort of the transportation system.

B. INTELLIGENT TRANSPORTATION SYSTEMS (ITS) AND AUTONOMOUS INTERSECTION MANAGEMENT (AIM)

Intelligent transportation systems (ITS) manage traffic by using new services for various transport modes [23]. The objective of ITS is to provide an improved system by informing users about traffic situations and by making mobility coordination safer and smarter [24]. In recent years, ITS has been widely applied along with the development of IT technologies such as robotics, signal and image processing, computing, sensing, and communications [25]. By using V2V, V2I, and I2V communication and AV technologies, AIM is expected to improve the efficiency of existing intersections [26]. For instance, Austroads analyzed the potential benefits of C-ITS in Australia and found that V2V communication can reduce serious road collisions by up to 35% [27].

IV. RESEARCH AND IMPLEMENTATION

We followed the Kitchenham *et al.et al.* SLR process, which was conducted in [28].

A. RESEARCH METHOD AND RESEARCH QUESTIONS

As shown in Table 1, in this SLR we focused on pure AV and mixed traffic in signalized and unsignalized four-way intersection(s). We reviewed papers that proposed methodologies to improve intersection performance by considering data collection, data sharing, traffic control, and other aspects.

To achieve our objectives, we formulated three main research questions:

- ***RQ1.*** What factors did intelligent intersection management studies address in terms of utilizing AVs?
- ***RQ2.*** What kinds of methodologies have been proposed to address the potential problems related to intelligent intersection management systems?
    - ***RQ2.1.*** What kinds of ITS methodologies have been proposed for traffic flow consisting of only AVs?
    - ***RQ2.2.*** What kinds of ITS methodologies have been proposed for traffic flow consisting of a mixture of autonomous and human-driven vehicles?
- ***RQ3.*** What challenges and opportunities remain?

B. CONDUCTING THE REVIEW

We focused on articles available online and published in English between January 2008 and May 10, 2019. We included the following digital libraries:

- Scopus
- IEEE
- Compendex
- Inspec
- Transport-Ovid
- ACM
- Web of Science

We used keyword-based searches to identify primary studies and followed six steps to filter relevant articles, as shown in Fig. 1. Table A-1 in Appendix A shows the search strings used in the Scopus digital library as an example.

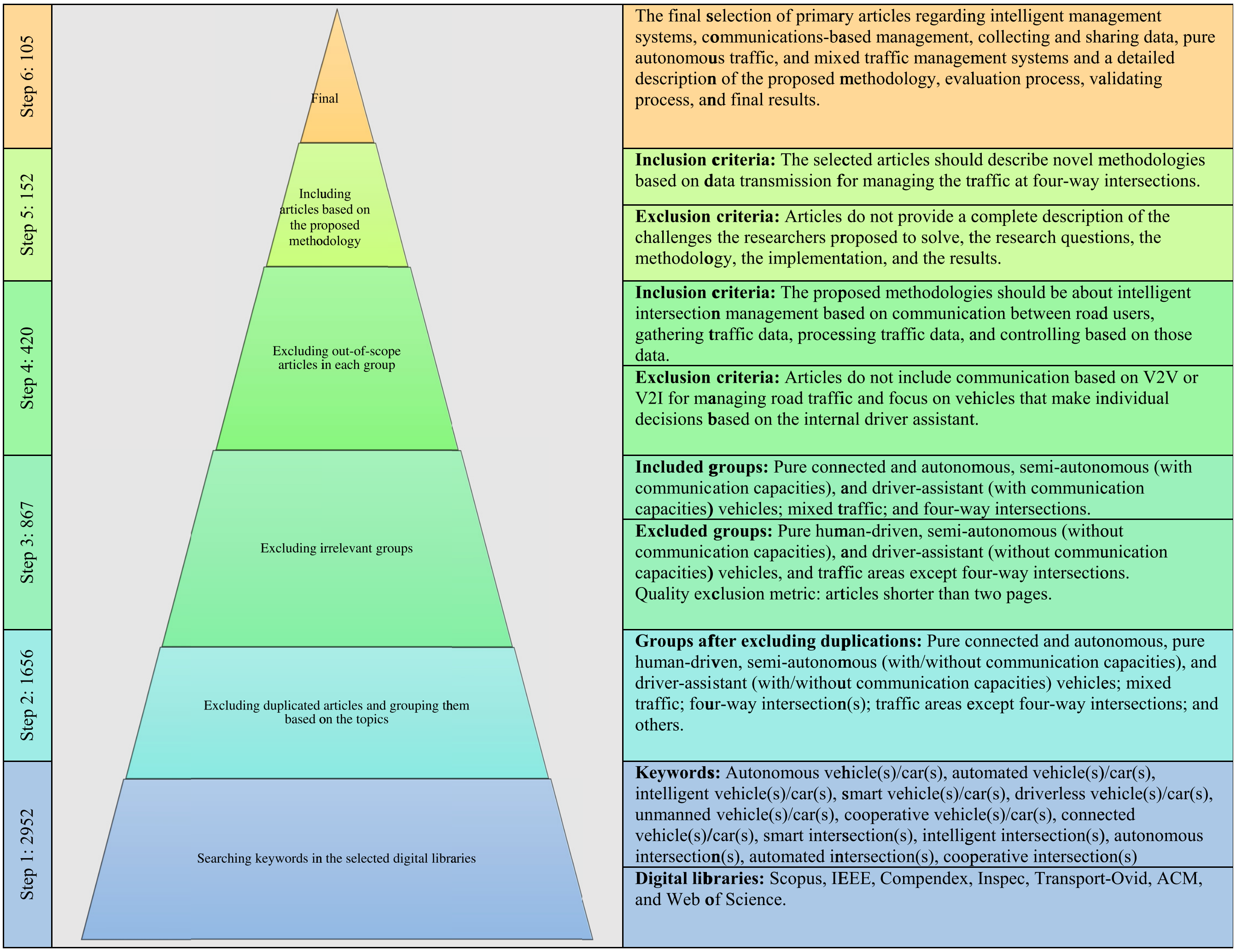
C. RESULTS OF RESEARCH QUESTIONS

As shown in Fig. 2, the number of papers published on this topic has increased in the last few years. The lower publication number in 2019 is influenced by our search parameters, as our search included articles published only until May 10, 2019.

The top five countries, which generated about 79.6% of the articles, are the United States, China, France, Sweden, and Germany, as shown in Fig. 3.

1) RESULTS OF RQ1

Based on the thematic analysis, we categorized the goals of the primary studies as efficiency, safety, ecology, passenger comfort, and others. The "other" class includes an article about data sharing features. Some goals include several subgoals to make this analysis more precise. The results are shown in Fig. 4.



The final selection of primary articles regarding intelligent management systems, communications-based management, collecting and sharing data, pure autonomous traffic, and mixed traffic management systems and a detailed description of the proposed methodology, evaluation process, validating process, and final results.

Inclusion criteria: The selected articles should describe novel methodologies based on data transmission for managing the traffic at four-way intersections.

Exclusion criteria: Articles do not provide a complete description of the challenges the researchers proposed to solve, the research questions, the methodology, the implementation, and the results.

Inclusion criteria: The proposed methodologies should be about intelligent intersection management based on communication between road users, gathering traffic data, processing traffic data, and controlling based on those data.

Exclusion criteria: Articles do not include communication based on V2V or V2I for managing road traffic and focus on vehicles that make individual decisions based on the internal driver assistant.

Included groups: Pure connected and autonomous, semi-autonomous (with communication capacities), and driver-assistant (with communication capacities) vehicles; mixed traffic; and four-way intersections.

Excluded groups: Pure human-driven, semi-autonomous (without communication capacities), and driver-assistant (without communication capacities) vehicles, and traffic areas except four-way intersections.
Quality exclusion metric: articles shorter than two pages.

Groups after excluding duplications: Pure connected and autonomous, pure human-driven, semi-autonomous (with/without communication capacities), and driver-assistant (with/without communication capacities) vehicles; mixed traffic; four-way intersection(s); traffic areas except four-way intersections; and others.

Keywords: Autonomous vehicle(s)/car(s), automated vehicle(s)/car(s), intelligent vehicle(s)/car(s), smart vehicle(s)/car(s), driverless vehicle(s)/car(s), unmanned vehicle(s)/car(s), cooperative vehicle(s)/car(s), connected vehicle(s)/car(s), smart intersection(s), intelligent intersection(s), autonomous intersection(s), automated intersection(s), cooperative intersection(s)

Digital libraries: Scopus, IEEE, Compendex, Inspec, Transport-Ovid, ACM, and Web of Science.

