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SURVEY

State-of-the-Art Review on Traffic Control Strategies for Emergency Vehicles

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ABSTRACT Emergency vehicles (EVs) play an essential role in emergency services. One of the most intuitive indicators of the emergency service process is the response time of EVs. This survey reviews the latest traffic control strategies to reduce response time during EV's traveling. Firstly, it classifies traffic control strategies into route optimization, signal preemption, lane reservation, and mixed traffic control strategies. Then, a systematic literature review of traffic control strategies with different algorithms is presented. Besides, this survey classifies the articles by objective metrics. In addition to response time, several other objective metrics are summarized. Finally, this survey reviews the limitations of existing emergency traffic control strategies and critically analyzes them. Based on this, it indicates the core problems and proposes potential research areas to be explored.

INDEX TERMS Emergency vehicles, traffic control, route optimization, traffic signal preemption, lane reservation.

I. INTRODUCTION

Emergency vehicles (EVs), including ambulances, fire trucks, police cars, and engineering rescue vehicles, play a critical role in timely emergency service delivery. According to the World Health Organization, more than 5 million people die yearly due to delayed trauma treatment. The mortality rate can be reduced by about 10% if emergency resuscitation is timely [1]. The response time of an EV represents the time required to travel from the starting point to the location of an emergency event. Current strategies to improve emergency response speed and reduce emergency response times fall into facility enhancement and traffic control. The former refers to increasing emergency service resources, such as purchasing more ambulances or building wider roads while the latter improves the utilization and efficiency of existing facilities, thereby reducing emergency response time. This survey focuses on traffic control strategies.

In the traffic control strategy, the response time of EVs depends on several static parameters, such as the rescue distance and the number of intersection signals on the route, and dynamic parameters, such as traffic flow and the average speed. Such parameters make it complex and challenging to reduce EV response time [2]. With the rise of the internet of vehicles (IOV), connected autonomous vehicles, and big data technology in recent years, several new trends have emerged in the traffic control field [3], [4], [5], [6]. The traffic emergency response involved in EVs has become a hot topic nowadays. The emergency response problem differs from the vehicle routing problem (VRP). VRP aims to achieve the comprehensive benefit of all participants by optimizing vehicle task allocation and route [7], [8]. In contrast, the critical objective of the emergency response problem is to reduce EV response time by optimizing EV routing, preempting signals, and removing regular vehicles.

There are some literature reviews of emergency traffic control strategies. Aringhieri et al. review the planning issues of the urgent care process and its relationship to related management and organizational problems from the patient's perspective [9]. Reuter-Oppermann et al. comprehensively describe the management issues that arise in the emergency medical services process, focusing on the dependencies between the

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planning issues and the level of planning [10]. However, both reviews do not provide a systematic classification and summary of the problems of EVs in road traffic control. Weibull et al. study risk factors that cause accidents during EV traveling and focus on investigating traffic control strategies for vehicles in cooperative intelligent transportation systems to avoid traffic accidents of EVs [11]. However, in this study, most traffic strategies are aimed at preventing accidents with EVs, and investigating methods to shorten EVs' response time is inadequate. Lee et al. aim to analyze EV response time in fatal traffic accidents and explore the factors that influence them [12]. This review shows that EV response time are related to accidents, road, environment, and socioeconomic factors. However, this review is insufficient to investigate emergency traffic control strategies. Some researchers have deeply discussed this problem and proposed solutions from different perspectives. Humagain et al. classify strategies for reducing EV response time into route optimization and preemption and provide a systematic review of both strategies [2]. Kamble and Kounte investigate different preemption strategies and analyze the gaps that have not been effectively addressed in the existing literature [13]. The survey classifies EV preemption models into three main categories: routing-based, scheduling-based, and miscellaneous strategies. In contrast to existing work, this study reviews the state-of-the-art solutions for traffic control, as shown in Fig. 1. We classify traffic control strategies into three categories according to the controlled objects: route optimization, signal preemption, and lane reservation.

1) Route optimization refers to the EVs dynamically selecting the best route during their driving to obtain the shortest response time.

2) Signal preemption, also known as "traffic signal priority," gives priority to special vehicles such as EVs by adjusting traffic lights.

3) Lane reservation usually refers to the advance evacuation of traffic along an emergency route. Specifically, regular vehicles are guided away while preventing regular vehicles from entering the way of the EV.

The primary research question of our literature review is: "What traffic control strategies are available in academia and industry that can effectively reduce the response time of EVs?" To make the literature as diverse and informative as possible, we search in the academic search engine Google Scholar, the leading international academic publishers IEEE, Science Direct, Springer, Hindawi, and the professional social network ResearchGate. We search for existing works using keywords such as route optimization, signal preemption, lane reservation, road pre-clearance, emergency vehicles, and traffic control. The purpose of the literature review is to collect traffic control strategies for EVs during their traveling, which can effectively reduce their response time. Therefore, we have selected 81 articles for a detailed review. Among them, 27 papers propose route optimization for EVs, 35 papers report techniques for signal preemption, and 12 papers propose lane reservation and road pre-clearance for regular vehicles. The remaining seven articles present hybrid traffic control strategies.

Fig. 2 carefully classifies the emergency traffic control strategies regarding the objects to be controlled and objective metrics, respectively. For the former, the traffic control strategies are divided into route optimization for EVs, traffic signal preemption, lane reservation for regular vehicles, and mixed traffic control strategies. Subsequently, we further divide the traffic control strategies according to the type of algorithms. Regarding objective metrics, the core of all traffic control strategies is the fast response to emergency services and timely arrival at the incident scene. However, it is not enough to focus only on the response time of EVs. Therefore, we further study the objective metrics of the research articles, such as the cost of EVs, the negative impact on regular vehicles, and the robustness of emergency routes. The main contributions of the survey are summarized as follows:

1) The main objective of this survey is to review currently proposed solutions to reduce EV response time. It examines 81 research articles, of which about 84% are from 2017 to 2022, to ensure the real-time performance of this study.

2) Traffic control strategies can be broadly classified into route optimization, signal preemption, lane reservation, and mixed traffic control strategies. Subsequently, we further divide their traffic control strategies according to the type of algorithms and comprehensively review the advantages and limitations of these strategies.

3) Additionally, objective metrics referred to by the studies are classified for comparison and analysis.

4) Finally, the pending problems and challenges in reducing EV response time are discussed, which provides necessary guidance for future research in the field of emergency traffic control.

