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*Research Article*

# A Collaborative Control Framework: Achieving Emergency Vehicle Priority While Minimizing Negative Impact on Ordinary Vehicles at Signalized Intersection

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When an emergency vehicle (EV) passes through an isolated signal intersection, it is crucial to ensure the efficient passage of the EV while minimizing the negative impact on ordinary vehicles (OVs), particularly in high-traffic flow scenarios. Given the constraints on temporal and spatial resources within intersection areas, OVs ahead of EV often face challenges in finding safe gaps for giving way, resulting in significant obstructions to OVs. This research introduces a novel collaborative control framework to jointly optimize dynamic emergency lane settings and signal schemes, considering EV priority and OVs benefits for a single signalized intersection. Firstly, we propose a dynamic emergency lane control algorithm to help obstructed EV in roadway segments by extending and reallocating temporal and spatial resources for vehicles. Then, we establish a collaborative control model considering EV priority and OVs benefits. Assigning the highest priority to the emergency priority phase, this model optimizes signal schemes to prevent interphase conflict, taking into account OVs benefits. Finally, our collaborative control framework also employs an Eco-Driving algorithm for the optimization of OV speed to reduce fuel consumption. The case study results reveal that in comparison to other baseline methods, our proposed model significantly reduces EV travel time, simultaneously lowering the travel time and fuel consumption of OVs. Sensitivity analysis of varying traffic flow scenarios reveals that, as vehicle volumes increase, our proposed method demonstrates more pronounced reductions in both EV and OV travel time. In addition, there is a progressive increase in the proportion of dynamic emergency lane utilization, with activation occurring at earlier locations.

## 1. Introduction

The severity of hazards arising from emergency incidents increases substantially over time. Empirical evidence indicates that for every additional minute in emergency response time, there is a significant increase in fatality hazards, ranging from 8% to 17% [1, 2]. Emergency vehicle (EV) travel time is the critical component of emergency response time [3]. Consequently, reducing EV travel time has emerged as a focal point of interest among researchers. Related studies have indicated that intersections are among the most frequent congestion-prone areas in the city [4]. Signal interference and obstruction by vehicles are the primary reasons for significant delays when EV pass through the intersection [5]. Effectively improving the efficiency of EV pass through intersection areas is an imminent challenge for urban emergency response systems.

Currently, research on the priority of EV pass through intersection areas can be classified into three categories. The first category involves greedy signal preemption to prevent obstructions by the red phase [6, 7]. Many studies employ devices like RFID and video to detect EV presence. Subsequently, they adjust the signal schemes by switching to the original schedule [8] or dynamically adjusting it based on indicators such as traffic flow and saturation [9] to implement EV priority [10]. The common signal optimization schemes still rely on fixed signal timing plans, such as green phase splitting or extension [11]. Existing research indicates that signal preemption can reduce EV travel time by 14% to 35% [12]. However, a greedy signal preemption method can lead to a substantial negative impact on ordinary vehicles (OVs) from conflicting directions, thereby significantly degrading overall traffic efficiency. Benefiting from the development of connected and autonomous vehicles (CAV) [13–16], real-time optimization of vehicle trajectories and signal schemes has become feasible [17–19]. In the CAV environment, the new method involves controlling the trajectory of OVs to yield the right of way to EV, thereby reducing hindrances they encounter from OVs. The second category involves optimizing vehicle trajectories ahead of EV or forming platoons to facilitate collaborative lane-changing, thereby avoiding hindrance caused by OVs in road segments [20]. For instance, Wu et al. [21] introduced an emergency lane preclearance algorithm that coordinates the control of EV and OVs. Liu et al. [20] proposed a method of control for the platoon to give way to the EV, taking into account traffic congestion, number of vehicles, initial state, and speed limit. However, the formation of vehicle platoons typically necessitates considerable distances and time, rendering it less practical for the relatively short distances between intersections in urban areas and more suitable for application on highways and expressways [21, 22]. The third category involves the collaborative optimization of OVs trajectories and signal schemes, with limited reported studies in this area. Qin and Khan [23] proposed segregating OVs into two groups: passing and yielding, to reduce obstruction to EV, and they considered optimizing signal schemes based on the state of upstream intersections. Djahel et al. [24] estimated traffic congestion and emergency severity using fuzzy logic. OV was removed from the emergency route and signal preemption was used to reduce congestion. However, in the intersection situations of high-traffic flow scenarios, providing sufficient road space for OVs to yield becomes challenging.

The above research results indicate that signal priority and trajectory control can effectively alleviate EV delays. Nonetheless, two challenges continue to endure: (1) During emergency events, the traffic volumes at intersections often surge, and depending solely on the above methods may not clear OVs, leaving the possibility of EV obstructions still prevalent. (2) The previous research has not adequately solved the benefits to OVs. Consequently, there is a necessity to explore methods that enhance EV efficiency while simultaneously minimizing negative impact on OVs.

Under the CAV environment, lane function settings at intersections can be optimized based on real-time traffic information [19, 25, 26]. CAVs can also adjust their lateral and longitudinal trajectories to adapt to the received control strategies. This advancement has also brought about new approaches to solving the problem of special vehicles (such as buses and EVs) pass through intersection areas and has provided convenience and widespread application in urban traffic domains [27, 28]. For instance, Ding et al. [19] proposed a model to optimize signal timings and variable lane settings in the CAV environment. Wu et al. [29] explored the benefits of providing dynamic exclusive bus lanes to provide a very high level of priority for buses. In conclusion, changing lane functionality in response to real-time traffic demands improves overall traffic efficiency [30–32]. Hence, this paper proposes the utilization of a portion of the reversible lane as a dynamic emergency lane (DEL) to extend the spatial resources available for EV. Simultaneously, an emergency priority signal (EPP) is incorporated into the signal timing scheme at the intersection to prevent conflicts between EV and OVs and achieve collaborative optimization of DEL and EPP. Based on the above concept, this study aims to propose a collaborative control method for signal timing considering EPP and DEL; furthermore, the study incorporates vehicle trajectory control to coordinate these control strategies.

The research contributions of the paper are as follows: (1) explicit EV priority solutions on signal intersection are proposed, EV does not entail parking in high-traffic flow scenarios; (2) The influence of EVs on the OVs from conflicting directions is minimized by the Collaborative Control Model considering EV Priority and OVs Benefits; (3) Through a speed optimization method based on eco-driving, the paper ensures that vehicles pass the stop line when the green light is activated, simultaneously reducing fuel consumption.

The remainder of this paper is organized as follows. Section 1 describes the problem and presents the notations. Section 2 formulates the collaborative control framework (CCF) to optimize intersection signaling schemes and EV and OVs trajectories. Section 3 presents Cases studies. Finally, conclusions and recommendations are provided in Section 4.

## 2. Problem Description and Model Parameters

*2.1. Problem Description.* As shown in Figure 1, the solid lines represent the paths of EV within the intersection area. The orange and red lines correspond to EV using and not using the DEL as they pass through the intersection area. After taking into account several factors, such as the location and the speed of vehicles in the roadway segments, EVs face a crucial choice. These choices involve determining the path of the EV, the specific timing and location for activating DEL, and selecting signal schemes that give priority to the EV. From Figure 1, it becomes evident that EVs encounter hindrances from OVs, leading to a significant increase in the time required for EVs to pass through the intersection. This paper introduces the concept of DEL and EPP, securing absolute right-of-way for EVs within the intersection. Additionally, it employs the Collaborative Control Model considering EV Priority and OVs Benefits to minimize the negative impact of EV priority on OVs. All these measures are seamlessly integrated into a CCF, presenting a more efficient method for EV priority.

