EP-MPC: An Emergency Vehicle Priority Method at Isolated Intersections in mixed Connected Environment*

Tianran Zhang[1], *Student Member, IEEE*, Sixuan Xu[2], *Student Member, IEEE*, Lei Zhao[3], Stefan Nastic[4], Weihua Zhang[5], and Chen Wang[6]*, *Member, IEEE*

***Abstract*— Emergency Vehicle Priority (EVP) is a crucial component in Intelligent Transportation Systems (ITS). To improve the efficiency of emergency vehicles (EVs) at isolated intersections in mixed traffic environments comprising human-driven vehicles (HVs) and connected vehicles (CVs), this study proposed a novel EVP method named Emergency Priority Model Predictive Control (EP-MPC). Firstly, a trajectory reconstruction model based on limited CV data is developed to estimate lane-level traffic states at an isolated intersection. Secondly, spatial-temporal priority strategies are introduced to ensure the right-of-way of EVs, and an algorithm based on the Model Predictive Control (MPC) framework is designed for optimizing EV's trajectory. Finally, the proposed EP-MPC method is compared with two baseline scenarios (i.e., passive EVP, and no EVP) using the Simulation of Urban MObility (SUMO) software. Experimental results demonstrate that the proposed EP-MPC method can significantly reduce the delay of EVs while maintaining the efficiency of social vehicles. Furthermore, sensitivity analysis reveal that increasing the CV penetration rate and traffic volume further enhances the performance of EP-MPC.**

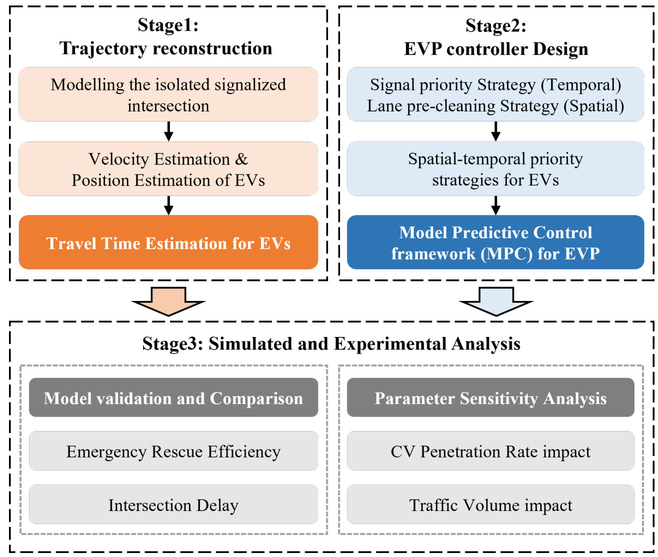

Fig. 1. The flow chart of this research

I. INTRODUCTION

Emergency Vehicle Priority (EVP) represents a critical component of modern Intelligent Transportation Systems (ITS), enabling improvements in emergency rescue through strategic traffic management. Although Emergency vehicles (EV) are special in ITS with a series of priority rules, reducing the response time of emergency rescue (i.e., the temporal interval spanning from initial alarm receipt to on-scene arrival of EVs) is still a great challenge [1], [2].

Conventional EVP methods were proposed based on fixed detectors (e.g., RFID), which were able to respond to the presence of emergency vehicles upstream of the roadway and provide appropriate priority phase at the downstream intersection [3], [4]. These methods have been validated to increase the emergency response efficiency to some extent. However, their inherent dependence on reactive response paradigms substantially diminishes their operational reliability when EVs encounter unanticipated perturbations in traffic flow dynamics, such as traffic congestion.

With the advancement of connected vehicle (CV) technologies, fine-grained, multi-source traffic data offer great potential for improving the reliability and efficiency of emergency vehicle preemption (EVP) methods [5]. Agarwal et al. proposed a lane-level dynamics model based on V2V communication to enhance EV performance under complex conditions [6], while Vít Obrusník et al. introduced a queue discharge-based EVP strategy using V2I to improve rescue efficiency and reduce social disruption [7]. In addition to such temporal priority strategies, spatial strategies (e.g., lane pre-cleaning) have also proven effective by enabling cooperation with surrounding CVs [1], [8]. However, most existing studies presume full CV penetration. Given the gradual deployment of CVs and intelligent infrastructure, mixed traffic involving both CVs and human-driven vehicles (HVs) will persist [9]. As HVs lack connectivity and cooperation, there is an urgent need for proactive, robust EVP strategies tailored

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[1]Tianran Zhang is with Intelligent Transportation System Research Center, Southeast University, 2 Southeast University Road, Jiangsu District, Nanjing, 210096, P.R., China 220243471@seu.edu.cn