We examine the latest route optimization and preemption techniques in Sections II and III. Section IV presents the existing strategies for lane reservation, and Section V reviews a combination of these strategies. Section VI presents the objective metrics of the above research articles. In Section VII we discuss the current challenges and future research directions. The conclusion is shown in Section VIII.

II. ROUTE OPTIMIZATION

Traditional route planning, such as the Dijkstra's algorithm [14] and A* algorithm [15], finds the optimal route according to the weighted road network. However, the dynamic nature of traffic often makes a previously planned route no longer optimal. Therefore, it is crucial to dynamically change the route according to the real-time traffic conditions in the vehicle's driving. The route optimization strategy can dynamically realize the selection of the optimal route under the preconditions and constraints. Therefore, route optimization is also regarded as dynamic route planning.

The algorithms for route optimization are divided into the following categories: 1) Traditional optimization algorithms, such as greedy algorithms, local search algorithms, and neighborhood search techniques; 2) Intelligent optimization

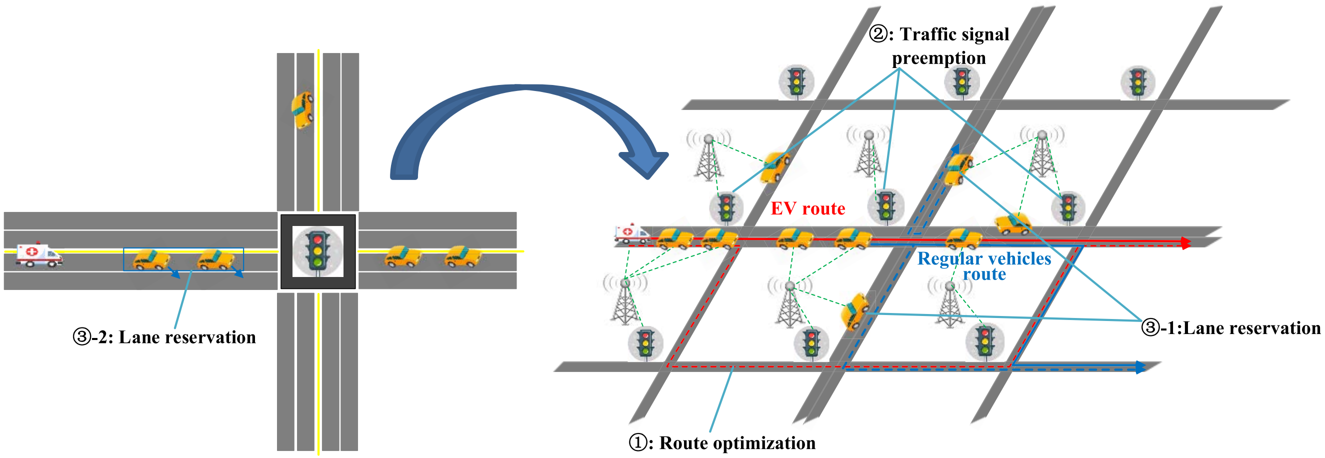

FIGURE 1. Strategies for reducing EV response time.

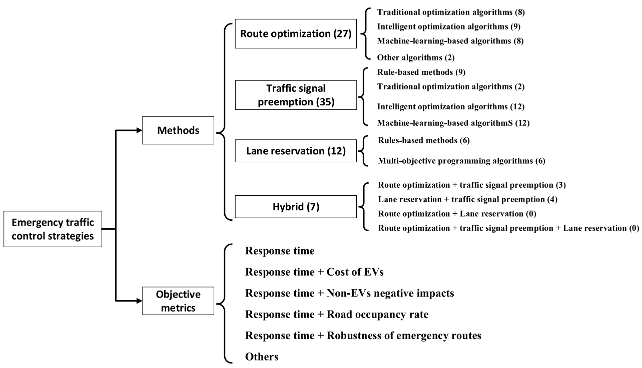

FIGURE 2. Structure of this review.

algorithms including the ant colony algorithm, genetic algorithm, particle swarm optimization algorithm; 3) Machine-learning-based algorithms such as reinforcement learning, deep convolutional neural networks, and Markov decision-making models; 4) Other specific algorithms such as the branch and bound algorithm, dynamic programming method, and approximation algorithm. Table 1 compares the route optimization strategies used to reduce EV response time, including the type of algorithms, the technique or specific algorithms, the stochastic characteristic, and the evaluation.

A. TRADITIONAL OPTIMIZATION ALGORITHMS

Traditional optimization algorithms are generally designed for structured problems with more explicit constraints. In terms of route selection, Rosita et al. propose a multi-objective decision-making method combining the vector normalization technique and the Dijkstra's algorithm [16]. The optimal route is selected by assigning different decision priorities to various parameters, such as cost, distance, congestion, and risk. Yang et al. map a road network with spatio-temporal characteristics into a dynamic road network graph that changes over time and ranks all grids according to the real-time capacity of the road network [17]. Based on this, a search algorithm based on contextual grids is proposed. This algorithm is used to plan the vehicle route by considering the road network's changing factors.

Vehicle resource consumption also needs to be considered. Guo et al. improve the traditional Dijkstra's algorithm for route planning and establish an economical and environmentally friendly vehicle route planning method. This method uses the dynamic traffic network to reduce fuel consumption and emissions during vehicle running [18]. Liu et al. construct a three-dimensional velocity-time network model for describing the state information of vehicles in space and time based on real-time road traffic flow, traffic lights, and vehicle statuses, such as the driving speed and direction [19]. The model uses a novel energy-efficient dynamic route planning method for connecting self-driving vehicles to minimize routes' time and energy consumption by mixed-integer linear programming.

When a large-scale disaster occurs, in addition to planning emergency rescue routes, planning emergency evacuation routes is also an essential part of the emergency response process, and both rescue and evacuation routes' planning need to be performed simultaneously. Chen et al. propose a new bi-directional route planning method for emergency rescue and evacuation, considering intelligent obstacle avoidance [20]. A dynamic grid approach refreshes the road network environment in real time. The Dijkstra's algorithm is used to calculate the bidirectional route model of linear programming, and the optimal evacuation and rescue route is estimated while avoiding potential conflicts. Liu et al. study a two-way traffic organization problem of rescue and evacuation under different rescue entrance opening schemes [21]. A two-stage optimization method for evacuation rescue traffic organization is proposed by using mixed-integer linear programming models.

A single objective model is often not feasible. As a result, Zhao et al. construct a mixed integer linear programming model for constrained multi-objective route optimization based on rescue response time, road reliability, and

TABLE 1. Comparisons of EV route optimization strategy.