*2.2. Model Assumptions.* Taking references from the relevant literature [19, 32], the following assumptions are made in the study:

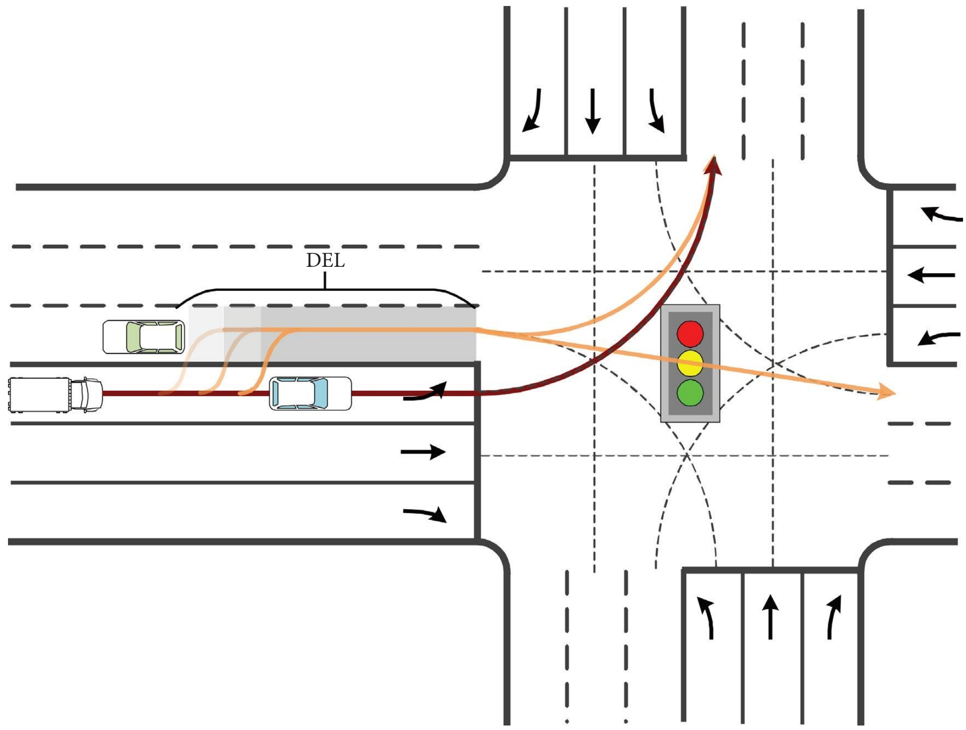



FIGURE 1: Typical intersection.

(1) All vehicles are equipped with V2X communication capabilities, enabling real-time reception of control instruction and facilitating speed control.
(2) OVs have been organized into platoons according to their travel demands.
(3) The lane-changing actions are assumed to be instantaneous.

*2.3. Parameter Specification.* The model parameters are described in Table 1, while the model variables are detailed in Table 2.

## 3. Formulation of a Collaborative Control Framework

Figure 2 shows the CCF used in this study. The collaborative framework aims to prioritize EV pass through intersections while simultaneously maximizing the benefit of OVs in high-traffic flow scenarios. The core of the CCF is an optimization model of DEL setting and EPP signal timing. Using the vehicle information as input, the dynamic emergency lane control algorithm provides the EV trajectory control and determines the DEL setting (i.e., using or not using). Simultaneously, the collaborative control model, considering EV priority and OVs benefits provides a signal timing scheme to ensure EV prioritization. Then, the eco-driving vehicle speed optimal method is employed to reduce OVs' fuel consumption.

*3.1. Dynamic Emergency Lane Control Algorithm.* EVs, such as ambulances, police cars, and fire engines, play a crucial role in rapidly reaching their destinations for mission-critical purposes, ensuring the safety of lives and property [33]. Congestive intersections are the most difficult point that EV needs to overcome. In our research, we propose a segment of the exit lane as DEL and optimize the speed of OVs to facilitate EVs priority pass through at the congestion intersection.

*3.1.1. Problem Definition.* EVs are granted permission to surpass the designated road speed, allowing them to enter intersections at optimal speeds to minimize EV travel time. However, the heightened speeds of OVs pose safety risks, prompting the traffic manager to establish a maximum speed limit for OVs. As illustrated in Figure 3(a), this speed restriction results in potential obstructions for EVs encountering OVs within the intersection. Previous research indicates that merely controlling the speed of OVs is inadequate to prevent obstruction. EVs are compelled to decelerate and follow behind OVs through the intersection. While some studies propose that lane-changing maneuvers by OVs could alleviate obstructions for EVs, in scenarios characterized by high traffic flow, signalized intersections often contend with a significant number of OVs on the exit lanes, leaving inadequate space for the OVs in front of EVs to change lanes and yield.

As depicted in Figure 3(b), this paper introduces a novel method of temporarily allocating a segment of the exit lane as a DEL to expand the spatial resources available for the

Table 1: Input parameters.

| Parameters | Meanings |
|---|---|
| *Lane* | |
| $i$ | The arms where $i = 1, 2, 3, 4$, denote the west, south, east, and north |
| $m$ | $m = 1, 2$ represents moving directions, that is, left-turn, straight ahead |
| $i, m$ | The platoon in arm $i$ with direction $m$ (phase) |
| $d_{\text{ins}}$ | Intersection vehicle passage distance |
| $L_{i,m}$ | The lane length of phase $i, m$ |
| $v_0^{\text{EV}}, v_{i,m}^0$ | EV and OVs initial speed |
| $x_{i,m}^{\text{d}}, x_{i,m}^c$ | The distance from the trailing car in the lane and DEL |
| $v_{\max}^{\text{OV}}, v_{\max}^{\text{EV}}$ | The maximum speed of OVs and EV |
| $a_{\max}^{\text{OV}}, a_{\max}^{\text{EV}}$ | The maximum acceleration of OVs and EV |
| $a_{\min}^{\text{OV}}, a_{\min}^{\text{EV}}$ | The maximum deceleration of OVs and EV |
| $\psi$ | The set of all OVs |
| $\psi_1, \psi_2$ | The set of incompatible and non-incompatible OVs $(\psi_1, \psi_2 \epsilon \psi)$ |
| $\psi_{1s}, \psi_{1l}$ | The set of OVs for straight and left-turning $(\psi_{1s}, \psi_{1l} \epsilon \psi)$ |
| *Phase* | |
| $n_{i,m}$ | Total number of OVs in phase |
| $d_{i,m}$ | The initial position of OVs in phase |
| $v_{\text{EV}}^{\text{con}}$ | The speed limits for EV turning |
| $\varepsilon$ | The minimum clearance times |
| $x, y$ | The major and minor axes of the ellipse |
| $M$ | A large constant (for example: 9999) |
| *Trajectory control* | |
| $l_{i,j}^A$ | Regression coefficient of velocity and acceleration during deceleration |
| $k_{i,j}^A$ | Regression coefficient of velocity and acceleration during acceleration |
| $\psi_{n-s}, \psi_s$ | The set of OVs for no-stopping and stopping $(\psi_s, \psi_{n-s} \epsilon \psi)$ |

Table 2: Control variables.

| Variables | Meanings |
|---|---|
| *Lane* | |
| $t_{\text{EV}}$ | The minimum passage time of EV through the intersection area |
| $t_{\text{OV}}$ | The passage time of OV with uniform acceleration to the maximum speed and then traveling at a constant speed through the inner area |
| $d_{\text{re}}$ | The positions where EV and OV conflict |
| $t_{\text{re}}$ | The timing of conflict between EV and OV |
| $d_{\text{cf}}$ | The positions where conflicts occur between EV and COV (the earliest position where EV can change lane) |
| $d_{\text{all}}$ | Lane changing in the range of EV |
| $d_{i,m}^{\text{EV}}(t), d_{i,m}^{\text{OV}}(t), d_{i,m}^{\text{COV}}(t)$ | The positions of EV, OV, and COV at time t |
| $v_{i,m}^{\text{EV}}(t), v_{i,m}^{\text{OV}}(t), v_{i,m}^{\text{COV}}(t)$ | The velocities of EV, OV, and COV at time t |
| $a_{i,m}^{\text{EV}}(t), a_{i,m}^{\text{OV}}(t), a_{i,m}^{\text{COV}}(t)$ | The accelerations of EV, OV, and COV at time t |
| *Phase* | |
| $T$ | Total travel time for OV |
| $T_{i,m}^{\text{EV}}, G_{i,m}^{\text{EV}}$ | Green light start time and duration for the EPP |
| $T_{i,m}^{\text{OV}}, G_{i,m}^{\text{OV}}$ | Green light start time and duration for the ordinary signal phase |
| $t_{\text{inc}}^{\text{EV}}$ | The time by EV within the intersection area |
| $t_{\text{inc}}^{\text{OV}}$ | The time by OV within the intersection area |
| $\varphi(i, m, j, k)$ | 0-1 variable (representing the order of EPP and ordinary phase) |
| $\mu(j, k, i, m)$ | 0-1 variable (representing the order between two ordinary phases) |
| *Trajectory control* | |
| $t_{i,m}^{\text{begin}}$ | Earliest time to reach the intersection stop line |
| $t_{i,m}^{\text{end}}$ | Time to leave the intersection stop line |
| $t_{i,m}^{r(n)}$ | Different steps of OV movement $n \in 0, 1, 2, 3, 4$ |
| $a_n(t)$ | Different steps of acceleration and deceleration $n \in 0, 1, 2, 3, 4$ |
| $\text{MOE}_{A,n}$ | Fuel consumption model |