[2]Sixuan Xu is with Intelligent Transportation System Research Center, Southeast University, 2 Southeast University Road, Jiangsu District, Nanjing, 210096, P.R., China 230238937@seu.edu.cn

[3]Lei Zhao is with Intelligent Transportation System Research Center, Southeast University, 2 Southeast University Road, Jiangsu District, Nanjing, 210096, P.R., China lei_zhao@seu.edu.cn

[4]Stefan Nastic is with Distributed Systems Group, TU Wien, Argentinierstraße 8, 1040 Vienna, Austria snastic@dsg.tuwien.ac.at

[5]Weihua Zhang is with Intelligent Transportation System Research Center, Southeast University, 2 Southeast University Road, Jiangsu District, Nanjing, 210096, P.R., China 230219399@seu.edu.cn

[6]Chen Wang is with Intelligent Transportation System Research Center, Southeast University, 2 Southeast University Road, Jiangsu District, Nanjing, 210096, P.R., China wkobec@hotmail.com

for mixed connected environments [10], [11], [12], [13].

To address existing research gaps, this study proposes a novel Emergency Priority Model Predictive Control (EP-MPC) method to enhance emergency response efficiency in mixed connected environments. Firstly, a trajectory reconstruction approach is developed to estimate lane-level traffic states under varying CV penetration rates. Secondly, a combination of temporal priority strategies (e.g., red truncation and green extension) and spatial strategies (e.g., dynamic pre-cleaning distance) is introduced to ensure EV right-of-way at isolated intersections. Finally, an MPC-based framework is proposed to optimize EV trajectories through signal phase adjustments, thereby enhancing rescue efficiency while minimizing delays for social vehicles. The main contributions are three-fold:

- A novel EVP method at isolated intersections named EP-MPC is proposed for mixed traffic flow scenarios, which is characterized by limited CV trajectories.
- A spatial temporal priority strategy is proposed and integrated into the EP-MPC, which can make full use of the limited road capacity.
- Compared with other baseline methods, EP-MPC can improve the efficiency of EVs and reduce the delay of social vehicles.

II. METHODOLOGY

The effectiveness of Emergency rescue is mainly related to the accuracy and reliability of travel time estimation and spatial or temporal EVP strategies. Therefore, the flow chart of the proposed method is shown in Fig.1.

A. Trajectory Reconstruction

The social vehicles in the mixed connected environment are mainly divided into two types: CVs and HVs. Thereinto, the trajectories of HVs cannot be directly observed while the trajectories of CVs can be exchanged among surrounding CVs and infrastructures [4]. The schematic of mixed traffic flow is elaborated in Fig.2.

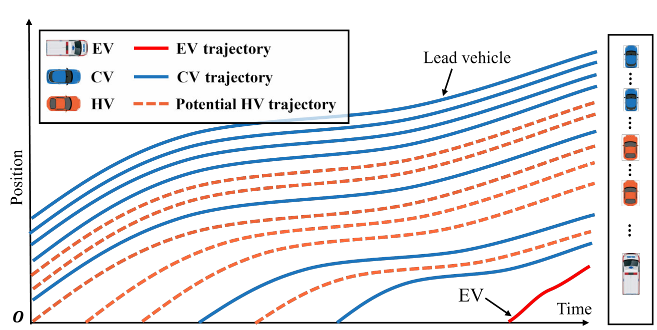


Fig. 2. The schematic of mixed traffic flow

In this section, the intelligent driver model (IDM) is introduced to depict the car-following behaviors of different CVs and HVs [14]. Then, the process of trajectory reconstruction is shown in Fig.3. Thereinto, x_{cv}, x_{HV}, v_{CV}, v_{HV} represent the matrix containing both the position and velocity data of multiple social vehicles across different time instances. N_{HV} represents the number of possible trajectories in the current spatial-temporal gaps among CVs. $\tilde{a}$ presents the estimated acceleration. Δx is the following distance between two social vehicles.

As illustrated in Fig.3, after obtaining the estimated velocity and acceleration of the inserted HVs, we can compare the estimated accelerations with those derived from kinematic calculations. To estimate the speeds of HVs positioned between two CVs at time interval t, the feasible region is partitioned into multiple independent sub-regions. Within each feasible sub-region, the estimated speed for a potential HV is based on an even distribution between the average speeds of the leading CV and the following CV. Subsequently, the speed of the i_{th} HV among N_{HV} is obtained by Eq. (1).

$$v_{HV,i} = v_{n-1}\left(t\right) - \frac{i}{N_{HV,n}+1}\left(v_{n-1}\left(t\right) - v_n\left(t\right)\right) \quad (1)$$

Then, the number of reconstructed trajectories should be estimated. Due to the limitation of vehicle length and safe distance, the maximum number of inserted trajectories between two CVs is shown in Eq. (2). Thereinto, the N_m represents the maximum of the insertion number, $x_{CV,n-1}$ represents the position of the $(n-1)_{th}$ CV, which is the leading vehicle for the n_{th} CV.