Types	References	Solution Methods	Randomness	Practicality
Traditional optimization algorithms	Rosita *et al*. [16]	Dijkstra's algorithm, Vector normalized technique, Multiple-criteria decision-making	Deterministic	Simulation environment
	Yang *et al*. [17]	Dynamic grid PageRank, Situational grid heuristic search algorithm, Pruning strategy based on time characteristics, Road network acceleration algorithm	Stochastic	Real-world test data
	Guo *et al*. [18]	Improved Dijkstra's algorithm	Deterministic	Real-world test data
	Liu *et al*. [19]	Velocity-space-time three-dimensional network, Dynamic route planning algorithm	Deterministic	Simulation environment
	Chen *et al*. [20]	Dynamic grid method, Two-way route planning of emergency rescue and emergency evacuation, Intelligent obstacle avoidance model	Deterministic	Simulation environment
	Liu *et al*. [21]	Two-staged optimization method for evacuation and rescue traffic organization	Stochastic	Simulation environment
	Zhao *et al*. [22], Wang and Liang [23]	Depth-first search, Nondominated sorting	Deterministic	Simulation environment
Intelligent optimization algorithms	Zhao *et al*. [24]	The *K*-paths algorithm, Shuffled frog leaping algorithm	Stochastic	Real-world test data
	Jose and Grace [25]	The *K*-paths algorithm, Exponential bird swarm optimization algorithm	Stochastic	Simulation environment
	Mouhcine *et al*. [26]	Ant colony optimization algorithm	Stochastic	Theoretical analysis
	Wu *et al*. [27]	Particle swarm algorithm, Ant colony algorithm	Stochastic	Real-world test data
	Rout *et al*. [28]	Fuzzy logic, Open-source routing machine	Stochastic	Simulation environment
	Constantinescu and Patrascu [29]	Genetic algorithm, Distributed architecture	Stochastic	Simulation environment
	Hu *et al*. [31]	Co-evolutionary path optimization, Ripple spreading algorithm	Stochastic	Simulation environment
	Wen *et al*. [32]	Timing co-evolutionary path optimization, Improved ripple spreading algorithm	Stochastic	Simulation environment
	Wen *et al*. [33]	Co-evolutionary optimization algorithm, Ripple spreading algorithm, Dijkstra's algorithm	Stochastic	Simulation environment
Machine-learning-based algorithms	Liu *et al*. [34]	A* algorithm, Reinforcement learning	Stochastic	Simulation environment
	Koh *et al*. [35]	Deep reinforcement learning	Stochastic	Simulation environment
	Yan *et al*. [36]	Markov decision process, Prioritized experience replay deep Q-network	Stochastic	Simulation environment
	Li *et al*. [37]	Long-short-term memory neural network, Value iteration network, Markov decision process	Stochastic	Real-world test data
	Yang *et al*. [38]	A hybrid cuckoo search algorithm, BP neural network model, Edge computing	Stochastic	Simulation environment
	Li *et al*. [39]	Optimized Regularization	Stochastic	Real-world test data
	Lin *et al*. [40]	Social clustering method, Game evolution, Social vehicle route selection	Stochastic	Real-world test data
	Lin *et al*. [41]	Distributed deep learning, Long-short-term memory neural network, Vehicle routing decision	Stochastic	Simulation environment
Other algorithms	Andelmin and Bartolini [42]	K-path cuts, Cut-and-column generation algorithm	Deterministic	Simulation environment
	Elalouf [43]	Exact pseudo-polynomial algorithm	Stochastic	Simulation environment

intersection safety indicators [22]. They use a multi-objective optimization algorithm. The algorithm relies on depth search and non-dominated sorting to obtain the optimal set of solutions for the optimal rescue route. It selects the optimal rescue route from the perspective of multiple optimization objectives. According to the transportation cost and transportation risk of hazardous materials, Wang and Liang propose a new algorithm by combining the depth-first algorithm with fast non-dominated sorting [23]. This algorithm obtains the Pareto-undominated solution set between two random points in the road network through the mixed integer linear programming model, which can be used by decision-makers to choose traffic routes according to their preferences.

B. INTELLIGENT OPTIMIZATION ALGORITHMS

Traditional optimization algorithms fail to solve route optimization accurately within a limited time. Therefore, intelligent optimization algorithms have emerged, seeking a balance between the solving time and accuracy. Zhao et al. propose a two-stage shortest route algorithm consisting of a K-paths algorithm and a shuffle frog-jumping algorithm [24]. The K shortest paths for EVs are calculated by predicting the road travel time. The optimal route is obtained with the goal of the shortest travel time and minor traffic congestion. For the same problem, Jose and Grace incorporate the concept of exponentially weighted moving average into a bird swarm algorithm and propose a hybrid exponential bird swarm optimization algorithm [25]. The algorithm selects the optimal path for EVs from the K shortest paths.

For the EV route planning, Mouhcine et al. propose a novel distributed system based on an ant colony optimization algorithm to help EVs obtain the optimal route [26]. The proposed method generates dynamic EV routes based on speed limits, traffic congestion, and road conditions to compute alternative routes to guide the vehicles. To cope with the impact of temporary road blockage on traffic flow and to better adjust EVs' dynamic routes, Wu et al. propose a dynamic route planning method for congested traffic based on an improved ant colony algorithm [27]. The algorithm combines particle swarm and ant colony algorithms to make it more suitable for dynamic route planning on congested roads by quantifying attributes such as urban road length, lanes, and incoming and outgoing traffic flow. Rout et al. propose a fuzzy logic-based decision support system for estimating congestion at a specific location on the road network and assisting an open-source routing machine server to generate the shortest and congestion-aware route [28]. Constantinescu and Patrascu find a route for EVs based on a genetic algorithm that minimizes road occupancy and dynamically adjusts the optimal route during the journey [29].

EVs' dynamic route planning problem is usually constrained by time efficiency, resource requirement, and road network reliability. Based on the phenomenon of natural ripple propagation, Hu et al. propose a novel ripple propagation algorithm (RSA) for route optimization [30]. Hu et al. propose a co-evolutionary route optimization method for vehicle route optimization in a dynamic routing environment [31]. Wen et al. propose a time-series co-evolutionary route optimization algorithm [32]. This algorithm has strong robustness without loss of efficiency. In addition, considering the dynamic nature of urban roads, an improved RSA is used for emergency rescue route planning. Subsequently, Wen et al. further investigate dynamic vehicle route planning and propose a co-evolutionary algorithm to solve the route planning problem for emergency rescue [33], where the optimal route is calculated using the Dijkstra's algorithm and RSA. The optimal route is periodically optimized as the dynamic traffic environment changes.