FIGURE 1. The process of selecting primary articles.

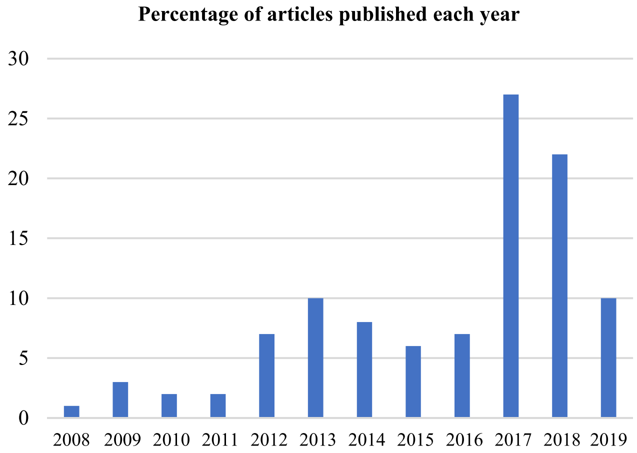


FIGURE 2. Study trends between January 2008 and May 10, 2019.

2) RESULTS OF RQ2

We divided this question into two sub-questions that yielded the following results:

a: RESULTS OF RQ2.1

In this section, we focus on intelligent intersection management methodologies with pure AV traffic. The proposed methodologies have been grouped based on the goals mentioned in RQ1. Some papers proposed new methodologies by focusing on one goal, for example, efficiency, whereas others considered multiple goals, for example, efficiency, safety, and ecology.

Efficiency:

Several methods have been proposed to improve the efficiency of AVs in intersections. Various researchers considered different sub-goals, such as decreasing traffic delay, increasing intersection throughput, and mitigating congestion possibility. We reviewed methodologies suggested to improve efficiency at intersections.

To minimize the evacuation time of a set of vehicles, Yan et al. [29], proposed an approach based on a dynamic programming algorithm to find the optimal vehicle passing sequence according to the arrival and passing time of a vehicle. Likewise, in [30], the authors applied heuristic smallest

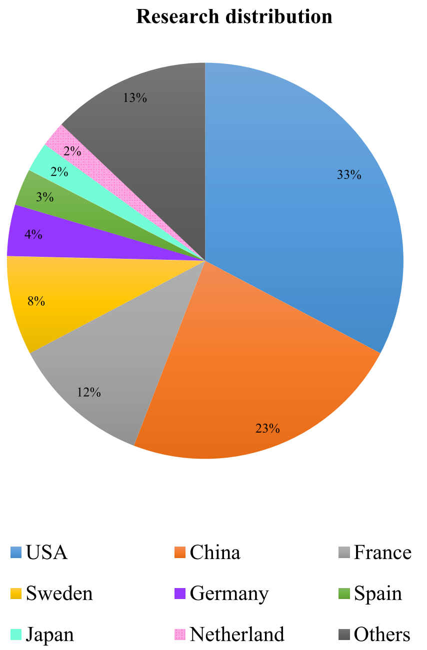


FIGURE 3. Publication distribution based on countries.

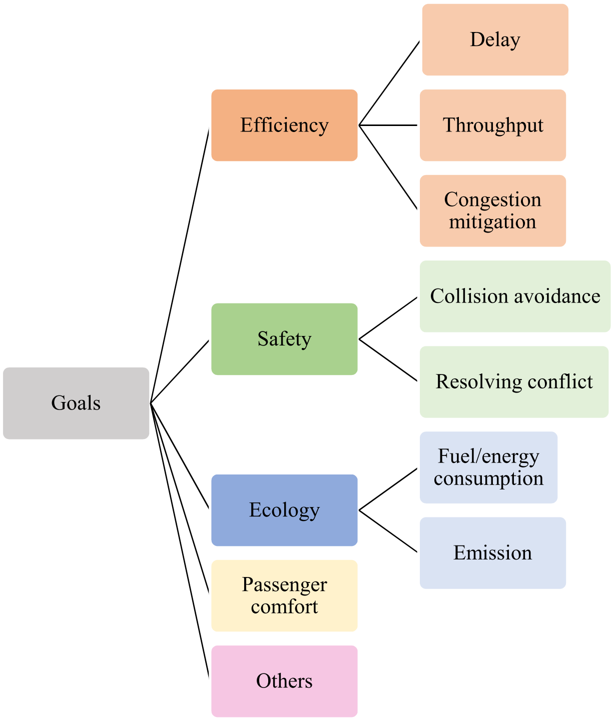


FIGURE 4. Research goals and sub-goals.

extra time (SET) and a dynamic programming algorithm. Yan *et al.* compared the performance of the genetic, dynamic programming, heuristic, and branch-and-bound algorithms to the traditional fixed-cycle-time and adaptive control systems. The results showed that the proposed method can improve evacuation time and reduce average queue length and average vehicle waiting time. Additionally, to improve the performance of the intersection, ShangGuan *et al.et al.* [31], proposed a time delay petri net-based (TdPN) control approach to develop a cooperative vehicle–infrastructure system. The results indicated that when the traffic flow rate is higher than 1,200 vehicles per hour, the TdPN method provides better performance than traditional signal control systems in terms of delay, average speed, average queue length, and average stop time.

Wu *et al.et al.* [32] proposed an unsignalized intersection control approach considering a new information and communication system for intelligent vehicles based on dynamic programming. They compared the center controller, V2V communication, and global solution based on simulation results and found that the global solution has a greater ability to reduce average queue length than the other two methods. Moreover, to determine the best access order of the intersection, Wu *et al.* [33] suggested a new scheduling model by viewing the intersection management problem as a machine scheduling problem, with vehicles treated as jobs and the intersection as a machine. The proposed method is based on dynamic programming. Compared to traditional signal control, the proposed method can reduce average waiting time and queue length, and improve throughput. Furthermore, by considering individual vehicle and real-time intersection control, Wu *et al.* [34] presented an AIM strategy based on an ant colony system and discrete optimization algorithm to solve real-time control problems considering a large number of vehicles and lanes. The proposed method outperforms the existing methods in terms of evacuation time, mean vehicle delay, throughput, and mean queue length.

To enhance mobility, Vasirani *et al.*and Ossowski [35] designed a competitive computational market approach for intersection management. In the competitive computational market, the driver agents and the intersection-manager agents trade the use of intersection capacity. The proposed approach outperforms the traffic-light system in terms of average travel time and congestion. Additionally, in [23] Vasirani and Ossowski presented a novel scheduling model and suggested a hybrid methodology based on the distributed market–inspired approach and reservation-based intersection control model to reduce the delays for drivers who have a higher value of travel time by submitting higher bids. Their idea is to combine the competitive traffic assignment strategy (CTA) with the auction-based (AC) policy, in what is called a CA-CTA mechanism, for traffic control. This model is an extension of the reservation-based intersection control mode, which combines the auction-based policy and reservation concept. The proposed method decreases the probability of deadlock in the reservation concept proposed by Dresner *et al.*and Stone [36]. The results showed that compared to a first-come-first-served (FCFS) policy, the suggested approach decreases average travel time by more than 70%.

Furthermore, a time-sensitive programming method was proposed in [37] to address the round-trip delay (RTD) problem. It performs better than AIM under high input-flow conditions.

Zhang *et al.et al.* [38] presented a reservation-oriented priority scheduling method, called PriorFIFO, to solve the autonomous passing-through problem. Additionally, novel reservation-based scheduling processing, named csPriorFIFO, was proposed by [39] to model and establish the traffic objects, such as centralized scheduler I-Agent, service-oriented heterogeneous vehicles, and their uniform behavior states. Both of these methods outperform the FCFS method in terms of delay and scheduling performance, respectively.

Moreover, Wei *et al.et al.* [40] proposed a reservation-based control policy called Batch-Light, which is an adaptive intelligent intersection control policy for AVs. In [40], Wei *et al.* used a greedy-based conflict matrix decision algorithm to increase the possibility of reservation with fairness. They further applied a k-shift optimization algorithm to help unlucky vehicles pass through the intersection. By simulating the unbalanced and balanced traffic at the intersection, the proposed method outperforms FCFS and traditional traffic-light control policies in terms of average delay and number of vehicles crossed the intersection successfully in one hour.