If we obtain the estimated vehicle kinematic status of social vehicles at each time step, the spatial distribution and velocity profiles, which demonstrate uniform characteristics, can be consequently inferred. As such, the velocity and the position of the first HV following the $(n-1)_{th}$ CV are shown in Eq. (3) and (4).

$$v_{HV,n,1} = v_{CV,n-1} - \frac{v_{CV,n-1} - v_{CV,n}}{N_{HV,n}+1} \quad (3)$$

$$x_{HV,n,1} = x_{CV,n-1} - \frac{x_{CV,n-1} - x_{CV,n}}{N_{HV,n}+1} \quad (4)$$

Based on the observed CV trajectories, the acceleration of an HV ($\tilde{a}_{HV,n,1}\left(t\right)$) can be calculated according to the IDM model [14]. Simultaneously, the acceleration of an HV can also be derived from the estimated velocity. As such, the optimal number of inserted HVs at time interval t can be obtained by solving the following optimization equation:

$$N_{HV,n}\left(t\right) = \underset{N_{HV,n}}{Argmin} \left(\widetilde{a_{HV,n,1}}\left(t\right) - a_{HV,n,1}\left(t\right)\right)^2 \quad (5)$$

On this basis, the optimal number of inserted HVs can be obtained based on Eq. (6).

$$N_{HV,n} = \min\left[N_{HV,1}\left(t\right), N_{HV,2}\left(t\right), ..., N_{HV,n}\left(t\right)\right] \quad (6)$$

Moreover, the absolute error is used to find the best distance between the vehicles. Considering the safety condition of HVs from surrounding vehicles, the i_{th} HV in the n_{th} gap of CVs at time interval t should satisfy the following constraints in Eq. (7):

$$\left\{ \begin{array}{c} x_{n,i-1} + s_0 + l \le x_{n,i} \le x_{n,i+1} - s_0 - l \\ x_{n,1} < x_{n-1} - s_0 - l \end{array} \right. , \quad i = 2, 3, \cdots N_{HV,n} \quad (7)$$