C. MACHINE-LEARNING-BASED ALGORITHMS

Machine learning continuously improves performance by acquiring new knowledge or skills and reorganizing existing knowledge structures. Since the A* algorithm does not apply to dynamic networks, Liu et al. design a hybrid algorithm based on the reinforcement learning strategy of prior knowledge and the A* algorithm of search optimization to help intelligent driving vehicles choose the optimal path in traffic networks in emergencies [34]. This algorithm can help intelligent vehicles dynamically plan optimal traffic routes under constraints such as accidents and congestion. For optimal solutions in complex urban environments, Koh et al. propose a new deep reinforcement learning-based vehicle route optimization method for finding the best route for vehicles to reach their destinations and avoid congestion in complex urban traffic networks [35]. For a similar problem mentioned above, Yan et al. develop a refined rescue route planning environment based on the Markov decision process for congested urban arterial roads [36]. A value-based deep reinforcement learning algorithm is used to plan EVs' routes in this environment, aiming to reach the accident scene in the shortest time and reduce the length of road vehicle queues in the road network.

Combining machine learning with intelligent transportation systems has recently been a trend. Li et al. propose a dual reward value iterative network for traffic flow prediction to plan time-saving routes [37]. It uses a long and short-term memory network to predict short-term traffic states and construct a dual reward value iterative network for route generation to learn the routing behavior of experienced drivers based on current and future traffic conditions. Yang et al. propose a hybrid cuckoo search algorithm based on K optimal routes to optimize the weights and thresholds of a back propagation neural network model to determine the optimal routes in dynamic road networks [38]. Li et al. focus on the ambulance driving environment during the rescue process and propose a framework based on optimal regularization [39]. Specifically, by extracting road features and surrounding environmental conditions, the algorithm establishes a regularized linear loss function to optimize rescue route selection. Lin et al. combine social clustering with game evolution and propose a social vehicle route selection algorithm to optimize vehicle routes [40]. Combining multi- intelligent deep reinforcement learning, Lin et al. propose a distributed learning-based vehicle route decision algorithm for online adaptive adjustment of vehicle routes [41].

D. OTHER ALGORITHMS

In addition to the above three algorithms, Andelmin and Bartolini develop an exact algorithm for the green vehicle routing problem based on an ensemble partitioning formulation strengthened by subset row inequalities and K- path cuts [42]. In addition, Elalouf uses an exact pseudo-polynomial algorithm to find the best time-dependent route under uncertain traffic conditions using real-time data [43]. The algorithm uses dynamic programming to decompose complex problems into simple subproblems. Finally, they improve the solution using an ε-approximation algorithm by restricting the results to allowable lower and upper bounds of the cost function.

III. SIGNAL PREEMPTION

Traffic signals and other infrastructure are essential parts of intelligent transportation systems. In recent years, with the explosive growth of vehicles, proper optimization of signal phases has played a crucial role in relieving traffic pressure to ensure smooth traffic flow. In particular, EVs can effectively shorten the delay of vehicles reaching their destinations by reasonably preempting the phase of traffic signals.

Traffic signal preemption strategies are classified into the following categories: 1) rule-based methods, 2) traditional optimization algorithms, including quadratic programming and multi-objective programming, 3) intelligent optimization algorithms such as the genetic algorithm, artificial bee colony algorithms, and fuzzy logic-based control algorithms and 4) machine-learning-based algorithms such as reinforcement learning, deep convolutional neural networks, deep reinforcement learning models, multi-agent models, and combinatorial models.

A. RULE-BASED METHODS

The frequently-used method of traffic light control is to design priority reasonably for traffic flow from different directions. Asaduzzaman and Vidyasankar propose a priority-based signal control method [44]. The algorithm uses signal priority techniques to adjust the signal phases for EVs. More importantly, the algorithm reduces the delay impact on regular vehicles due to signal preemption by EVs. Considering the vehicles in conflicting directions, Ma et al. suggest assigning different priorities to these vehicles [45]. A priority signal control model for multiple requests is introduced to generate the optimal service order. Radiofrequency identification (RFID) technology can be used for image processing and solve many traffic control problems. Therefore, Sharma et al. propose a new method using RFID to realize the traffic light control system with priority for EVs [46]. The method is simulated in real-time and achieves good results in a multi-lane and multi-vehicle scenario.

EVs always have priority over regular vehicles when crossing signalized intersections. Younes and Boukerche propose a dynamic and efficient signal scheduling algorithm [47]. They use the real-time traffic distribution and dynamically adjust the green light phase to make EVs pass the intersection. To avoid delays of EVs at intersections due to traffic congestion, Ren et al. propose an adaptive signal control method to prevent potential intersection blockage [48]. The method relies on realistic and feasible vehicle speed measurements to adaptively allocate the signal phases. Most previous studies have used control of traffic light signals for centralized management. However, optimization methods for traffic light signal control based on traffic flow conditions also have some practicality. Younis and Moayeri propose dynamically collecting road conditions through devices deployed at the roadside and propose a novel distributed algorithm to decide when to switch traffic lights to alleviate congestion [49].

Some methods are proposed to obtain real-time traffic information in the IOV to ensure EVs cross intersections smoothly. Noori et al. propose a novel traffic signal control model and use a networked vehicle infrastructure to reduce the response time of EVs [50]. It changes the state of the signal before the arrival of an EV to provide a green phase for the EV. The application of wireless sensor networks (WSN) has proved beneficial in designing adaptive dynamic traffic light systems. Goel et al. use a WSN to implement an intelligent dynamic signal control system for the EV priority [51]. The system minimizes the waiting time of vehicles and adaptively manages traffic load at intersections. To solve congestion in Indian cities, Abishek et al. control and optimize the duration of the green light and the number of vehicles passing the intersection within a given time interval with a WSN-based solution [52].

B. TRADITIONAL OPTIMIZATION ALGORITHMS

Traditional optimization algorithms build programming models to simulate the traffic light preemption to ensure the EVs pass the intersection. Yao et al. propose a coordinated control model and design traffic signals with a two-level programming method [53]. The work considers different priorities for various EVs. Mu et al. propose a path-based signal preemption control method to reduce the time delay of EVs at intersections [54]. According to detecting the current traffic lights at the EV route intersections, they get the earliest start time and the latest start time of each green light. The signal preemption method reduces the EV delay. The number of passing regular vehicles through the whole system is increased, and the vacuuming efficiency of the system is improved.