To optimize arrival time and speed via planning technologies, Au and Stone suggested a multi-objective optimization-based method [41]. The authors proposed a planning-based motion controller to prevent stopping before the intersection and to increase throughput. Compared to the optimistic heuristic method described in [42], the proposed method reduces average delay, improves maximum throughput, and improves efficiency. To enforce liveness and prevent deadlock, Au *et al.* [43] proposed a new intersection management policy called the batch policy of reservation in AIM.

Additionally, Carlin *et al.* [44] proposed an auction-based intersection system that calculates the total bids for all directions to adjust vehicle order in the intersection. Considering increasing fairness, it pays attention to keeping travel time reasonable for drivers with a low budget. When it was simulated on the road networks in four urban cities, the proposed auction-based method outperformed base cases in terms of trip time, except in Baton Rouge.

Wuthishuwong and Traechtler [26] focused on the coordination of traffic information between infrastructures and vehicles. To balance the traffic in the network of intersections, they introduced the coordination method, which considers a network with multiple autonomous intersections. Furthermore, they proposed distributed control for a graph-based intersection network to control traffic at a macroscopic level and implemented a discrete time consensus algorithm to coordinate the traffic density with its neighbors. They used the Greenshields model to define the boundary conditions of various traffic flows to corresponding traffic density and speed. Compared to the traditional traffic signal system, the proposed method can improve the overall traffic flow by up to 20%. In addition, the proposed method outperforms the traffic signal system in terms of flow rate, average traffic speed, and throughput.

To prevent network deadlock and decrease computational delay, Perronnet *et al.* [45] used hierarchical architecture for cooperative intersection management. They proposed a deadlock-free protocol, which is called the advanced cooperative vehicle-actuator system (ACVAS). It can avoid computational overhead, detect and rectify deadlock, and make quick decisions.

Among the methods targeting improved efficiency, we classified methods as rule-based (e.g., [35], [23], and [37]), optimization (e.g., [29], [30], and [32]), and hybrid (e.g., [31]). Most of the proposed methods and base cases were tested in the simulation environment. Overall, the proposed methods outperform the base cases by 14–99.8%, considering different performance indicators. Further, most of the studies used a single intersection with simplified traffic conditions to validate the proposed methods. Details of the efficiency of the surveyed approaches are listed in Table B-1 of Appendix B.

Safety:

Improving the safety of a targeted intersection is one of the major goals of AIM. Several methods have been proposed to achieve this goal by focusing on various sub-goals such as avoiding collisions and resolving possible conflicts.

Campos *et al.* [46] presented a cooperative driving strategy for intersection crossing to decrease the number of accidents and avoid collisions. They proposed a decentralized solution that allows vehicles to sequentially solve local optimization problems to help themselves to cross the intersection safely. Similarly, for considering real-time collision detection, Guangquan *et al.* [47] proposed a rule-based method to determine proper vehicle order and safe deceleration. The approach is based on the speed control strategy to avoid collisions, clarify the sequence of vehicles, and allow them to pass through the uncontrolled intersection.

In [48], a collaborative method was proposed to minimize collisions between AVs at an unsignalized intersection. The proposed method calculates the optimal action of the vehicle based on cost function when a conflict is detected. Additionally, Riegger *et al.* [49] proposed a centralized model predictive control (MPC) to control the AVs passing through the intersection and to prevent collisions. They formulated the problem as a convex quadratic program in space coordinates to generate optimal trajectories. They further considered penalized time gaps to increase safety in case of sensor errors. In a similar vein, Altché *et al.* [50] designed a real-time intersection supervisor based on a mixed-integer quadratic programming (MIQP) approach to monitor the control inputs and improve the safety of vehicles. To guarantee the safe navigation of vehicles, the intersection supervisor can override the vehicle control orders.

Jiang *et al.* [51] suggested using a distributed and parallelizable algorithm, named the augmented Lagrangian-based alternating direction inexact Newton (ALADIN) method, to solve the coordination problem at intersections. To achieve collision avoidance at the intersection, each vehicle solves its own optimal control problem and exchanges information (e.g., arrival and departure times) with its neighbors. To provide the optimal control for AVs to safely cross the intersection, Murgovski *et al.* [52] applied a centralized control strategy with convex modeling steps and transformed the problem from time to space.

Finally, Rahmati *et al.*and Talebpour [3] developed a game theory–based decision framework for unprotected left-turn maneuvers. It assumes two vehicles as two players who are trying to maximize their awards by deciding to wait or continue. This approach provides the correct result in 80% of test cases.

As shown in Table B-2 in Appendix B, the methods to improve safety can be classified as rule-based (e.g., [47] and [3]), optimization (e.g., [48]–[50]), and hybrid (e.g., [46]) methods to develop collision-free intersection management strategies. Most of the proposed methods and base cases were tested in the simulation environment. Most can guarantee collision avoidance at the intersection (e.g., [46]); other methods minimize conflicts (e.g., [51]). However, collisions can still occur during rush hour.

Efficiency and Safety:

Creating the ideal balance between several goals plays a key role in increasing the usability of proposed methodologies in real-world settings. Therefore, this section includes articles that simultaneously considered efficiency and safety.

To minimize delays and improve safety, Adams *et al.* [53] proposed a coordination mechanism that modifies the centralized method proposed by Dresner *et al.*and Stone [54] by turning it into a distributed version. The simulation results showed that the proposed method performs approximately 35–45% better than traffic signal control systems. Fayazi *et al.* [55] proposed an optimal scheduling strategy considering the arrival time of AVs at the intersection. They applied mixed-integer linear programming (MILP) to solve the scheduling problem, which helps to avoid accidents and reduces the number of stops and delays at intersections. Compared to traditional traffic signal systems, the proposed method reduces average travel time and average stopped delay by 7.5% and 52.4%, respectively. Chen *et al.* and Kang [56] presented a novel reservation management scheme, called win-fit, to reduce average trip delay and increase the average number of vehicles passing through the intersection with guaranteed safety and with starvation avoidance. In comparison to the existing method, the proposed method can reduce the average trip delay by 31–95%.

Moreover, Aoki *et al.*and Rajkumar [57] presented a safe and practical method called configurable synchronous intersection protocol (CSIP), which is a more general and resilient version of the ballroom intersection protocol (BRIP). Considering the potential for accidents caused by positioning errors in BRIP, CSIP utilizes a specific inter-vehicle distance to overcome this limitation and decreases the number of stops at the intersection, which maximizes intersection throughput. According to the simulation results, CSIP outperforms BRIP in terms of the number of collisions and trip delay. In addition, in [58], Elhenawy *et al.* proposed a game theory–based algorithm, based on the chicken game, to control the movements of AVs and to reduce average travel time at the intersection. The simulation showed that the proposed method reduces average travel time by 49% and delay by 89% in comparison with the all-way stop-sign intersection.

Savic *et al.* [59] set out a novel distributed intersection algorithm to avoid collisions and to minimize delays at the intersection in case of communication failure. They found that the proposed method effectively handles unknown and large numbers of communication failures. To minimize total delay and number of accidents, Zohdy *et al.*and Rakha [60] presented a method based on game theory decision within a cooperative adaptive cruise control (CACC) system to optimize the movement of AVs at the intersection. In comparison with the stop-sign control intersection, the proposed method reduces total delay by approximately 70%.

Abdelhameed *et al.* [61] proposed an intelligent intersection control system (ICS) to improve intersection throughput, utility, average and maximum delay, and predicted collision avoidance. ICS uses a hybrid fuzzy-genetic controller to determine proper action for vehicles. In comparison with the existing traffic-light systems and the fuzzy logic controller, the proposed method improves throughput, average delay time, and maximum delay time by 90.7%, 61.6%, and 72.4% respectively. Additionally, considering real-time data processing, Chang *et al.*and Edara [62] suggested a new methodology called autonomous reservation-based intersection control (AReBIC) to decrease conflict and total delay and to improve mobility in an emergency evacuation. The proposed method, which combines reservation methodology and movement priority, outperforms the existing traffic control method in terms of average speed, total delay, and conflicts.

To decrease delays and guarantee safety at intersections, Müller et al. [63] proposed an optimal arrival time strategy, which determines the optimal arrival time and movement for each vehicle. Compared to fixed-time traffic-signal controls, the proposed method reduces average delays by 97.99–98.88% and average virtual queues by 27.27–98.70%. Additionally, it improves average vehicle speed by 133.35–447.09%.