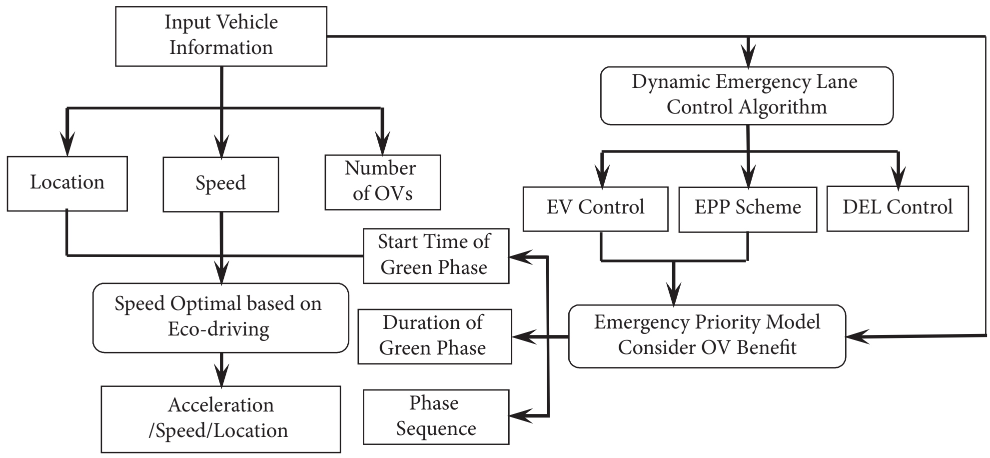



Figure 2: Formulation of collaborative control framework.

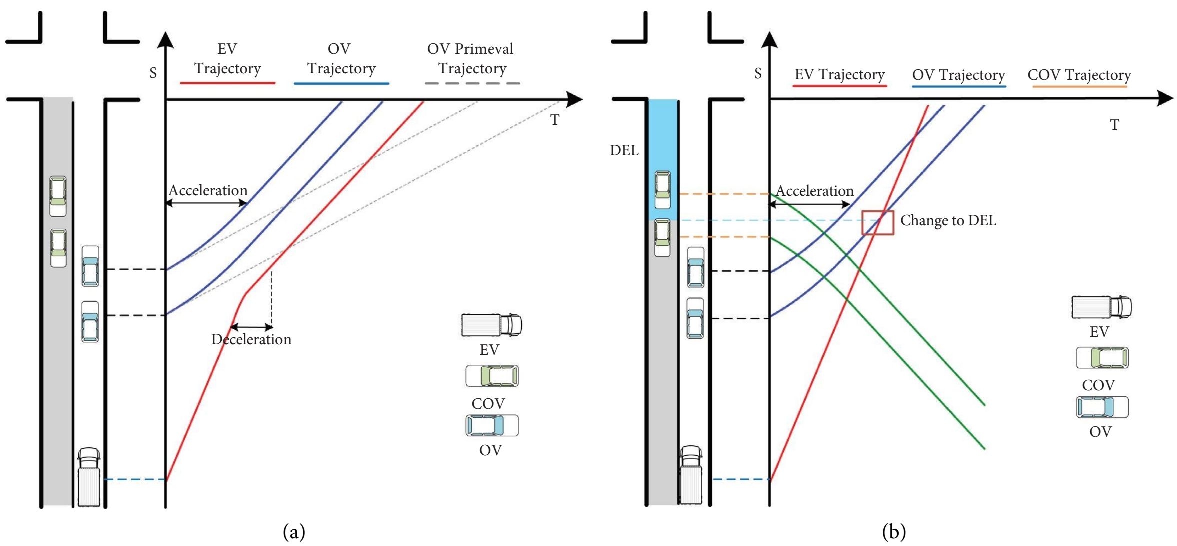



Figure 3: Vehicle trajectory (a) DEL is not turned on (b) DEL is turned on.

priority passage of EV. We devise an algorithm to assess whether an EV needs to utilize the exit lane as a DEL, taking into account the positions and speeds of EV, OVs, and contraflow ordinary vehicles (COVs). If utilization is deemed necessary, the optimal opening location and time for the DEL must be determined. Through the implementation of the Dynamic Emergency Lane Control Algorithm, EVs can circumvent obstructions by utilizing the DEL, thereby mitigating delays at the intersection [20].

*3.1.2. Conflict between EV and OVs.* The first step involves evaluating whether the EV encounters obstructions from OVs. EVs possess the highest priority among all vehicles [34], necessitating immediate acceleration by OVs ahead to prevent obstruction. The acceleration process for OVs in two distinct scenarios: ① Uniform acceleration to reach and maintain maximum speed ② Continuous uniform acceleration. The minimum time $t_m$ required for the EV to pass through the intersection without OVs interference maintains the highest speed and follows a uniform motion, as calculated in equation (1). The moment when OVs in front hinder the EV is denoted as $t_b$. The $t_b$ modeling equations are presented in equations (2) and (3), respectively.

$$t_m = \frac{L_{i,m}}{v_{i,m}^{\mathrm{EV}}(0)}, \tag{1}$$

$$t_b = \begin{cases} \dfrac{\left(v_{i,m}^{\mathrm{EV}}(0) - v_{i,m}^{\mathrm{OV}}(0)\right) + \sqrt{\left(v_{i,m}^{\mathrm{EV}}(0) - v_{i,m}^{\mathrm{OV}}(0)\right)^2 - 2a_{\max}^{\mathrm{OV}} x_{i,m}^{d}}}{a_{\max}^{\mathrm{OV}}}, & \text{if } v_{i,m}^{\mathrm{OV}}(t_b) < v_{\max}^{\mathrm{OV}}, \\ \dfrac{x_{i,m}^{d} + v_{i,m}^{\mathrm{OV}}(0)t_a + 1/2a_{\max}^{\mathrm{OV}} t_a{}^2 - v_{i,m}^{\mathrm{OV}}(t_b)t_a}{v_{i,m}^{\mathrm{EV}}(0) - v_{\max}^{\mathrm{OV}}}, & \text{if } v_{i,m}^{\mathrm{OV}}(t_b) = v_{\max}^{\mathrm{OV}}, \end{cases} \tag{2}$$

$$t_a = \frac{v_{i,m}^{\mathrm{OV}}(t_b) - v_{i,m}^{\mathrm{OV}}(0)}{a_{\max}^{\mathrm{OV}}}. \tag{3}$$