C. INTELLIGENT OPTIMIZATION ALGORITHMS

Compared with traditional optimization methods, intelligent optimization algorithms have strong adaptability to the uncertainty of the calculating data. Therefore, many scholars use intelligent optimization algorithms for traffic light control. Marcianò et al. utilize a genetic algorithm to develop a signal setting model and a dynamic path selection model. They set up the signals by using the behavioral rules of various users. The signal setting model dramatically reduces the total delay and vacuuming time on the network. The complexity problem is also an issue worth to be studied in traffic light scheduling [55]. Gao et al. propose an improved artificial bee colony algorithm to solve the urban traffic signal scheduling problem. The algorithm overcomes the potentially high computational complexity [56].

Most studies on traffic signal control have ignored the effect of right-turning vehicles. Therefore, it is necessary to establish a traffic flow model to prevent queue overflow. Bi et al. propose a type-2 fuzzy coordination method to allocate the green time of traffic lights [57]. This work uses a gravity search algorithm to achieve optimization alternately to avoid queue overflow in traffic models. In addition, Collotta et al. propose a new method to manage the isolated traffic light phase dynamically [58]. They use parallel fuzzy controllers to determine the duration of the green signal in four stages. Shelke et al. also use fuzzy logic to dynamically assess road sections' priority [59]. The method uses sensor nodes to monitor traffic information and transmits it to the traffic management center. Fuzzy logic is applied to traffic light control. Miletić et al. compare the performance of the rule based on fuzzy logic with that based on vehicle tracking arrival time and queue length [60], [61]. They find that the former is more adaptable and has better performance. Besides fuzzy logic, Qin and Khan adopt a two-phase algorithm [62]. The algorithm comprises a relaxation method and a step-up search strategy for EV signal preemption control strategies. This work overcomes the difficulty in solving the optimal control model and minimizes the impact of the EV operation in general traffic.

Because of its advantages in describing dynamic systems with concurrency and asynchrony, Petri nets (PNs) are compatible with traffic control characteristics and can reflect the traffic signal control logic. Therefore, PNs have been used to design EV signal preemption by many scholars. Huang et al. use timed Petri nets (TPNs) to simulate the preemption of the EV system and propose an EV preemption strategy to ensure that EVs can move through intersections with less delay [63]. Mu et al. use the preemption control problem of EVs by using the timed colored PNs to make an efficient and safe operating environment for EVs [64]. Qi et al. design a two-stage strategy in signal intersection [65]. The first level is the prohibited signal strategy, and the second is the warning strategy. They use TPN to design a smart traffic light control system to prevent traffic congestion on urban roads caused by accidents. Further, Qi et al. propose a re-routing model based on PN, in which traffic signal controller and dynamic message sign are considered [66]. The model can help vehicles pass crowded intersections without stopping or changing routes.

D. MACHINE-LEARNING-BASED ALGORITHMS

In recent years, machine learning and reinforcement learning relevant technologies have been successfully applied in computer vision, speed recognition, and natural language processing. Therefore, many scholars attempt to use them in intelligent transportation systems, especially traffic signals. Wei et al. investigate recent reinforcement learning-based methods for traffic signal control and present some interesting real-life case studies [67]. Inspired by the current research on reinforcement learning, Guo et al. propose a reinforcement learning method using Q-network as an approximator [68]. They design intelligent traffic signals to manage real-time and high-dimensional traffic information. The technique has significant convergence and generalization performance, and the model can reduce vehicles' queue length and waiting time at intersections.

Delays of EVs at intersections have been a matter of interest. With the development of machine learning techniques, deep neural networks are the primary focus method for solving such traffic problems. Building on recent advances in deep neural networks, Mnih develops a novel artificial agent termed a deep Q-network. It can learn successful policies directly from high-dimensional sensory inputs using end-to-end reinforcement learning [69]. Deep Q-network can be well applied to traffic signal control, improving traffic congestion and reducing vehicle delays. Liang et al. propose a double dueling deep Q-network with prioritized experience replay [70]. The model can learn a good policy during rush hour and normal traffic flow. After simulation experiments, the proposed model reduces the average vehicle waiting time by more than 20% and outperforms other models in learning speed. Li et al. propose an algorithm for deep neural networks [71]. The core idea is to design a signal timing plan by deep reinforcement learning and find the appropriate signal timing strategy to control the action and system state changes by implicit modeling. Zaatouri and Ezzedine propose a real-time traffic light control algorithm based on deep convolutional neural networks for real-time target detection [72]. The algorithm optimizes the traffic signal phase based on the collected preemptive information, such as queue length and waiting time. Kumar et al. propose an intelligent traffic light control system based on a deep reinforcement learning and fuzzy inference model [73]. The system uses real-time traffic information as input to adjust the traffic light duration. Then, the system can reduce the vehicles' average waiting time.

In the IOV, each traffic signal is no longer a separate entity. Therefore, EVs need multiple traffic signals to collaborate in performing their tasks. Most research work has focused on applying deep reinforcement learning to multi-intelligence cases. Louati et al. use a longest queue first-maximal weight matching algorithm to control traffic lights [74]. This paper is the first work to integrate the algorithm into a multi-agent system to manage signalized intersections efficiently. Chu et al. propose for the first time a fully scalable and decentralized multi-agent reinforcement learning algorithm for the most advanced deep reinforcement learning agent, the dominant actor critic, in the context of adaptive traffic signal control [75]. It is superior to other decentralized multi-agent reinforcement learning algorithms in optimality, robustness, and efficiency of sampling. Van der Pol and Oliehoek propose a scalable multi-intelligence method using a transfer scheme and a maximum additive coordination algorithm [76]. This method reduces the delay time of vehicles compared to the previous methods based on the reinforcement algorithm.

In addition, many scholars also design new frameworks based on deep learning. Tan et al. propose a deep cooperative reinforcement learning framework [77]. The model can solve the problem that reinforcement learning agents cannot simultaneously monitor multiple signal lights in different areas. Cao et al. propose a new multi-agent shared parameters deep reinforcement learning framework [78]. The overall workflow of the model can be divided into pre-training, training, and running phases, as shown in Fig. 3. In the pre-training phase, the agent randomly selects actions and generates enough samples $[s_t, a_t, r_t, s_{t+1}]$. Then, in the training phase, they train the Q-network as an estimator for the maximum Q-value. At the end of the training phase, the agent eventually learns to achieve a high cumulative reward by reacting to different flows. Finally, the trained deep Q network is applied in practice to perform EV preemption control on traffic signals. Combined with the reward calculation algorithm, the framework of the EV can not only ensure the EV's fast pass in various situations but also alleviate congestion in conflicting directions.