To improve the performance of the target intersection, Chai et al. [64] proposed a preassigned-slots method using location optimization on sequence evaluation (LOOSE) and the cooperative optimization method for the previous allocation alternatively transforming (COMPACT) for safety and improved efficiency. Applying the proposed method can reduce average delay, and vehicles can cross the intersection without stopping or colliding.

Moreover, Kamal *et al.* [65] proposed a coordination scheme for AVs to cross an unsignalized intersection safely and efficiently. The evaluations the authors conducted indicated that the proposed coordination scheme outperforms the traditional control method in terms of traffic flow when the turning rate is less than 20%.

To manage AVs at an isolated intersection, Perronnet *et al.* [66] presented a sequence-based protocol called transparent intersection management. The major advantage of this protocol is that it is robust under conditions of communication latency. Compared to traffic-light systems and existing methods, the proposed method reduces communication latency and evacuation time, with guaranteed safety. Similarly, Lamouik *et al.* [67] developed a smart multiagent traffic coordinator to provide safe and fast intersection crossing. The proposed method is based on reinforced learning (RL) and deep neural networks designed to learn and estimate the best action for each vehicle. In addition, Kim [68] proposed an intersection-crossing protocol, which is formulated as a model predictive control problem, to provide a safety-guaranteed trajectory for a vehicle. They further proposed intervehicle coordination rules, a lane-changing protocol, and a yield protocol.

Considering V2I communication, Xie *et al.*and Wang [69] presented a smart in-vehicle decision-support system and used a probabilistic sequential decision-making process to help AVs to make better stop/go decisions and to reduce unnecessary stops. Moreover, to solve the traffic coordination problem, De Campos et al. [70] developed a decentralized coordination approach based on model-based decision heuristics and sequential optimal control. The proposed method is suitable for fast online implementation, and it avoids collisions. Likewise, Katriniok *et al.* [71] built a distributed MPC for intersection priority management to let AVs pass an unsignalized intersection efficiently.

To avoid collisions, Ze-hua *et al.* [72] used a discrete control strategy based on a hybrid automata theory to improve the collaboration between AVs at the intersection. They also introduced a market mechanism to improve collaboration efficiency in specific areas. To improve the safety of intersection management systems, Zheng *et al.* [73] proposed a delay-tolerant protocol that considers communication and network delay. The proposed method outperforms traditional traffic lights in terms of average travel time and performance, and it avoids collisions.

Furthermore, Gregoire and Frazzoli [74] developed a hybrid centralized/distributed architecture to coordinate AVs and allow vehicles to safely and efficiently cross intersections. The architecture uses a centralized approach based on a job scheduler to define the crossing time with maximum speed and a decentralized approach to avoid collisions. In the same vein, in [75], Zhang *et al.* modeled and designed a uniform cooperative mechanism for AVs to help them pass intersections safely, and they created the reserve advance, act later (RAAL) and high-QoS-in-prior policies to achieve these goals.

To avoid collisions and reduce waiting times, Aloufi and Chatterjee [76] proposed a model to schedule the AVs at the intersection, which is based on the production line technique. Additionally, they applied the K-Nearest Neighbors (KNN) algorithm to predict the right-turn movement of vehicles. The simulation outputs showed that the proposed model provides higher efficiency than the existing model in the case of average and random-pattern traffic flow.

Considering delay, Chouhan and Banda [77] proposed a heuristic approach to avoid space-time conflicts at the intersection. The simulation results show that the proposed approach outperforms the traditional traffic light, FCFS, and CIVIC [78] in terms of average trip delay. Moreover, Creemers *et al.* [79] designed a centralized supervisory controller based on MPC. The simulation results indicated that the proposed approach achieves a faster transient response and lower average delay than FCFS policy and traditional traffic lights.

To handle external disturbances and model mismatches, Khayatian et al. [80] proposed a time- and space-aware technique for managing intersections with CAV traffic. Experiments on a 1/10 scale intersection with CAVs have shown that the proposed method can improve throughput on average compared to velocity assignment techniques. To navigate CAVs cross the signalized or unsignalized intersection safely and efficiently, Liu *et al.* [81] proposed a distributed conflict resolution mechanism via V2V communication. The results of their study indicated that the proposed approach can improve intersection efficiency by decreasing the average delay time.

To ensure safe and efficient traffic flow in intersections, Lu and Kim [82] proposed a mixed-integer programming-based intersection coordination algorithm (MICA). Based on the simulation outcomes, the proposed approach outperforms the optimized traffic-light mechanism and discrete-time occupancies trajectory-based intersection traffic coordination algorithm [83] in terms of throughput.

To improve traffic throughput, Mo *et al.* [84] introduced multiple-collision-set strategies by extending the traditional single collision-set (CS) algorithm. Numerical results indicated that the proposed method can provide safe and efficient traffic coordination.

Steinmetz *et al.* [85] proposed a collision-aware resource allocation (CARA) strategy, based on a self-triggered approach, to coordinate vehicles and to manage the intersection. Moreover, to improve the quality of service (QoS), Wang et al. [86] proposed a dynamic coordination framework based on the queuing theory. Simulation and theoretical analysis results showed that road stability is guaranteed and good QoS can be provided by the proposed method. Wei *et al.* [87] proposed a game-in-game framework to maximize intersection throughput and mitigate traffic accidents. The simulation outcomes indicated that the proposed framework can decrease accidents and increase throughput.

Cruz-Piris *et al.* [88] proposed a new method to optimize the throughput of intersections automatically by utilizing the genetic algorithm. A cellular automata simulator was developed to provide a realistic simulation environment. Based on the simulation output, the proposed method can improve throughput by 9.21–36.98% compared to the traditional method.

To deal with the limitation of centralized traffic management systems, Gonzalez *et al.* [89] suggested a distributed management system to control intersections. The simulation results showed that the proposed method outperforms a conventional traffic control system in terms of throughput. Likewise, to improve the safety and efficiency of an unsignalized intersection, Liu *et al.* [90] proposed an approach based on trajectory planning for autonomous intersection management (TP-AIM) to assign priority and trajectory to vehicles and determine collision-free trajectory by considering delay. Consequently, the average evacuation time is decreased while the throughput is increased by more than 20%. Moreover, in comparison with the classical traffic light, intersection delay decreases to less than 10%.

Lu and Kim [83] proposed an algorithm, named discrete-time occupancies trajectory-based intersection traffic coordination algorithm (DICA), to facilitate safe and efficient intersection crossing. The simulation result showed that DICA improves computational efficiency. Furthermore, enhanced DICA outperforms the optimized traffic light in terms of the standard deviation of trip time and average trip time.

To minimize delays and avoid collisions at the intersection, Wu *et al.* [91] proposed the decentralized coordination learning of autonomous intersection management (DCL-AIM) to optimize control policy. The sequential movement of vehicles is modeled as multiagent Markov decision processes (MAMDPs) and solved by using reinforcement learning, especially multiagent reinforcement learning. The simulation results showed that the DCL-AIM outperforms existing control methods.

Mirheli at al. [92] proposed a distributed cooperative control to guide connected and autonomous vehicles across an unsignalized intersection without conflict. It is called a distributed coordinated signal-free intersection control logic (DC-SICL). Based on the simulation results, the proposed method outperforms an optimized actuated signal control in terms of travel time, throughput, and safety.

Considering V2I communication, Wuthishuwong and Traechtler [93] proposed a discrete model to manage AVs crossing an intersection without collisions and improve intersection efficiency. The proposed method decreased the waiting time at the intersection compares to the traditional traffic light.

By considering all-direction turn lanes (ADTL), He *et al.* [94] proposed a conflict-avoidance-based approach for coordinating vehicles at the unsignalized intersection. The simulation results indicated that the proposed approach outperforms traditional traffic lights in terms of throughput and travel time, with guaranteed collision avoidance. Additionally, Xu *et al.* proposed a scheduling solution to improve the throughput of an unsignalized intersection without collision risk. They developed the individual and platoon-based arrival model, which utilizes the heuristic algorithm and optimal entering time scheduling (OETS) algorithm. The proposed approach decreases traffic delay and improves efficiency compared to traditional traffic lights [95].