*3.1.3. Optimization of DEL.* Subsequently, our study involves calculating the optimal time and location for transforming the partial exit lane into DEL to satisfy the priority requirements of EVs. This process entails defining the time window $t_p$ and spatial range $d_p$ for DEL activation. The determination of $t_p$ depends on two crucial factors: ① the clearance time of the exit lane, denoted as $t_c$. The earliest moment at which an EV can pass through the exit lane without traffic conflicts is $t_c$. This objective is realized through a collaborative control of speed for COVs and signals. This method not only ensures the quick exit of COVs from the exit lane but also prevents OVs from entering the lane. ② The time it takes for an EV to pass through the intersection without encountering interference, denoted as $t_m$. The process is modeled through the equations (4)–(6). The time range for the activation of DEL, is determined based on two scenarios: ① When EV encounters hindrance from OVs. The activation range is determined by the earliest opening location of the DEL $(d_c)$ and the position at which EV and OVs cause conflict $(d_b)$. ② When EV encounters no hindrance from OVs, the activation range extends from the earliest opening location of the DEL to the intersection's stopping line. These are formulated in following equations:

$$t_c = \begin{cases} \dfrac{\left(v_{i,m}^{\mathrm{EV}}(0) + v_{i,m}^{\mathrm{COV}}(0)\right) - \sqrt{\left(v_{i,m}^{\mathrm{EV}}(0) + v_{i,m}^{\mathrm{COV}}(0)\right)^2 + 2a_{\max}^{\mathrm{COV}} x_{i,m}^{\mathrm{c}}}}{a_{\max}^{\mathrm{CSV}}}, & \text{if } v_{i,m}^{\mathrm{COV}}(t_c) < v_{\max}^{\mathrm{CSV}}, \\ \dfrac{x_{i,m}^{\mathrm{c}} - v_{i,m}^{\mathrm{COV}}(0)t_d - 1/2a_{\max}^{\mathrm{COV}} t_d{}^2 + v_{i,m}^{\mathrm{COV}}(t_c)t_d}{v_{i,m}^{\mathrm{EV}}(0) + v_{\max}^{\mathrm{COV}}}, & \text{if } v_{i,m}^{\mathrm{COV}}(t_c) = v_{\max}^{\mathrm{CSV}}, \end{cases} \tag{4}$$

$$t_d = \frac{v_{i,m}^{\mathrm{COV}}(t_c) - v_{i,m}^{\mathrm{COV}}(0)}{a_{\max}^{\mathrm{OV}}}, \tag{5}$$

$$t_p = [t_c, t_m], \tag{6}$$

$$d_c = v_{\mathrm{EV}} t_c, \tag{7}$$

$$d_b = v_{\mathrm{EV}} t_b, \tag{8}$$

$$d_p = \begin{cases} [d_c, d_b], & \text{if } t_b < t_m, \\ [d_c, L_{i,m}], & \text{if } t_b = t_m. \end{cases} \tag{9}$$

The optimization of DEL activation entails considering the travel time, positions, and speeds of both EV and OVs. The EV travel time comprises two components: the time spent traversing road segments, denoted as $t_r$, and the time of passing through the internal intersection, denoted as $t_i$.

The $t_r$ represents the temporal difference between when an EV enters and exits the road segment. It encompasses three primary scenarios: when an EV does not use DEL, when an EV utilizes DEL without OVs interference, and when an EV does not use DEL despite OVs interference. The details of these scenarios, each involving distinct trajectories and constraints for left-turning and straight movements, such as the following equations:

$$t_r = \begin{cases} t_m, & \text{if } t_b < t_m, \\ t_n, & \text{if } t_b \geq t_m, \end{cases} \tag{10}$$

$$t_n = \frac{d_{i,m} - v_{i,m}^{OV}(0)t_a - 1/2a_{\max}^{OV}{t_a}^2 + v_{\max}^{OV}t_a}{v_{\max}^{OV}}, \tag{11}$$

$$t_i = \begin{cases} \dfrac{d_i}{v_{\max}^{EV}}, & \text{if EV} \in \text{STR}, \\ \dfrac{d_i}{v_{\text{con}}^{EV}}, & \text{if EV} \in \text{LEFT}, \end{cases} \tag{12}$$

$$d_i = \begin{cases} \sqrt{x^2 + y^2}, & \text{if EV} \in \text{STR}, \\ \dfrac{\pi b + 2(a-b)}{2}, & \text{if EV} \in \text{LEFT}. \end{cases} \tag{13}$$

The total travel time for OVs ($T_S$) encapsulates the sum of the time required for OVs to pass through the intersection. It is equivalent to the weighted sum of the duration time for various green phases, with the weights defined by the number of vehicles in each respective phase. The specific computation method for $T_S$ is expounded upon in Section 2.2.

*3.2. Collaborative Control Model considering EV Priority and OVs Benefits.* Extending the green phase is a commonly employed method to facilitate the efficient passage of EVs through intersection [35]. In most cases, it falls short of completely addressing the issue of EVs being obstructed by OVs. As detailed in Section 3.1, we propose the utilization of DEL and EPP to improve the situation of EVs within the intersection. Simultaneously, the challenge remains with EVs causing significant disturbances to OVs. To tackle this issue, in Section 3.2, we optimize OV benefits by considering vehicle speed and position to optimize the starting time, duration, and sequencing of signal phases. Since these two strategies (utilizing or not utilizing the DEL) are suitable for different traffic conditions in the road segments, the framework chooses the method based on practical considerations.

*3.2.1. Objective Function.* In this study, a movement-based method is applied for signal timing, with the objective function aiming to minimize the total travel time of OVs. Given the context of CAV, we adjust the speeds of OVs to ensure their passage through the stop line when the green phase is activated. Therefore, the total travel time $T$ is calculated as the sum of the start time and duration for each green phase, with the weighting coefficient being the number of OVs in each phase. Hence, the following objective function is established.

The status of the DEL impacts the objective function of the proposed model. When EV must utilize DEL to prevent potential obstructions caused by OVs, resulting in convoy grouping $(i, m)$ denoted as $\psi_1$. Conversely, EV will not utilize DEL, convoy grouping $(i, m)$ is represented as $\psi_2$. The objective function is presented in the following equation:

$$T = \begin{cases} \min T_S = \min \sum\limits_{(i,m)\in\psi_1} \left(\left(T_{i,m}^{OV} + G_{i,m}^{OV}\right) \cdot n_{i,m} + \left(T_{i,m}^{EV} + G_{i,m}^{EV}\right) \cdot n_{i,m}\right), \\ \min T_E = \min \sum\limits_{(i,m)\in\psi_2} \left(\left(T_{i,m}^{OV} + G_{i,m}^{OV}\right) \cdot n_{i,m} + \left(T_{i,m}^{EV} + G_{i,m}^{EV}\right) \cdot n_{i,m}\right). \end{cases} \tag{14}$$

*3.2.2. Start Time of Green Phase.* To minimize the time spent by EVs in parking and waiting during red phases, the initiation of the EPP should correspond to the earliest expected arrival time of the EV at the intersection's stop line. When the EV utilizes the DEL, the DEL starting time aligns with the arrival time of the EV, as determined in Section 3.1. In schemes where the EV does not use DEL, the EV can only follow OVs through the intersection, and to avoid OVs arriving early, causing a waste of temporal and spatial resources within the intersection, we employ a speed optimal model in Section 3.2.5 to help the EV and OVs in forming a new platoon. The starting time of the green phase is then set to the arrival time of the lead vehicle in the new platoon. The calculation for $T_{i,m}^{EV}$ can be expressed as follows:

$$T_{i,m}^{EV} = \begin{cases} t_m, & (i,m) \in \psi_1, \\ t_m - t_{\text{inc}}^{OV} \cdot \left(n_{i,m} + 1\right), & (i,m) \in \psi_2. \end{cases} \tag{15}$$

To avoid wasting time due to the early arrival of OV at the stop line before the phase starts, the start time of ordinary green phases must be later than the earliest arrival time of OVs, as follows:

$$T_{i,m}^{\mathrm{OV}} \geq \frac{v_{i,m}^{\mathrm{OV}} + \sqrt{v_{i,m}^{\mathrm{OV}^2} + 2a_{\max}^{\mathrm{OV}} d_{i,m}}}{a_{i,m}^{\mathrm{OV}}}, \quad (i,m) \in \psi_1, \psi_2. \tag{16}$$

*3.2.3. Duration of the Green Phase.* The minimum duration of the green phase must exceed the time it takes for vehicles to pass through the intersection. The duration of the phase is equivalent to the time required for the vehicles to traverse the intersection area, as determined by the vehicle movement. To describe the vehicular movement in the inner area of the intersection, the description model includes one and two-dimensional. Several works have been done using various methods [36–39], including the two-dimensional car-following model, the social force-based model, and the optimal trajectory guidance model, which has the possibility of describing the two-dimensional moving process of vehicles. However, this paper focuses on solving the priority passage of EVs at high-traffic flow signalized intersections. This is achieved primarily by introducing EPP and optimizing the phase sequence to avoid conflicts between vehicles. Hence, the paper adopts a one-dimensional movement assumption; the EV trajectory in the straight-through and left-turning phases is defined as a straight line and an elliptical arc, respectively.