IV. LANE RESERVATION

Lane reservation provides a non-congested and safe traffic environment for special-use vehicles. Evacuation and merging of regular vehicles in advance are the primary way to complete the lane reservation. Therefore, it is necessary to carefully decide which lanes must be reserved and design reasonable traffic measures. We will classify the studies

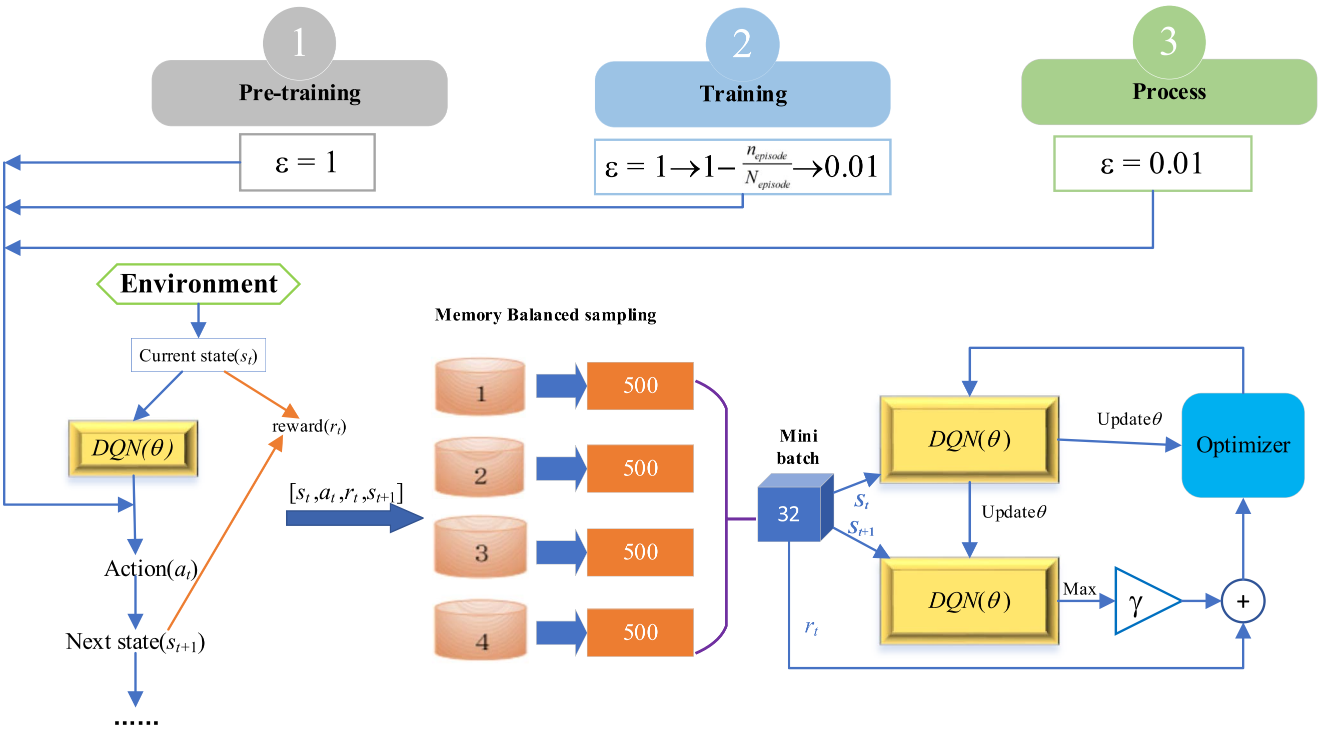

FIGURE 3. Training process of the intelligent model.

according to 1) rule-based methods and 2) multi-objective programming algorithms.

A. RULE-BASED METHODS

Designing algorithms or methods that conform to traffic rules is the research direction of most scholars. Wu et al. studies a task merging lane reservation problem (LRP-TM), which aims to optimize the choice of reserved lanes in the road network and design a time-critical route for each task combination [79]. This paper develops two new integer linear programming models of LRP-TM. The authors combine a fast and effective improved differential evolution algorithm. The validity and effectiveness of the model are validated. Yoo et al. use sensor networks to respond to EVs [80]. They design reserved road schemes to ensure EVs can reach their destinations on time.

To improve pavement conflict in emergency traffic, Mitrovic et al. propose a combination of alternate direction lane allocation and reserved-based intersection control (CADLARIC) method for organizing directional unrestricted traffic flow in an autonomous vehicle environment [81]. The scheme assigns different turning flows to separate lanes in an alternating manner. In this way, all left and right movements pass through an intersection without conflicts, reducing the potential conflicts to only vehicles moving through the intersection. The alternating traffic pattern helps to minimize disputes between EVs and regular vehicles at intersections. In 2022, Azadi et al. propose a flexible lane allocation and reserved-based intersection control (CFLARIC) method [82]. Compared with fixed time control, fully reserved crossover control, and CADLARIC, the CFLARIC strategy outperforms the other three strategies in terms of both reducing vehicle delay and reducing the number of conflict situations.

In addition, scholars design a reasonable system to achieve the expected effectiveness. Hannoun et al. propose a semi-automated system that provides instructions to downstream vehicles [83]. It facilitates the movement of emergency response vehicles through transport links. Chen et al. design a new reservation framework for urban roads based on police cordons [84]. The framework alleviates the traffic congestion within the warning line and presents better comprehensive network performance.

B. MULTI-OBJECTIVE PROGRAMMING MODELS

Considering the development prospects of connected vehicles, combining multiple objectives can achieve better results. Cheng et al. study a discontinuous reserved lane and consider heterogeneous traffic requirements [85]. They present a discrete two-level programming model. The upper layer determines the reserved sections, and the lower layer optimizes the route selection. Numerical experiments verify that the model reduces the target travel time of special-use vehicles and the negative impact on regular vehicles. Considering the traffic impact, Wu et al. prioritize EVs by co-driving with surrounding connected vehicles (CVs) [86]. They implement pre-clearing measures for CVs on EV lanes. They design the optimal trajectory for the EV and surrounding vehicles and minimize the impact on normal traffic. Hannoun et al.

TABLE 2. Hybrid strategies.