As shown in Table B-3 in Appendix B, rule-based (e.g., [53], [56], and [57]), optimization (e.g., [55], [60], and [65]), hybrid (e.g., [61], [63], and [68]), and machine learning (e.g., [67], [76], [84], and [91]) methods have been developed to improve intersection efficiency while considering safety. Researchers claimed that four of the optimization methods are suitable for real-time or online implementation ([70], [71], [84], and [92]). Most of the proposed methods and base cases were tested in the simulation environment. Overall, the proposed methods outperformed base cases with increases of 5–447.09% and decreases of 0–25% when considering different performance indicators. Most of the studies used a single intersection with simplified traffic conditions to validate the proposed methods.

Efficiency and Ecology:

Some articles considered both efficiency and ecology in managing AV traffic at intersections and proposed various methodologies to achieve this goal.

To reduce travel time, fuel consumption, and pollutant emissions, Jin *et al.* [96] implement the optimal scheduling of vehicle agents based on departure times in a multiagent system. Compared to the FIFO-based method [97], the proposed method can reduce travel time variability and the number of partial stops by 56–59% and 49–60%, respectively.

By using V2I communications, Saust *et al.* [98] proposed a cooperative system by considering signal control and vehicles' driving strategies. The idea is based on optimizing longitudinal and lateral control strategies for AVs to reduce delays, emissions, and fuel consumption. The outcomes showed that the total number of required stops decreased by 25%. Likewise, Xu *et al.* [99] proposed a strategy they named ''cooperation between traffic signal and vehicles (CTV),'' which calculates the optimal signal timing, vehicle order, and vehicle arrival time. Meanwhile, optimal control is applied to optimize the trajectory, engine power profile, and acceleration/deceleration behavior of AVs. Compared to the actuated signal control method, the proposed method reduces average trip delay and average fuel economy by 19.7% and 23.7%, respectively.

To improve energy consumption, emissions, and traffic throughput, Wang *et al.* [100] developed an approach called cluster-wise cooperative eco-approach and departure application (coop-EAD), which includes initial vehicle clustering, intra-cluster sequence optimization, and cluster formation control. Compared to the existing ego-EAD method, the proposed coop-EAD improves energy consumption and traffic throughput by 11.01% and 50%, respectively. Additionally, it decreases pollutant emissions by 2.29–19.91%. Tlig *et al.* [101] created the two-level decentralized multiagent system based on stop-free strategies to optimize network-level traffic flow and make vehicles pass through an intersection without stopping. The results of the simulation confirmed that the proposed method can significantly reduce vehicle-level energy consumption.

As shown in Table B-4 in Appendix B, optimization methods (e.g., [96], [98], [99], and [101]) and the hybrid method (e.g., [100]) have been developed to improve intersection efficiency and environmental impact. Overall, the proposed methods outperform the base cases by 2.29–60%, considering different performance indicators. Moreover, most of the studies used a single intersection with simplified traffic conditions to validate the proposed methods.

Ecology, Passenger Comfort, and Safety:

One article paid attention to three goals, namely ecology, passenger comfort, and safety in managing the traffic. Zhang et al. [102] suggested a decentralized optimal control framework to minimize fuel consumption and passenger discomfort during turning at an intersection while guaranteeing safety. The outcomes of the study [102] indicated that the proposed method is suitable for online implementation. The details of the study [102] appear in Table B-5 in Appendix B.

Efficiency, Safety, and Ecology:

This section deals with the articles that simultaneously focused on three goals: efficiency, safety, and ecology.

To optimize energy consumption and collision avoidance, Makarem and Gillet [103] developed a new decentralized navigation function for AV coordination at intersections. Compared to traffic lights, the mean energy consumption of every vehicle is decreased by 13.29–73.11%. Furthermore, compared to the existing intersection management strategies, the proposed method can improve energy consumption and maximum throughput by 24.34% and 7.33–94.40%, respectively, compared to the central controller. To enhance traffic safety, traffic efficiency, and fuel consumption at an unsignalized intersection, Kamal *et al.* [104] proposed the vehicle-intersection coordination scheme (VICS) based on the MPC framework. In contrast to a traditional signalized intersection, the proposed method improved intersection performance factors, such as stop delay of vehicles, traffic flows, fuel consumption, and intersection capacity. In addition, Hacıoğlu and Söylemez [105] proposed a new intersection model based on the multiagent reservation approach to decrease total delays and power loss and to improve accident detection by dividing the intersection into three main zones of communication. This strategy decreased the total delay time and total power loss. Moreover, to avoid collisions, improve energy loss, and cross an intersection without stopping, Tlig et al. [106] presented a synchronization-based intersection control to provide proper vehicle speed and arrival time. Considering the worst case, the average vehicle delay of the proposed method does not exceed 6 seconds. However, the average vehicle delay of the signalized intersection exceeds 20 seconds.

Additionally, a multi-objective evolutionary algorithm (MOEA) was proposed [107] to calculate safe routes for AVs in an intersection by routing vehicles in an efficient and safe manner. The method is suitable for low-volume traffic conditions, according to the simulation results. Mirheli *et al.* [108] further proposed signal-head-free intersection control logic (SICL) to find near-optimal trajectories for CAVs without any conflicts in intersections. The proposed method uses the stochastic lookahead technique to maximize intersection throughput, reduce travel time, decrease the number of stops to zero, and reduce fuel consumption. Considering different traffic situations, the proposed approach can reduce travel time by 59.4–83.7% compared to signal control methods. Malikopoulos *et al.* [109] proposed a decentralized energy-optimal control framework to minimize travel time, and energy and fuel consumption, and maximize the throughput of an unsignalized intersection with guaranteed safety. Compared to traditional traffic signal control methods, the proposed method can reduce fuel consumption and travel time by 46.6% and 30.9%, respectively.

Based on reservation policy and cost function, Bashiri *et al.* [110] introduced a centralized platoon-based controller named platoon-based autonomous intersection management (PAIM) to improve delay and its variance at the intersection. The proposed approach outperforms traffic lights in terms of delay and fuel consumption.

Medina *et al.* [111] introduced a decentralized solution, named cooperative intersection control (CIC) strategy, to decrease the number of accidents and improve the traffic at the intersection. The simulation results showed that the proposed method outperforms the traditional traffic light in terms of throughput and delay.

Bichiou and Rakha [112] proposed a new intersection management algorithm considering the nonlinear vehicle dynamic model and weather conditions. Based on the simulation results, the proposed method decreased delay, CO_2 emission, and fuel consumption by up to 80%, 40%, and 42.5%, respectively. However, the proposed algorithm may require a high computational cost to find the optimal solutions.

Philip *et al.* [113] suggested an approach based on collaboration between AVs and the road-side unit to improve intersection efficiency and decrease fuel consumption. The proposed method outperforms both conventional fixed switching and the state-of-the-art algorithm.

Xu *et al.* [114] proposed a cooperative method to optimize traffic signal and control the speed of AVs at the intersection. The simulation results indicate that the proposed method yields lower fuel consumption and trip time compared to actuated signal control when the traffic demand is between 800 and 3,200 vehicles per hour.

Bashiri and Fleming [115] proposed platoon-based approaches to manage the AVs through the intersection. The results showed that the proposed method outperforms stop sign policy in terms of average delay and travel delay variance.

Zhao *et al.* [116] presented a cooperative speed advice system, named CoDrive, to save vehicular fuel consumption at signalized intersections. Based on the simulation outcomes, fuel consumption is reduced by 7.9–38.2% compared to the GreenDrive.

As shown in Table B-6 in Appendix B, optimization (e.g., [103], [104], and [107]), rule-based (e.g., [105], [106], and [110]), and hybrid (e.g., [112]) methods have been developed to improve intersection efficiency, decrease environmental impact, and maintain traffic safety. Overall, the proposed methods outperform the base cases by 2.7–94.40%, considering different performance indicators.

Again, most of the studies used a single intersection with simplified traffic conditions to validate the proposed methods.

Efficiency, Safety, and Passenger Comfort:

As efficiency, safety, and passenger comfort play essential roles in managing traffic, in this section we review articles that simultaneously considered these goals.

Considering efficiency, passenger comfort, and collision avoidance, Krajewski *et al.* [117] proposed a decoupled and decentralized approach, which uses graph-based methods to optimize longitudinal trajectories for multiple vehicles at urban intersections. Compared to the intersection control method for human-driven vehicles and a noncooperative control approach, the proposed method can improve intersection performance.