Moreover, it is crucial to note that the minimum duration of the green phase for EV priority and ordinary phases differs based on the different demands, and they should be discussed separately.

*(1) Emergency Priority Phase.* When the EV utilizes the DEL, the duration of the EPP ($G_{i,m}^{EV}$) is equivalent to the time required for the EV to traverse the intersection area, as determined by the EV trajectory. When the EV does not utilize the DEL, extending the duration of the green phase becomes necessary to ensure EV priority. The $G_{i,m}^{EV}$ is calculated as the sum of the time it takes for both the EV and OVs to pass through the intersection area. The equations are as follows:

$$t_{\mathrm{inc}}^{\mathrm{EV}} = \begin{cases} \dfrac{\sqrt{x^2 + y^2}}{v_{\max}^{\mathrm{EV}}}, & (i,m) \in \psi_s, \\[2ex] \dfrac{\pi y + 2(x - y)}{2v_{\mathrm{con}}^{\mathrm{EV}}}, & (i,m) \in \psi_l, \end{cases} \tag{17}$$

$$G_{i,m}^{\mathrm{EV}} \geq \begin{cases} t_{\mathrm{inc}}^{\mathrm{EV}} + \varepsilon, & (i,m) \in \psi_1, \\ t_{\mathrm{inc}}^{\mathrm{EV}} + t_{\mathrm{inc}}^{\mathrm{OV}} \cdot \left(n_{i,m} + 1\right) + \varepsilon, & (i,m) \in \psi_2. \end{cases}$$

*(2) Ordinary Signal Phase.* The duration of the ordinary green phase should exceed the time required for OV to pass through the intersection area. The speed time of a single OV ($t_{\mathrm{inc}}^{\mathrm{OV}}$) to pass through the intersection is based on OV's trajectories and speeds. The duration of the ordinary green phase $G_{i,m}^{\mathrm{OV}}$ is determined by considering the time spent by OVs and the product, as illustrated as follows:

$$t_{\mathrm{inc}}^{\mathrm{OV}} = \begin{cases} \dfrac{\sqrt{x^2 + y^2}}{v_{\max}^{\mathrm{OV}}}, & (i,m) \in \psi_s, \\[2ex] \dfrac{\pi y + 2(x - y)}{2v_{\max}^{\mathrm{OV}}}, & (i,m) \in \psi_l, \end{cases} \tag{18}$$

$$G_{i,m}^{\mathrm{OV}} \geq t_{\mathrm{inc}}^{\mathrm{OV}} \cdot n_{i,m} + \varepsilon, \quad (i,m) \in \psi_1, \psi_2.$$

*3.2.4. Ordering of Incompatible Signal Phase.* To avoid conflicts among vehicles within the internal area of the intersection, we analyze the phase conflict relationships, as shown in Figure 4. Constraints are imposed on the starting time and duration of incompatible phases, preventing incompatible phases from being simultaneously activated.

*(1) Ordering of EPP and Ordinary Signal Phases.* The sequencing of incompatible phases between the EPP and ordinary phases is represented by a binary variable $\varphi$. Specifically, $\varphi(i,m,j,k) = 1$ denotes that phase $(i,m)$ begins before phase $(j,k)$, while $\varphi(j,k,i,m) = 0$ signifies the opposite. To prevent the overlapping of incompatible phases, constraints are set on the relationship between the starting time and duration of these phases, as follows:

$$\begin{aligned} &T_{i,m}^{\mathrm{OV}} \leq \varphi(i,m,j,k) T_{i,m}^{\mathrm{EV}} + (1 - \varphi(j,k,i,m))M, \ (i,m)(j,k) \in \psi_1, \psi_2, \\ &T_{i,m}^{\mathrm{OV}} \geq (1 - \varphi(j,k,i,m))\left(T_{i,m}^{\mathrm{EV}} + G_{i,m}^{\mathrm{EV}}\right), \quad (i,m)(j,k) \in \psi_1, \psi_2, \\ &\varphi(i,m,j,k) + \varphi(j,k,i,m) = 1, \quad (i,m)(j,k) \in \psi_1, \psi_2, \end{aligned} \tag{19}$$

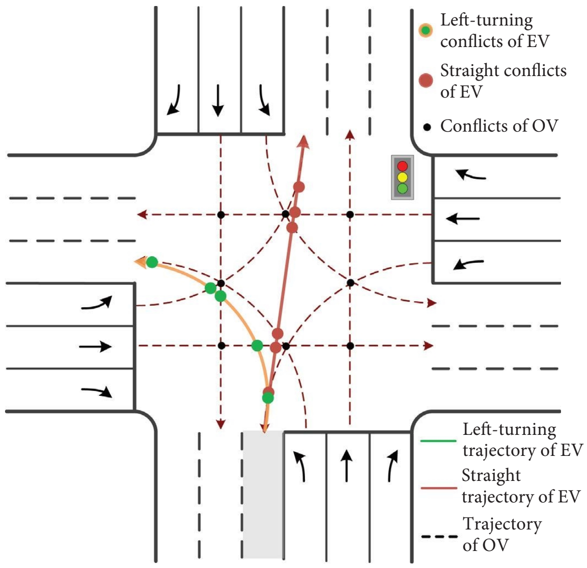



FIGURE 4: Traffic conflict between all phases.

*(2) Ordering between Ordinary Signal Phases*. Similar to the relationship outlined in the "Ordering of EPP and ordinary signal phases," the sequencing of ordinary signal phases that exhibit conflicts is represented by a binary variable $\mu$. Specifically, $\mu(i,m,j,k) = 0$ denotes that phase $(i,m)$ begins after the completion of $(j,k)$, while $\mu(i,m,j,k) = 1$ signifies the opposite. Constraints are formulated concerning the relationship between the starting time and duration of conflicting phases, as follows:

$$\begin{aligned} T_{i,m}^{OV} + \mu(j,k,i,m)M \geq T_{i,m}^{OV} + T_{i,m}^{OV}, (i,m)(j,k) \in \psi_1, \psi_2, \\ \mu(i,m,j,k) + \mu(j,k,i,m) = 1, (i,m)(j,k) \in \psi_1, \psi_2. \end{aligned} \tag{20}$$

*3.2.5. Speed Optimal Method considering Eco-Driving.* The Speed Optimal Method ensures the timely traversal of OVs across the intersection stop line at the start of the green phase, thereby preserving spatiotemporal resources at the intersection. Moreover, to minimize fuel consumption resulting from frequent acceleration, deceleration, and stops of OVs [40], this study incorporates a speed optimal method considering eco-driving. This section concentrates on optimizing OV speed, considering constraints such as the optimal signal timing scheme obtained in Section 3.2 and the current OV speeds and positions, with the objective of minimizing fuel consumption for OVs.