References	Route optimization		Signal preemption		Lane reservation		Simulation Tools	Limitations
	Strategy	Techniques/Algorithms	Strategy	Techniques/Algorithms	Strategy	Techniques/Algorithms		
Ogunwolu *et al.* [91]	√	Dijkstra's algorithm	√	RFID	\	\	Arc GIS Network Analyst, Proteus Simulator	Signal light seizure timing can be more optimal
Su *et al.* [92]	√	Improved Dijkstra's algorithm	√	Multi-agent advantage actor-critic	\	\	Simulation of Urban Mobility (SUMO)	Off-line training of multi-signal cooperation cannot adapt to dynamic changes in the environment
Min *et al.* [93]	√	Multi-criteria labeling method	√	Non-intrusive traffic preemption algorithm	\	\	Autonavi Navigation	No significant advantage in high traffic situations
Djahel *et al.* [94]	\	\	√	Fuzzy logic	√	Fuzzy logic, Multi agent system based next-turn re-routing	SUMO	Failure to consider the synergistic operation between signals
Xie *et al.* [95]	\	\	√	Dedicated short-range communication (DSRC)	√	DSRC	SMARTS simulator	Failure to consider the negative impact of EVs on traffic
Nguyen *et al.* [96]	\	\	√	V2X services, Wireless access in vehicular environment access in vehicular environment	√	Heuristic traffic clear-out coordination algorithm	SUMO	The dynamic character of traffic causes the previous route planning not to be optimal
Wang *et al.* [97]	\	\	√	Based on sections preemption control strategy inductive control	√	Bureau of public roads function (BPR function)	PTV-VISSIM	Failure to consider the negative impact of EVs on regular vehicles

propose the movement of the emergency vehicle through the transport link [87]. It reduces collision and confusion experienced by downstream vehicles.

The dangerous goods transport is a particular emergency scenario. Zhou et al. propose a new lane reservations algorithm to solve the transportation of hazardous goods [88]. They establish a bi-objective integer programming model for the problem. Considering the selection of reserving lanes for the government and planning routes for dangerous goods carriers, Zhang et al. propose a two-hybrid meta-heuristic algorithm [89]. The algorithm is based on a particle swarm optimization algorithm and a genetic algorithm to solve the bilayer model. The two-layer model can effectively reduce the risk of dangerous goods transport and assures the interests of hazardous goods carriers and ordinary passengers. Considering that reserved lanes require cost, Wu et al. propose a new dual objective integer linear programming model [90]. The model can determine the reserved lanes in time-limited special transportation networks, increase revenue, and effectively decrease the negative impact of reserved lanes.

V. HYBRID STRATEGIES

Using one of the above strategies to reduce the response time of EVs is not enough. Combining multiple strategies to determine the fastest route for EVs in intelligent transportation systems has received much attention. The studies on hybrid strategies have already achieved remarkable results, as shown in Table 2.

To reduce the travel time of EVs while reducing the average travel time of regular vehicles, Ogunwolu et al. optimize the route of EVs by using the Dijkstra's algorithm, and they preempt the signals on the route with radio frequency signals [91]. Su et al. propose a dynamic route optimization based on an improved Dijkstra's algorithm and a hybrid signal control strategy based on reinforcement learning [92]. Min et al. search for a reliable route with the shortest estimated arrival time under changing traffic conditions by path search and adopt elastic signal preemption to reduce the negative impact on the overall traffic flow due to prioritizing EVs [93].

In addition to the combination of route optimization and signal preemption strategy, signal preemption and lane reservation strategy also have been combined. Djahel et al. propose an adaptive traffic management system incorporating fuzzy logic [94]. Methods for signal preemption and clearing regular vehicles on emergency routes based on the severity of the emergency and the current level of traffic congestion estimated using fuzzy logic-based are used to speed up the progress of EVs while avoiding congestion around their routes. To ensure that EVs have a higher chance of reaching their destinations without slowing down, Xie et al. broadcast to regular vehicles and traffic signals on emergency routes a certain distance in advance using dedicated short-range communication to preempt roads and intersections [95].

With the power of high-definition real-time maps and a novel on-demand traffic control model, Nguyen et al. propose a forward-looking controlled path planning and traffic scheduling scheme [96]. The optimal emergency route is selected to ensure a delay-free lane on all road sections. The combination of lane reservation and signal preemption is applied to effectively alleviate the negative impact on regular vehicles caused by the EVs. Wang et al. develop a model for estimating the travel time of EVs under preemption control conditions [97]. Combining signal preemption and clearing regular vehicles on the route, these strategies will ensure that EVs have priority access.

TABLE 3. Summary of the objective metric.

Objective metrics	References			
	Route optimization	Signal preemption	Lane reservation	Hybrid
Response time	[17], [20], [26], [31], [34], [35], [37], [39], [40], [43]	[44], [46], [47], [51] [52], [54]-[56], [58], [64], [70], [72]	[80]	[95]
Response time + Cost of EVs	[18], [19]	[45], [49], [50]	[79], [84], [86]	\
Response time + negative impacts on regular vehicles	[36]	[48], [53], [57], [60]-[62], [68], [71], [74], [75], [77] [78],	[81]-[83], [85], [90],	[91], [92], [94], [96]
Response time + Road occupancy rate	[24], [27]-[29]	\	\	\
Response time + Robustness of emergency routes	[32], [33], [38]	\	\	[97]
Others	[16], [21]-[23], [25], [41], [42]	[59], [63], [65]-[67], [69], [73], [76]	[87]-[89]	[93]

VI. OBJECTIVE METRIC

This section analyzes the current state of research by categorizing the objective metrics of the examined articles, as shown in Table 3. The response time of EVs is one of the most frequently-studied objective metrics. However, it is not enough for a traffic control strategy to focus only on the shortest response time. A reasonable strategy should consider more objective metrics and the interests of multiple parties. Therefore, we categorize the objective metrics of the reviewed articles, such as the cost of EVs, including route length and energy consumption, the negative impact on regular vehicles, road occupancy, and robustness of emergency routes.

In terms of route optimization, Guo et al. [18] and Liu et al. [19] aim to minimize the time and energy cost of the routes. Chen et al. consider that the ultimate goal of planning bidirectional routes for emergency rescue and emergency evacuation in Chemical Industrial Park is to find the route with the shortest distance, which in turn reduces the emergency response time [20]. Constantinescu and Patrascu aim to find a route with low road occupancy to shorten the EV response time [29]. Yan et al. provide optimal path planning for EVs to reach the scene of traffic accidents with the shortest time and the least length of road queuing [36]. Yang et al. propose optimization objectives for path reliability and emergency response time [38]. Zhao et al. use the emergency response time, link reliability, and intersection security as evaluation metrics to construct a constrained multi-objective path optimization model and use the multi-objective optimization algorithm [22].