Dai *et al.* [118] designed an autonomous intersection control (AIC) to improve the travel experience of passengers, travel time, throughput, system fairness, and safety. The authors proposed a quality-of-experience-oriented autonomous intersection control (QEOIC) algorithm to schedule vehicles and make them cross the intersection efficiently and smoothly. Moreover, by predefining the decision zone and dividing the intersection into multiple collision areas, they created a schedule rule to determine the priority of the vehicles in different collision areas, which linearized the collision constraints. They further claimed that the proposed method can be used for real-time traffic control.

In a similar vein, Mladenović *et al.*and Abbas [119] proposed a self-organizing and cooperative framework to guide vehicles across an intersection without conflict. The proposed method outperforms the regular actuated operation in terms of total delay. To decrease the waiting time of the vehicle at the intersection while avoiding collisions, Wuthishuwong *et al.* [120] introduced the virtual personal traffic signal based on V2I communication protocols and a node reservation algorithm. Compared to the existing traffic-flow model ([121] and [122]), the proposed method improves throughput with guaranteed safety.

In addition, Wang *et al.* [123] developed a novel intersection driving assistance system (IDAS) designed to deal with multiple objectives and based on V2I communication. IDAS consists of three parts: 1) passing support (PS), which provides a speed recommendation; 2) a traffic-light violation warning to inform the driver in advance about lights changing; and 3) rear-end collision warning. The results of the research indicated that the proposed IDAS can make full use of the capabilities of an infrastructure–vehicle communication system in the way that it not only maintains driving safety but also simultaneously improves passenger comfort and traffic efficiency at the intersection.

As shown in Table B-7 in Appendix B, optimization (e.g., [117], [118]), rule-based (e.g., [119], [120]), and hybrid (e.g., [123]) methods have been developed to improve intersection efficiency and environmental impact while considering traffic safety and passenger comfort. Overall, the proposed methods outperform the base cases in terms of total delay and throughput. Additionally, most of the studies used a single intersection with simplified traffic conditions to validate the proposed methods. One method (i.e., [123]) was validated by conducting a field test in a nonpublic intersection.

Efficiency, Safety, Ecology, and Passenger Comfort:

If the proposed traffic management methodology can consider all four types of goals at the same time, and create an acceptable balance between them, it might be an ideal approach to use in the future.

Ding *et al.* [124] proposed a centralized cooperative intersection control approach for unsignalized intersections, which is formulated as a nonlinear constrained programming problem. Compared to actuated intersection control, the proposed method can improve traffic flow, reduce traveling time, and improve fuel consumption by 10.49–17.61%, 88.56–95.38%, and 17.18–37.81%, respectively. In addition, it reduces CO_2 emissions by 61.13–67.6%. To improve on-time arrival probability, travel time, driver satisfaction, accident rate, fuel consumption, and emissions, a semi-decentralized multiagent-based vehicle routing approach was developed in [125], considering travel time prediction and computational efficiency. Experimental results confirmed its superior performance over existing methods ([126]–[128]) in areas such as average total travel time, fuel consumption, and air pollution. Qian *et al.* [129] proposed a decentralized MPC approach for smooth coordination of AVs at intersections to ensure collision-free travel, avoid deadlocks, and improve ecofriendly facets. Compared to MPC, the proposed method reduces fuel consumption by 4%. Furthermore, compared to the bang-bang (BB) law, energy saving is improved by 10%. To avoid collisions and increase traffic throughput, Azimi *et al.* [5] proposed spatial-temporal intersection protocols (STIP) based on V2V communication and vehicle speed optimization. The proposed method improved the throughput of the intersections up to 87.82% in comparison to traffic lights.

Zhao *et al.* [130] presented a multi-objective optimization method to coordinate the CAVs at unsignalized intersection to improve fuel consumption, traffic efficiency, and driving comfort. Simulation results showed that the proposed approach improves the efficiency, fuel consumption, and ride comfort of CAVs with low computational cost and guaranteed safety.

To decrease travel time and fuel consumption, Meng *et al.*and Cassandras [131] proposed a new approach to guide CAVs across an intersection by using traffic-light information and infrastructure-to-vehicle communication. Based on the simulation results, the proposed algorithm outperforms human-driven vehicles in terms of energy consumption and travel time.

As shown in Table B-8 in Appendix B, optimization (e.g., [124], [125], and [129]) and rule-based (e.g., [5]) methods have been developed to improve intersection efficiency and environmental impact while considering traffic safety and passenger comfort. Overall, the proposed methods outperform the base cases in terms of throughput, fuel consumption, and travel time. Most of the studies used a single intersection with simplified traffic conditions to validate the proposed methods.

Other: Data Sharing:

An extended version of AIM is presented in [132] to decrease the complexity and amount of data sharing in AIM. To avoid redundancy in transmission data, the authors designed an incremental data synchronization policy called ksync for driver agents to optimize the usage of bandwidth and reduce the amount of data transferred. Experimental evaluations indicated that the average data compression rate can improve by more than 80%. The details are shown in Table B-9 in Appendix B.

b: RESULTS OF RQ2.2

CAV technologies are likely to be progressively implemented over time, and CAVs and human-driven vehicles are likely to share the same road network. Consequently, intersection management systems with mixed traffic consisting of autonomous and human-driven vehicles have gained increased attention in recent years. Therefore, in this subquestion, we considered articles that proposed new methodologies for managing mixed traffic at intersections.

Dresner *et al.*and Stone [36] proposed a new AIM policy, called FCFS-Light, by using a multiagent approach. It uses a reservation-based system for managing AVs and traffic lights for managing human-driven vehicles to meet the needs of mixed traffic. Based on the simulation results, the proposed method outperforms traditional intersection signal control in terms of delay and safety. By extending the presented model in [36], Sharon and Stone [133] proposed a new protocol named hybrid autonomous intersection management (H-AIM) to improve intersection performance under mixed traffic conditions. This protocol used the same FCFS reservation approach for ordering vehicles as FCFS-Light. However, FCFS-Light rejects reservation requests that carry the possibility of conflict on the green trajectory, whereas H-AIM considers conflicts with active green trajectories when rejecting reservation requests. Compared to the existing method, the proposed method can improve congestion and delay once the market penetration of CAVs exceeds 10%.

Li and Zhou [134] proposed a phase-time-traffic hypernetwork approach, which considers V2I communication, to minimize total control delay. The simulation results showed that the optimal intersection automation policies can serve CAV requests at its maximum potential and maintain acceptable traffic mobility. Similarly, Lin *et al.* [135] proposed a novel coordination method for CAVs by considering information about human-driven vehicles. Compared to traditional signal control, the proposed method reduces travel delay, the number of stops, and fuel consumption by 24.2–77.1%, 99%, and 22.1–52%, respectively.

Furthermore, based on the model predictive controller and V2I communication, Liu *et al.* [136] proposed a new intersection management system to manage mixed traffic. Considering the communication between vehicles and the roadside unit, Sayin et al. [137] proposed a novel information-driven intersection control based on payment-based incentive-compatible mechanism and a Vickrey–Clarke–Grove auction. The simulation results showed that the proposed method is universal and able to handle practical situations.

Based on the controller designed by [55], Fayazi and Vahidi [138] proposed a modified MILP-based intersection controller for autonomous and human-driven vehicle traffic. The proposed method outperforms traditional signalized intersections in terms of delay.

As shown in Table B-10 in Appendix B, optimization (e.g., [134], [135], [137], and [138]), rule-based (e.g., [36] and [133]), and hybrid (e.g., [136]) methods have been developed to deal with intersection management problems in the presence of a mixture of autonomous and human-driven vehicles. Overall, the proposed methods outperform the base cases. Most of the studies used a single intersection with simplified traffic conditions to validate the proposed methods.

In summary, several of the primary studies related to RQ2 focused on a single goal (e.g., [29] and [46]). Others worked to achieve multiple goals simultaneously (e.g., [55], [96], and [102]). Fig. 5 shows the number of published articles per goal(s) by considering the categories of the methods.

3) RESULTS OF RQ3

In this section, we discuss the remaining limitations and gaps in the primary studies considering two aspects—methodology and validation environment.

From the methodological aspect, according to the results examined under RQ2, we divided the existing methodologies into four major groups: rule-based, optimization-based, hybrid, and machine learning.