*(1) VT-Micro Model*. We chose the classic VT-Micro model [41], which is calibrated based on the vehicle's instantaneous speed and acceleration, to calculate fuel consumption for each vehicle. The model can be represented as follows:

$$\begin{aligned} &\mathrm{MOE}_{A,n} = \begin{cases} \sum_{i=0}^{3}\sum_{j=0}^{3}\sum_{t=0}^{t} \exp\left(k_{i,j}^{A} \cdot v_n(t)^i \cdot a_n(t)^j\right), a \geq 0, \\ \sum_{i=0}^{3}\sum_{j=0}^{3}\sum_{t=0}^{t} \exp\left(l_{i,j}^{A} \cdot v_n(t)^i \cdot a_n(t)^j\right), a < 0, \end{cases} (i,m) \in \psi_s, \psi_{n-s}, \\ &\min\left(\mathrm{MOE}_{A,n}\right), (i,m) \in \psi_s, \psi_{n-s}, \end{aligned} \tag{21}$$

*(2) Vehicle State Modeling*. Then the control of vehicle states can be formulated as an optimal control problem as follows [42, 43]: The dynamics of the vehicle are described in equation (22). Equations (23) and (24) define the initial and final states of the vehicle:

$$\begin{cases} \hat{d}_{i,m}^{OV}(t) = v_{i,m}^{OV}(t), \\ \hat{v}_{i,m}^{OV}(t) = a_{i,m}^{OV}(t), \end{cases} \tag{22}$$

$$\begin{cases} d_{i,m}^{OV}(0) = 0, \\ v_{i,m}^{OV}(0) = v_{i,m}^{0}, \end{cases} \tag{23}$$

$$\begin{cases} d_{i,m}^{OV}\left(T_{i,m}^{OV}\right) = d_{i,m}, \\ v_{i,m}^{OV}\left(T_{i,m}^{OV}\right) = v_{\max}^{OV}, \end{cases} \tag{24}$$

$$\begin{cases} a_{\min}^{OV} \le a_{i,m}^{OV}(t) \le a_{\max}^{OV}, \\ 0 \le v_{i,m}^{OV}(t) \le v_{\max}^{OV}, \end{cases} \tag{25}$$

*(3) Determination of OV Stopping.* Analyzing the position, speed, and platoon length of OVs enables the determination of whether they come to a stop upon reaching the intersection stop line. Consequently, OVs are classified into groups $\psi_s$ and $\psi_{n-s}$. Distinct speed optimal methods are then formulated for scenarios in which OVs come to a stop and situations in which they do not.

$$\begin{aligned} t_{i,m}^{begin} &= \frac{d_{i,m}}{v_{\min}^{OV}} - \frac{\left(v_{i,m}^{0} - v_{\min}^{OV}\right)\left(3v_{i,m}^{0} - v_{\min}^{OV}\right)}{2a_1 v_{\min}^{OV}} \\ &\quad - \frac{v_{\max}^{OV^2} - v_{\min}^{OV^2}}{2a_2 v_{\min}^{OV}}, \quad (i,m) \in \psi_1, \psi_2, \\ t_{i,m}^{end} &= T_{i,m}^{OV} + G_{i,m}^{OV}, \quad (i,m) \in \psi_1, \psi_2. \end{aligned} \tag{26}$$

*(4) Speed Optimal Method without Stopping.* In order to maximize the utilization of temporal and spatial resources within the intersection area, we require that OVs pass the stop line at their maximum speed. Our model moderates OVs acceleration and deceleration to minimize fuel consumption; however, frequent acceleration and deceleration may compromise passenger comfort [40]. Therefore, we restrict that OVs should not accelerate or decelerate more than once. The scenarios for speed adjustment in OVs are shown in Figure 5.

The constraints governing the relationship between the distance, speed, and acceleration of OVs on road segments, as well as the relationship between the speed and acceleration of OVs, are as follows:

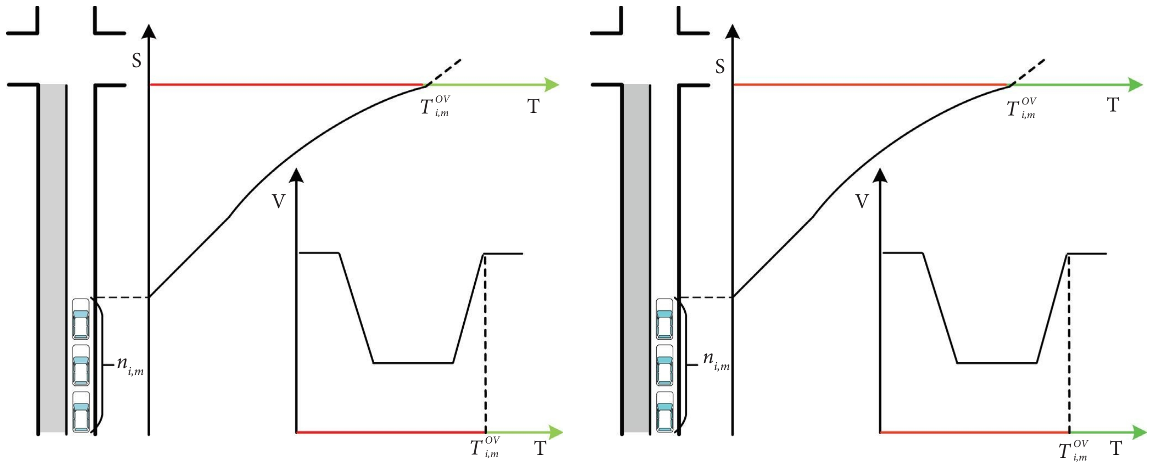
$$\begin{aligned} d_{i,m} &= V_0\left(t_{i,m}^{r2} - t_{i,m}^{r0}\right) - \frac{a_1}{2}\left(t_{i,m}^{r2} - t_{i,m}^{r1}\right)^2 + V_1\left(t_{i,m}^{r4} - t_{i,m}^{r2}\right) + \frac{a_2}{2}\left(t_{i,m}^{r4} - t_{i,m}^{r3}\right)^2, \quad (i,m) \in \psi_{n-s}, \\ a_1\left(t_{i,m}^{r2} - t_{i,m}^{r1}\right) &= V_0 - V_1, \quad (i,m) \in \psi_{n-s}, \\ a_2\left(t_{i,m}^{r4} - t_{i,m}^{r3}\right) &= V_1 - V_{\max}, \quad (i,m) \in \psi_{n-s}, \end{aligned} \tag{27}$$

*(5) Speed Optimal Method with Stopping.* When OVs are required to come to a stop at the intersection stop line, the acceleration and deceleration rules are consistent with the "Speed Optimization Method without Stopping." However, there is a modification in the speed optimal method for OVs, as depicted in Figure 6. The constraints can be expressed in the following equations:

$$D_{i,m} = v_{i,m}^{0}\left(t_{i,m}^{r2} - t_{i,m}^{r0}\right) - \frac{a_1}{2}\left(t_{i,m}^{r2} - t_{i,m}^{r1}\right)^2 + V_1\left(t_{i,m}^{r4} - t_{i,m}^{r3}\right) + \frac{a_2}{2}\left(t_{i,m}^{r4} - t_{i,m}^{r3}\right)^2, \quad (i,m) \in \psi_s, \tag{28}$$

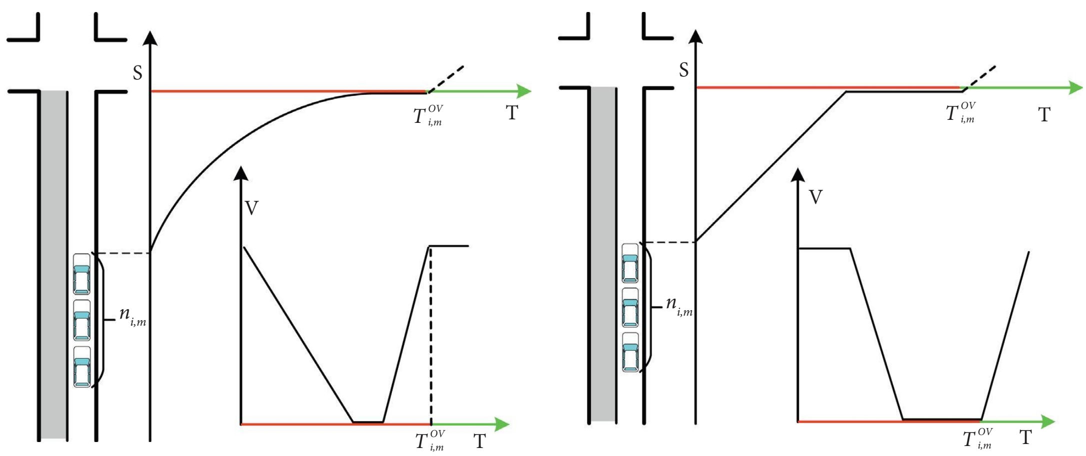
$$a_1\left(t_{i,m}^{r2} - t_{i,m}^{r1}\right) = V_0, \quad (i,m) \in \psi_s, \tag{29}$$

$$a_2\left(t_{i,m}^{r3} - t_{i,m}^{r4}\right) = V_{\max}, \quad (i,m) \in \psi_s. \tag{30}$$




(a) (b)

Figure 5: OV without stopping (a) before optimization (b) after optimization.