In terms of traffic light preemption, Younes and Boukerche adjust the optimal green phase time to allow each EV to pass smoothly and aim to reduce EV response time [47]. Younis and Moayeri aim to shorten EV response time and reduce environmental costs [49]. Ren et al. propose an adaptive signal control scheme that can effectively prevent intersection congestion and improve the performance of intersections in terms of vehicle delay and throughput [48]. Qi et al. propose a two-stage strategy to model traffic light control and use TPN to prove their strategy can prevent traffic congestion on urban roads caused by accidents [65].

In terms of lane reservation, Yoo et al. propose a road reservation scheme for safe and aim to EV fast response using sensor networks [80]. To highlight the effectiveness of the proposed traffic control strategy, Chen et al. propose the expected reservation effect in terms of total travel time and reduces the total cost of the road reservation system [84]. Wu et al. seek to minimize the disturbances on regular vehicles, and the proposed upper-level task attempts to reduce the interference on the EV [86]. Zhang et al. establish a two-level optimization model to minimize the risk of dangerous goods transportation and significantly reduce the solution time [89].

In terms of hybrid strategies, most studies are no longer limited to reducing the response time of EVs. Scholars consider more useful factors, such as reducing the negative impact on regular vehicles [91], [92], [94], [96], and choosing highly reliable rescue routes [97]. Min et al. aim to find reliable arrival time estimates under changing traffic conditions and reduce the negative impact of EVs on overall traffic flow [93].

VII. DISCUSSION

A. SUMMARY

We now summarize EV traffic control strategies discussed in the previous sections.

1) Traffic control strategies are classified according to the objects to be controlled, including route optimization strategies for EVs, pre-emption strategies for traffic signals, and road reservation strategies for regular vehicles. However, the current articles in the hybrid strategy research field are insufficient.

2) From the perspective of algorithms, traffic control strategies have shifted from the previous traditional optimization algorithms to the current intelligent optimization algorithms and machine-learning-based methods. It is worth noting that traffic control strategies are no longer based on a single class of algorithms but a combination of different types of algorithms.

3) The objective metrics of traffic control strategies show a development trend from single to multiple objective metrics. The reason is that multi-objective metrics focus on the interests of various participants in a traffic road network. Thus, multi-objective metrics provide strong support for the real-world deployment of traffic control strategies.

B. DIRECTION OF FUTURE RESEARCH

We discuss possible future directions for EV services.

1) Better transportation facilities and more intelligent transportation systems are the most effective for enhancing EV services. Due to the dynamic and complex nature of road traffic, it is crucial to improve the efficiency of transportation services. Emerging technologies, such as distributed systems, big data processing, and edge computing, can better serve road traffic [98], [99], [100].

2) The collaborative interaction between automatic driving emergency vehicles and traffic signals should be one of the research directions in the future [101]. Reinforcement learning provides the technology for implementing autonomous vehicles [102].

3) With the development of intelligent transportation and connected autonomous vehicles. It is foreseeable that future transportation will be a hybrid environment with mainly connected autonomous vehicles and human-driven vehicles. Therefore, the interaction between connected autonomous vehicles and human-driven vehicles will be an area worthy of research.

4) Intelligent traffic signals are one of the critical components of intelligent transportation systems. In the IOV environment, the interoperability of multi-agent systems improves traffic efficiency and ensures traffic safety [103].

5) The issue of vehicle-to-vehicle and vehicle-to-infrastructure communication is an essential direction for the present and future. The emergence of framework technologies such as software-defined networking has improved efficiency in the communication process [104]. In addition, the issue of reducing interference and communication costs while ensuring the accuracy and stability of communication is also worth considering.

6) An effective traffic flow prediction model is one of the essential prerequisites for deploying traffic control strategies [105]. Therefore, efficient and stable traffic flow prediction is indispensable.

7) The current traffic control strategies mainly focus on a single strategy, and practical results are not guaranteed. The combination of multiple strategies can be a research direction. From the current point of view, the combination of route optimization and signal preemption is a feasible solution. However, coping with the constant route optimization of EVs may not reduce should be an issue worth investigating. The combination of lane reservation and signal preemption is likewise a hot direction. First, the route of an EV is fixed once planned. The route planning is not only based on the current traffic conditions but should be integrated with historical traffic data for route planning. Secondly, the smoothness along the emergency route to make the EV travel at the desired speed is also worth considering and exploring.

8) Considering the realities of the environment, the travel of EVs under adverse weather, such as haze, will be the next consideration. The peculiarities of the climate result in high accident rates. The issue of how to mitigate the impact of traffic in adverse weather through intelligent transportation systems will be far-reaching in the future [106].

9) In addition, in the case of EVs, most studies are coordinated with the surrounding regular vehicles. Planning the traffic strategy in the particular case of two or more kinds of special-use vehicles could be a direction for scholars to consider. Designing an integrated management system that handles vehicular, pedestrian, and bicycle will be an inevitable choice for the future intelligent city transportation system.

10) The optimization problem is a core issue. A single objective makes the studies stay only at the theoretical and experimental simulation stage, which is not conducive to practical deployment. The selection of objective metrics should tend to develop in multi-objective research [107].

VIII. CONCLUSION

This survey reviews the emergency response problem, focusing on traffic control strategies for EVs. The traffic control is divided into route optimization for EVs, traffic signal preemption, lane reservation for regular vehicles, and mixed traffic control strategies for the three objects according to the objects to be controlled. We then classify the articles on these strategies based on algorithms. This survey attempts to provide insights into the emergency response problem and an overview and analysis of the currently proposed solutions for EV response time reduction and their objective metrics.

This survey suggests that researchers in emergency management services must focus on making optimized response time more dynamic through real-time traffic data. Beyond that, most current research considers only one of the three strategies, which have only been tested in simulations and are difficult to achieve commercial deployment. Further research should combine multiple strategies to address the challenging task of reducing response time. In addition to the objective metric focusing on the response time of EVs, future studies should consider the negative impact of regular vehicles, the overhead of all vehicles, and other factors. Therefore, there is a great potential and need for more significant research to minimize the negative impact of EVs and regular vehicles to contribute to emergency services significantly.

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