First, most of the existing rule-based methods (e.g., [35], [47], [53], and [36]) have been developed to improve the efficiency and/or safety of intersections with only AV traffic or with mixed traffic. Because of their computational simplicity, rule-based methods can be applied for real-time intersection management systems and vehicle control (e.g., [47]). Moreover, rule-based methods are used to create explainable and interpretable models. Several rule-based methods have been validated by field test or real-world data (e.g., [47]). However, the complexity of the rule-based method significantly increases with the goals and constraints considered in the model. Consequently, if more goals are considered in the rule-based method, the level of improvement of the target factors decreases. Another drawback of the rule-based method is that performance may vary with traffic conditions because the rule-based method involves statistical rules and cannot guarantee the optimality of the results.

Second, optimization-based methods (e.g., [29], [55], and [102]) have been developed to handle single-goal or multiple-goal problems. Different optimization structures or searching algorithms have been developed or applied to improve computational efficiency and to find optimal

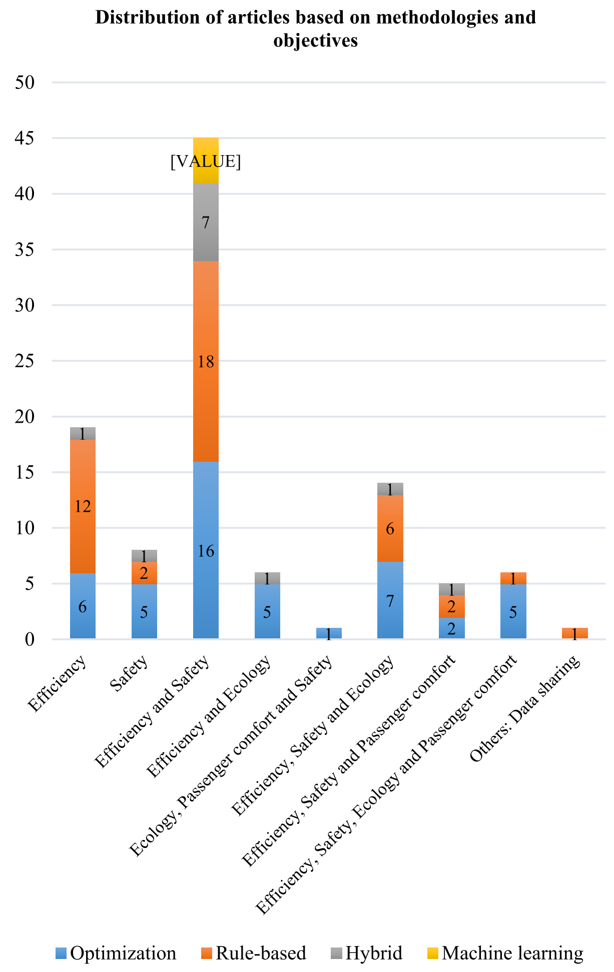


FIGURE 5. **Distribution of the published articles based on the proposed methodologies and objectives.**

solutions. The optimization-based method can easily handle multiple goals and complex conditions by changing objective functions, constraints, and searching algorithms. Optimization-based methods always search for optimal solutions for different traffic conditions. Hence, optimization-based methods guarantee optimum performance under different traffic conditions when optimality is guaranteed. Yet optimization-based methods may not always provide a global optimal solution in the time window required for intersection management. Furthermore, the computational complexity of optimization-based methods significantly increases with the traffic volume and complexity of the situation (e.g., [107]). Therefore, only a few of the existing optimization-based methods were deemed applicable for real-time control (e.g., [50], [71], [92], and [107]). The existing optimization-based methods have been validated based on simulation results.

Third, only a few studies (e.g., [46]) implemented hybrid methods to improve efficiency and safety-related intelligent intersection control problems. Hybrid methods combine both rule-based and optimization-based methods. Since hybrid methods are partially based on rules, their computational complexity is less than optimization-based methods, which leads to lower computational time for producing a solution. Meanwhile, the optimization part of hybrid methods improves their adaptivity compared to rule-based methods. Nevertheless, a different combination of rule-based and optimization-based methods may lead to significantly different performance. Thus, how to combine the rule-based method with the optimization-based method is a challenge. Another common challenge related to the existing methods is effectively balancing multiple goals and ensuring performance.

Furthermore, considering the validation environment of the proposed methodologies revealed several limitations and gaps. First, the traffic conditions considered in the validation process were too simplified to reflect real-world traffic at intersections. Several of the proposed methodologies were tested only under specific traffic conditions, with fixed traffic flow rates. However, the traffic flow rate varies with the time of day, the day of the week, weather conditions, and so on. For example, the approaches presented in [107] are more effective and efficient with low traffic volumes than with high volumes. Few methods (e.g., [51]) were validated by considering different traffic conditions and scenarios. Additionally, only balanced traffic at the intersection was considered in several works, whereas in the real world, traffic types and volumes from different directions of the intersection tend to vary.

Second, most of the vehicle characteristics and car-following behaviors were unrealistic. Deterministic vehicle characteristic (e.g., [37]) and car-following behavior parameters have been applied in existing studies, but driver-behavior parameters (e.g., time, headway, standstill distance, and so on) are stochastic for human-driven vehicles in real-world traffic. Moreover, different car producers are equipping the vehicles they produce with sensors that differ in quality, and they can use various algorithms for automatic movements. Further, the controllers for the different types of vehicles (e.g., truck, passenger car, van, and so on) with variations in size and weight may differ.

Third, most of the methods have been validated in simulation environments (e.g., [31]). Simulation platforms may not be able to present real-world situations accurately, such as geometric limitations, weather conditions, and pedestrian flow. Additionally, developing strategies for considering the limitations of V2X communication technology in simulations remains challenging.

V. DISCUSSION AND POTENTIAL RESEARCH DIRECTIONS

From the survey, we identified several potential research directions to address the limitations of the existing methods.

A. SENSING AND CONSIDERATIONS REGARDING PEDESTRIANS AND CYCLISTS

Pedestrians and cyclists should be considered in the development of intelligent intersection management strategies. AVs can identify pedestrians and cyclists in the sensing range. For signalized intersections, AVs can feed the intersection controller pedestrian and cyclist information. For unsignalized intersections, AVs should avoid conflicts with pedestrians and cyclist and improve intersection performance by exchanging the relevant information between AVs. With the development of the Internet of Things (IoT) and wearable technologies, pedestrians and cyclists are likely to be able to communicate with AVs and intersection controllers. Therefore, an advanced control method must be developed to coordinate AVs, pedestrians, and cyclists in the intersection.

B. LEARNING CONTROL RULES AND PREDICTING TRAFFIC CONDITIONS

The AI method can be applied to improve the smartness of intersection management systems. Additionally, multiple goals should be balanced by the intersection controller under dynamic traffic conditions. Additionally, the controller should be able to control real-time traffic. Hence, based on historical data and supervised learning, we can possibly improve the dynamic rules while considering real-time traffic conditions and balancing different goals. Furthermore, AI has been widely applied [139] to predict traffic conditions based on historical data. Therefore, it can help the controller to generate proper control plans a step ahead of the requirements of the traffic situation to improve traffic management at the intersection.

C. STANDARDIZING DATA COLLECTION

Based on our findings, more studies are required to address the challenges arising from the data aspect. In the extant studies, AVs collected and shared various data, such as vehicle size, position, destination, speed, acceleration/deceleration, and so forth. The summary of the most popular types of data collected is shown in Fig. 6. We suggest that the type of data collected by AVs should be standardized. Likewise, to decrease communication delays, it would be helpful to share only the primary and required data for decision making. For example, by accessing the current speed and location of vehicles, it is possible to calculate their arrival time. This will reduce the data transmission rate and delays, which is critical for real-time management at intersections.

D. IMPROVING COMMUNICATION AND DATA QUALITY

The other matter related to data is caused by communication and data quality problems, for example, communication delays and failures, security, package loss and duplication, bandwidth limitations, low-quality data, and the effect of inclement weather on the data collecting process. Solving these problems is critical for the safety and efficiency of traffic management. For example, the approach presented in [59] will experience a crossing delay in the case of highly correlated failures. The communication network may also cause problems because of a limited communication range. For example, the communication range is set as 500 m in [59], and the experiments showed that by increasing the distance to the intersection, the packet delivery ratio decreases. Similarly, this study [118] shows that by increasing the packet loss, the throughput is decreased and the standard deviation of travel time (SDTT) is increased at the intersection.