(a) (b)

Figure 6: OV with stopping (a) before optimization (b) after optimization.

## 4. Solutions and Results

### 4.1. Simulation Setup

*4.1.1. Simulation Scene and Solve.* To validate the proposed method in this research, experiments were conducted using a case study involving a typical signalized intersection with a dual-directional six-lane configuration. The dataset includes crucial information related to vehicle positions, speeds, and quantities. The data generation process employed independent random sampling techniques to ensure universality. Concurrently, to reduce unnecessary experimental numbers and time consumption, the Ngene tool was utilized to generate scenarios, and a D-optimal design was employed for evaluation [44, 45]. The results indicated that the reliability and robustness of the experiments could be ensured with just 800 experimental groups. Consequently, a comprehensive dataset comprising 1,000 sets of experimental data was generated.

The proposed model aims to minimize the total travel time and fuel consumption for OVs. The following decision variables are listed in Table 2. Various constraints are applied to the model to ensure its accuracy and practicality. For the building of the CCF, we used Python and AMPL (A mathematical programming language) to write. The CPLEX solver was employed for efficient and rapid solution-finding. The computational setup comprised an 11th Gen Intel(R) i5-1135G7 processor running at 2.40 GHz and 16.0 GB of memory. The average solving time was observed to be less than 75 ms, effectively meeting the real-time computational demands.

*4.1.2. Benchmarks.* To evaluate the effectiveness of our proposed model (collaborative control framework, **CCF**), we refer to relevant literature and compare it against the following three baseline methods:

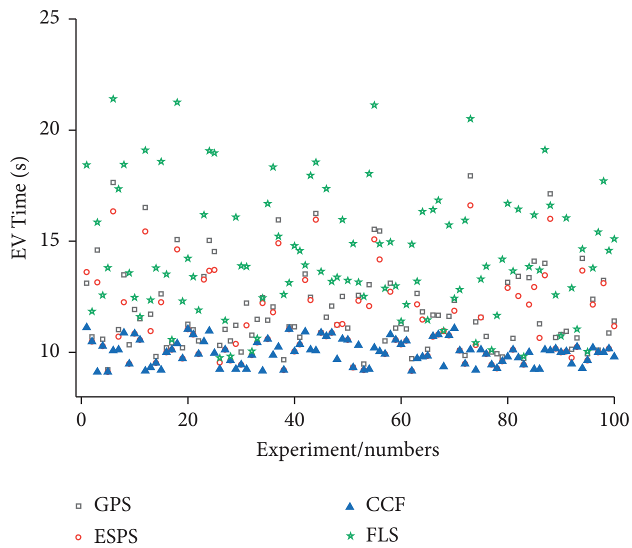



Figure 7: Comparison of the EV travel time (first 100 experiments).

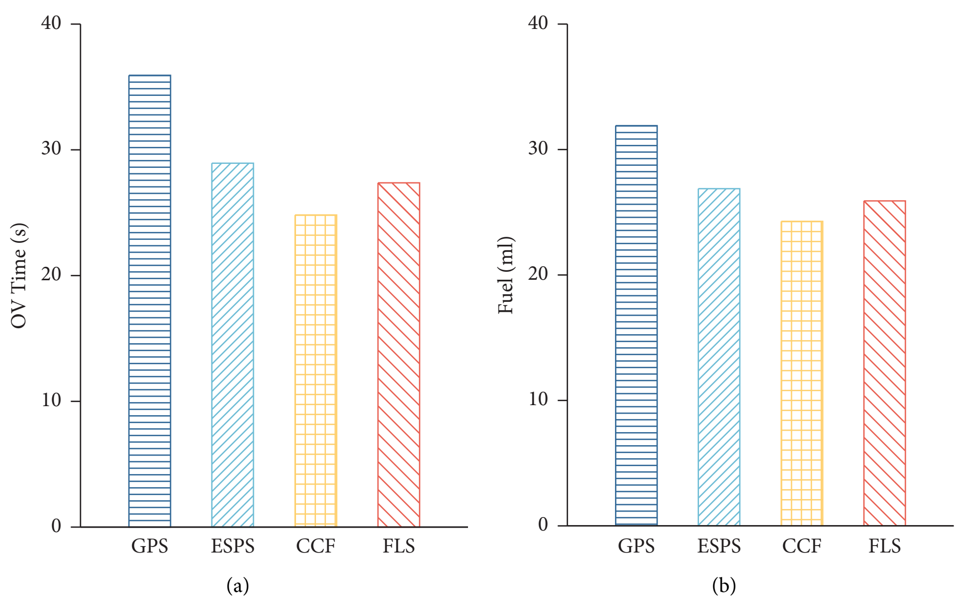



Figure 8: Comparison of the OV benefit (a) time (b) fuel.

Table 3: Measurement conversion.

| Mode | DEL opening ratio (%) | Location (m) |
|---|---|---|
| Straight | 51.37 | 146.35 |
| Left-turning | 43.67 | 142.61 |
| All | 47.52 | 144.48 |

*(1) Greedy Preemption Scheme (GPS).* An EV is granted a green phase when it arrives at an intersection until it exits. While this extreme approach achieves favorable EV performance, to a significant impact on OVs approaching from conflicting directions. This method has been widely employed as a benchmark in previous studies [6, 10].

*(2) Elastic Signal Preemption Scheme (ESPS).* The recent work proposes elastic signal preemption [2, 46]. The EV performance is the paramount goal for the Elastic signal preemption scheme. To fairly compare different methods, we modify this baseline to only control traffic signals using our signal algorithm for EVs and ignore the impact of path

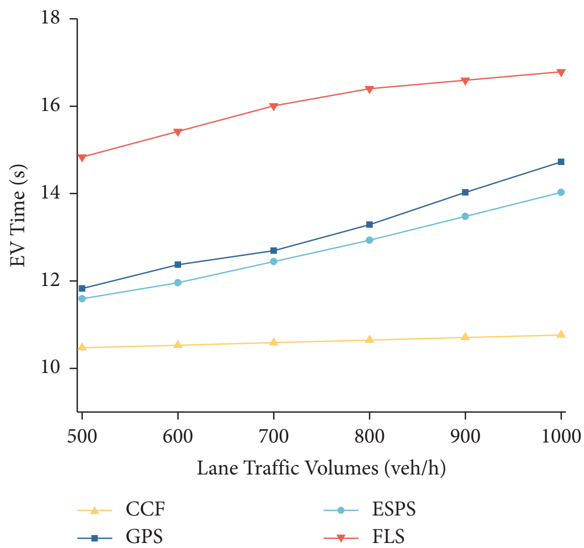



Figure 9: EV time under varied traffic volumes.

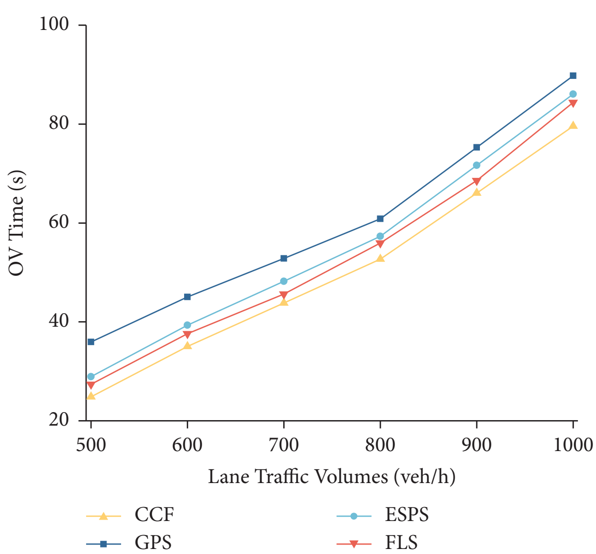



Figure 10: OV time under varied traffic volumes.

planning on EVs to optimal the schedules of traffic signal control for the fast passing of EVs through intersections.

*(3) Fuzzy Logic-Based Scheme (FLS).* The fuzzy logic-based approach is popular for traffic signal control of EV preemption [47]. Considering EV distance, EV queue length, occupancy level, and conflicting queue length, this scheme designs fuzzy rules to guarantee a fast emergency response while reducing the increase of congestion.

### *4.2. Results and Analysis*

*4.2.1. EV Travel Time.* As shown in Figure 7, the proposed method indicates that the time for an EV to pass through the intersection is consistently lower or equal to that of other

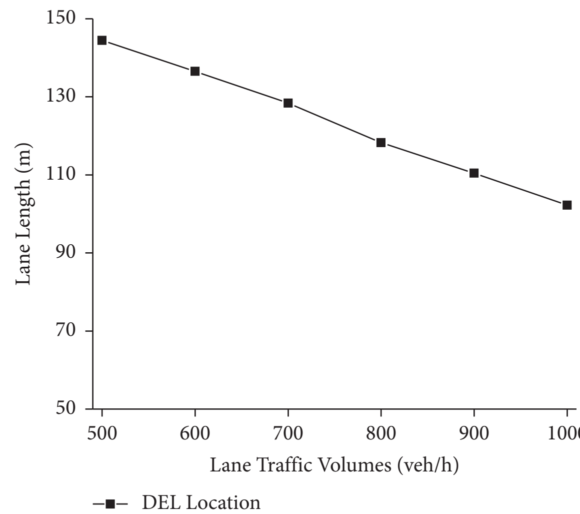



Figure 11: Position under various traffic volumes.

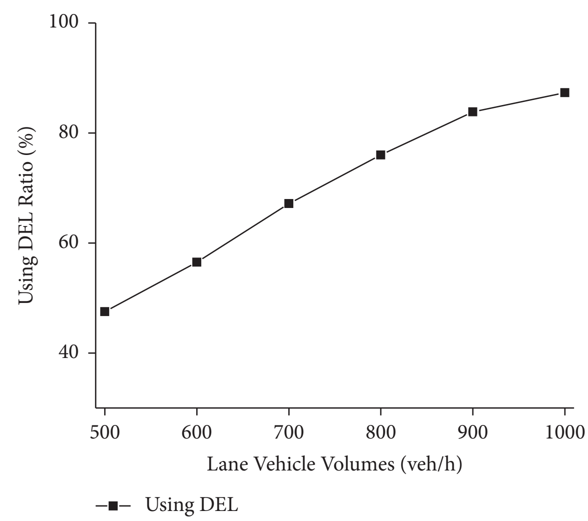



Figure 12: Ratio under various traffic volumes.

baseline methods. Specifically, compared to GPS, ESPS, and FLS, the EV travel time of the proposed method decreased by 12.92%, 10.71%, and 41.69%, respectively. Our proposed model attains this improvement through the collaborative optimization of DEL and EPP. This method effectively mitigates the risk of EV obstruction by preceding OVs, leading to a substantial reduction in the time required for the EV to pass through the intersection.

*4.2.2. OVs Benefits.* Figure 8 illustrates the significant benefits for OVs of our proposed method compared to other methods. When compared to GPS, ESPS, and FLS, our proposed method resulted in a reduction of 44.68%, 16.55%, and 10.26% in OVs' travel time, and a decrease in fuel consumption by 31.39%, 10.71%, and 6.65%.

Diverging from the signal timing schemes applied in the compared methods, our proposed method introduces heightened flexibility through the introduction of individual

EPP. Simultaneously, the method takes into account various factors, including vehicle volumes in different phases and the relationship of phase conflicts. Through optimization of sequencing, starting time, and duration of green phases, our proposed method enhances traffic efficiency.

*4.2.3. Analysis of Using DEL.* Based on the data presented in Table 3, it is evident that 47.52% of the experiments benefited from the DEL, enabling EVs to pass through the intersection without stopping. Among these EVs, approximately 144.48 m into the intersection, they necessarily used the DEL. Notably, if the DEL had not been used, EVs would have been obstructed by OV, causing obstructions of over 100 m. Furthermore, a slight variation was observed in the proportion of EVs (whether left-turning or straight) using the DEL and the corresponding locations of DEL utilization. This discrepancy can be attributed to the fact that when making a left turn within the intersection, EVs need to decrease their speed to ensure safety, reducing the urgency of occupying the intersection's temporal and spatial resources. In conclusion, utilizing DEL in most cases effectively decreases the time spent on EV pass through the intersection.

*4.2.4. Sensitivity Analysis.* To further validate the universality of our proposed method, we conducted a sensitivity analysis to evaluate EV travel time, benefits for OVs, and the probability and location of DEL utilization under varying vehicle volumes. This analysis is shown in Figures 9–12.

Figure 9 clearly demonstrates that our proposed method consistently maintains lower or equal EV travel time, even with an increase in vehicle volume. In stark contrast, the baseline methods exhibit a continual and substantial increase in EV travel times as vehicle volume increases. This difference is primarily attributed to the growing presence of OVs ahead of EVs, rendering the baseline methods ineffective in efficiently clearing the emergency lanes for EVs. Conversely, our proposed method introduces the utilization of DEL and EPP to achieve emergency priority, resulting in a reduction of EV obstructions caused by OVs.

Simultaneously, as illustrated in Figure 10, our proposed method outperforms the compared model in terms of travel time for OVs, even as vehicle volume rises. In summary, the advantages of our proposed method become more prominent, especially in addressing the issue of EV delays caused by lead vehicle obstructions in high-traffic flow scenarios, thereby improving overall traffic efficiency.

As depicted in Figure 11, with the rise in vehicle volume, the initiation point for the DEL utilization shifts from 144.48 m to 102.22 m. EVs encounter obstructions by OVs at an earlier stage, necessitating an earlier adoption of lane borrowing.

Figure 12 shows a consistent upward trend in the proportion of DEL utilization as vehicle volume increases. When lane vehicle volumes exceed 900 veh/h, over 80% of the experiments choose to utilize DEL to alleviate interference from OVs. This emphasizes the superiority and necessity of our proposed method in high-traffic flow scenarios.

## 5. Conclusions

In this paper, we introduce a collaborative control framework to facilitate the efficient passage of EVs and simultaneously minimizing interference for OVs, particularly in high-traffic flow scenarios. First, we introduce the dynamic emergency lane control algorithm, enabling EVs to utilize the DEL and circumvent delays caused by OV obstructions. Subsequently, we present the collaborative control model, considering EV priority and OVs benefits. This model incorporates the EPP at the intersection by considering phase conflict relationships and the earliest arrival time of OVs as constraints. It optimizes the phase sequence, the start time, and the duration of ordinary green phases. In addition, the speed optimal method based on eco-driving, ensures that OVs reach the stop line promptly when green lights start, reducing fuel consumption.

The case study results demonstrate that the proposed method markedly reduces the EV travel time, concurrently reducing travel time and fuel consumption for OVs. Sensitivity analysis conducted on varying traffic volumes indicates that, as traffic volumes increase, both EV travel time and OV travel time experience notable benefits compared to baseline methods. Additionally, there is an increased frequency of EV utilizing the DEL, with the DEL activation occurring at an earlier stage. Then, we plan to expand this method at the network level. The combination of the proposed method and the reservation-based models is also worth investigating.

## Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

## Conflicts of Interest

The authors declare that they do not have any conflicts of interest regarding the publication of this paper.

## Authors' Contributions

Kejun Long and Zhonggen Zhang conceptualized and designed the study. Siqi Zhong and Jian Gu collected the data. Zhibo Gao and Zhonggen Zhang analyzed and interpreted the results. Kejun Long and Zhonggen Zhang drafted the draft manuscript. All authors reviewed the results and approved the final version of the manuscript.

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