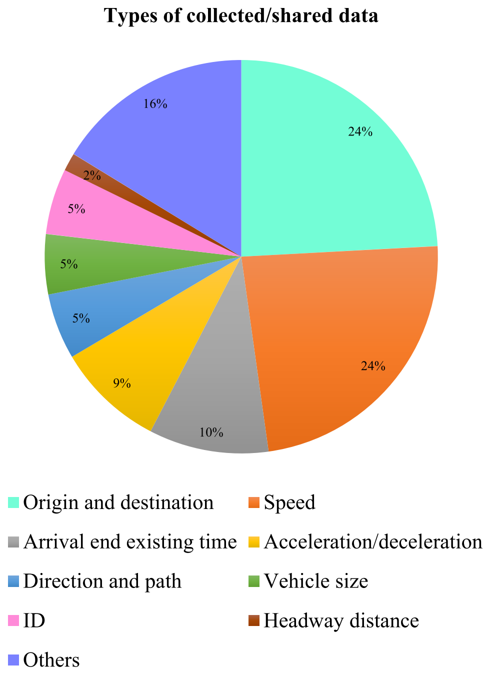


FIGURE 6. **Distribution of the data type.**

E. LOCAL VS. GLOBAL DATA SHARING

The data sharing method is another major factor to consider. Data may be shared locally, for example, only for decision making inside one vehicle or one intersection, or globally between more intersections. This leads to two connected questions: Which approach is more efficient, and what is the effect of the environment in choosing an approach?

Different types of communication exist between vehicles and intersections, which is called V2X. By using V2I communication, data are transferred from vehicles to the infrastructure. Vehicles are responsible for sensing and collecting data and sending this data to the infrastructure. In I2V communication, data are transferred from infrastructures to vehicles. The infrastructure is responsible for sensing and collecting data and processing this data to make a decision for traffic control. V2V communication assumes that there is no central controller, and vehicles are responsible for managing traffic by sensing, collecting, and processing data. The other communication method is a combination of V2I and I2V.

By using all types of communications and accessing the most relevant data, traffic might be managed more precisely. V2V and V2I communication could be continued or discrete. In continued communication, sharing data is possible all the time. In discrete communication, sharing data happens in specifies time slots. To improve efficiency by decreasing data transfer, we suggest sharing data only if some changes occur in the shared data that may improve the performance of data sharing for better traffic management at the intersection.

F. DATA SHARING IN MIXED TRAFFIC

The other research question that could be considered is how can we collect data related to mixed traffic? If the traffic is pure AVs, then AVs are responsible for sharing their data (e.g., [47]). The other idea that is proposed in [98] is that AVs are responsible for providing data about themselves and the surrounding road users. However, these approaches are not considered for mixed traffic, which is a possible condition we might face in the near future. One idea for collecting data in mixed traffic is equipping intersections and streets with roadside sensors, for example, connected vehicle center (CVC) systems and other roadside units responsible for observing vehicle movements (e.g., [135]). However, equipping all intersections with these kinds of devices is costly, and this approach may not be efficient in all weather situations and road conditions, such as the presence of heavy snow on the road or darkness at night.

In [36] and [133], the authors proposed combining light rules with FCFS policy. In those studies, AVs followed the reservation approach, and human-driven vehicles passed through the intersection based on traffic-light rules. Thus, using that approach, AVs could pass through an intersection based on a reservation in the red light, which may be confusing for drivers and other road users such as cyclist and pedestrians. The authors of [134] suggested using data collected from AVs to improve traffic signal timing. Although this is efficient with a low ratio of CAVs (less than 10%), it is not efficient with a higher rate of CAV because ''green light ahead'' requests are rejected. Although various methodologies have been proposed for managing mixed traffic at intersections, they were not suitable for the real world. A potential solution is using AVs to collect data and sharing the collected data with the intersection manager to control human-driven vehicle traffic by using a dynamic traffic light at the intersection.

G. DISTRIBUTED PROCESSING OF DATA

Where to process the abundant data generated by AVs is a crucial aspect of intelligent intersection management. In existing works, the data is generally processed by either the intersection controller or AV (e.g., [140], [51], and [32]). Considering the computational limitations of intersection controllers and AVs in handling large volumes of data, different computation technologies, such as Cloud, Fog, and distributed computation, should be applied to improve the performance of intersection controllers.

H. ENSURING THE PERFORMANCE OF DATA PROCESSING

It is important to estimate the performance of proposed methods in a realistic validation environment. Ideally, these methods should be applied to control real-world traffic. Due to safety reasons, several studies (e.g., [34] and [37]) have been validated using an isolated intersection with only experimental vehicles. With the development of sensing technology, IoT, big data, digital twin technology, and AI have been gradually introduced to mitigate unpredictable and undesirable emergent behavior in complex systems. In other words, digital twin technology can provide a digital copy of real-world intersections and traffic that can be used to test proposed methods without negative consequences. Additionally, stochastic human-driver behavior should be considered instead of using predetermined parameters in car-following models. Additionally, different vehicle types, such as buses, trucks, and passenger vehicles, should be considered to reflect real-world traffic in the simulation.

VI. THREATS TO VALIDITY

In this section, we discuss the possible threats to validity of our SLR.

A. SEARCH STRATEGY

The search strategy included selecting digital libraries and searching for predefined keywords. This step may face threats from some factors such as missing or excluding relevant articles. To mitigate this risk, we used three strategies. First, to increase the possibility of finding the relevant articles, we searched the seven digital libraries most relevant to our scope. Second, we included synonyms for the search to cover the possible keywords used by various authors. To achieve this, the first author was responsible for performing a primary search to extract and list the synonyms used by different authors for the selected keywords. The second author improved the coverage of the synonyms, and the third author validated this step by considering the predefined research questions and review scope. Third, we searched using different strings by creating various combinations of the selected keywords and synonyms. We did not apply the snowballing process because the first step of our search yielded 2,952 papers, which we believe covered most of the papers relevant to our scope.

B. STUDY SELECTION CRITERIA AND PROCEDURE

Choosing articles to include and discarding others also constitutes a threat to validity, as this can result in omitting relevant articles or including irrelevant articles. To minimize this threat, we predefined the inclusion and exclusion criteria, with all authors contributing to the validation of these criteria. We subsequently strictly adhered to these criteria during the paper selection process. For example, we included papers if the proposed methodology is based on V2I or V2V communication between road users, but we excluded studies involving vehicles that make an individual decision without any communication.

C. DATA EXTRACTION STRATEGY

In this step, threats arise from the potential for incomplete information extraction from the selected articles to answer the SLR questions. To mitigate this threat, after the first author listed the data categories to extract, the second and third authors confirmed the coverage of the data categories in terms of answering the research questions. All authors discussed the categories to finalize the list, and then the first and second authors extracted the data from the selected papers. To decrease bias in the first round, the third author checked and verified the extracted data.

D. DATA SYNTHESIS STRATEGY

To decrease the risk of researcher bias during the interpreting process, we strictly followed the thematic synthesis steps. The first and second authors synthesized the extracted data, and then all the authors discussed the data to validate it.

VII. CONCLUSION AND FUTURE WORK

We performed an SLR to study intelligent intersection management systems considering AVs and mixed traffic. We searched seven digital libraries for papers published from January 2008 to May 10, 2019. The initial search yielded 2,952 papers, which we reduced to 105 primary studies by excluding irrelevant candidates. Compared to the surveys published in 2016 [18], [19] and early 2019 [20], in this systematic literature review, we included more articles that were published recently. We included 27, 22, and 10 more articles published in 2017, 2018, and 2019, as shown in Fig. 2. Based on the data we extracted, we observed the following:

1) In the selected articles, 40% used rule-based methodologies, 44.76% optimization methodologies, and 11.43% hybrid methodologies. Only 3.8% of the selected papers used ML approaches. We analyzed and summarized the performance of the proposed methodologies in terms of efficiency, safety, ecology, and passenger comfort. We propose that AI-based traffic management systems may reduce some of the challenges mentioned by improving the data collection process, learning traffic features and human behaviors, predicting traffic features, and making more efficient traffic-management decisions.

2) Researchers used simulators, mathematics, numerical tests, and other tools to validate the concepts they proposed in 92.38% of the selected papers, whereas 7.62% used toy cars, real cars, or field tests. Because vehicle manufacturers install diverse types of sensors with different features and quality to collect data, the proposed methodologies should be evaluated more thoroughly to deal with sensor variation.

3) The data show that 93.33% of studies focused on pure AVs, whereas the reality in the near future will be a mixture of AVs, human-driven vehicles, pedestrians, and cyclists. Therefore, a possible research direction is using the features of AVs to collect environmental data in mixed traffic to improve the performance of traffic management systems.

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