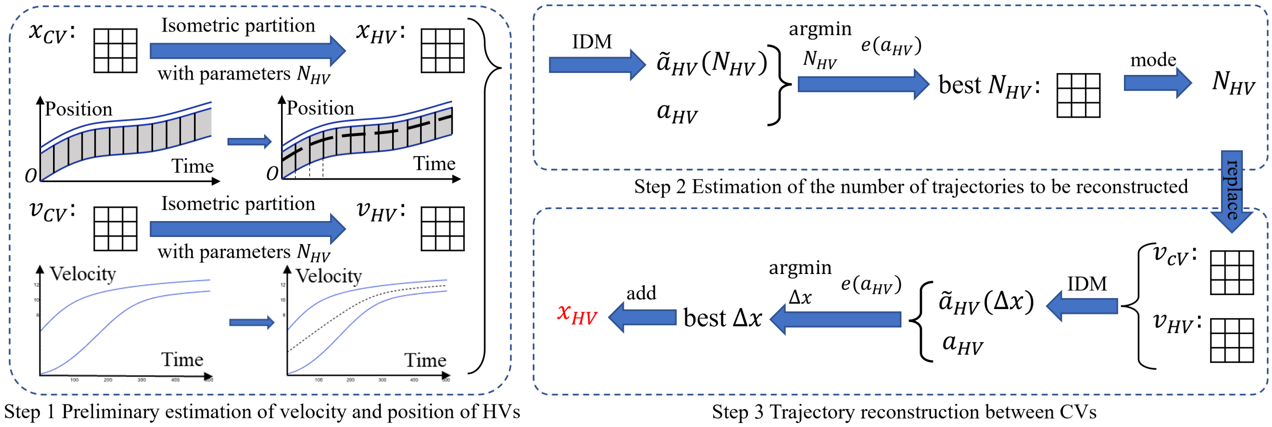


Fig. 3. Data flow diagram for the algorithm

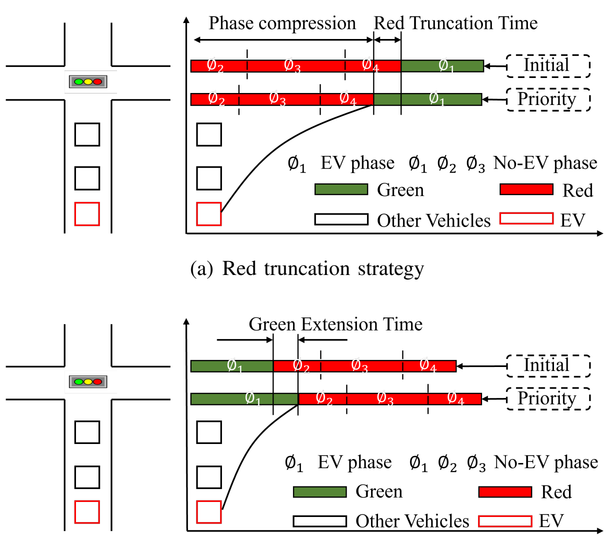
$$N_m = [\min\left(\frac{x_{CV,n-1}(0) - x_{CV,n}(0)}{s_0 + l}, \frac{x_{CV,n-1}(\Delta t) - x_{CV,n}(\Delta t)}{s_0 + l}, \cdots, \frac{x_{CV,n-1}(k\Delta t) - x_{CV,n}(k\Delta t)}{s_0 + l}\right)] \tag{2}$$

Thereinto, s_0 denotes the safety gaps, l is the length of vehicles. Then, the estimated acceleration of HVs $\tilde{a}_{n,i}(t)$ is derived based on the IDM, and the optimal trajectory (Δx) can be obtained by solving the constrained nonlinear programming problem considering the absolute error between the estimated acceleration and the ground truth acceleration $a_{n,1}(t)$ in Eq. (8).

$$\Delta x = \underset{\Delta x}{\arg\min} \; |\tilde{a}_{n,i}(t;\Delta x) - a_{n,1}(t)| \tag{8}$$

B. Spatial-Temporal Priority Strategies for EVs

After obtaining the estimated traffic status in front of the EV, it is necessary to design specific priority strategies for the EV to pass an isolated intersection efficiently.



(a) Red truncation strategy

(b) Green extension strategy

Fig. 4. Schematic diagram of Temporal Priority Strategies

Regarding temporal priority strategies, while appropriate signal control schemes can enable EVs to traverse isolated intersections without stopping, abrupt signal transitions may increase delays for social vehicles and even trigger congestion propagation across the network. Therefore, a well-designed temporal strategy is essential to balance EV efficiency with overall traffic performance. In this study, two strategies, Red Truncation and Green Extension, are proposed to ensure EV right-of-way. Specifically, the Red Truncation strategy is applied when an EV approaches during a red phase, allowing the red time to be shortened within the constraint defined in Eq. (9).

$$g_0 < r_{si} < r_{i+1} - r_{i+1\_min} \tag{9}$$

Thereinto, g_0 represents the time required for EVs to pass the intersection, r_{si} represents the shortened red time for phase i, r_{i+1} represents the red time for phase $i+1$, and r_{i+1_min} represents the shortest red time for phase $i+1$. The signal control scheme for red truncation strategy is shown in Fig.4(a). Besides, Green Extension strategy can be triggered when the remaining green time of the current phase is not enough for EVs to pass through the stop line. The extended green time should satisfy the constraint by Eq. (10).

$$g_0 < g_{ei} < g_{i+1} - g_{i+1\_min} \tag{10}$$

Thereinto, g_0 represents the time required for EVs to pass the intersection, g_ei represents the extended green time for phase i, g_{i+1_min} represents the shortest green time for phase $i+1$, and g_{i+1} represents the green light duration for phase $i+1$. The signal control scheme for green extension strategy is shown in Fig.4(b).

As for Spatial Priority Strategies, though EVs can warn surrounding vehicles to give way by sirens, they are always hindered by unexpected disturbances (e.g., the cut in behavior of social vehicles) [1]. To solve this problem, a dynamic lane pre-cleaning strategy is introduced. In specific, this priority zone is utilized to avoid the cut in behavior of social vehicles. Social vehicles in front of the EVs should give way meet the following constraint.

$$x_{last} - x_{EV} > s_c \tag{11}$$

As shown in Eq. (11), x_{last} represents the position of the vehicle in the priority lane, x_{EV} represents the position of the EV, and s_c represents the length of the dynamic pre-cleaning zone. It is important to note that only CVs can receive the information from EVs and infrastructures (e.g., warning instruction) via V2V and V2I communication respectively. It is also assumed that all social vehicles are willing to give way to the EV as long as the target lanes remain a safety clearance for lane changing. Only CVs can receive the instructions sent by the EV or the infrastructures through V2X technologies. The schematic diagram of the proposed Spatial Priority Strategies is illustrated in Fig.5.

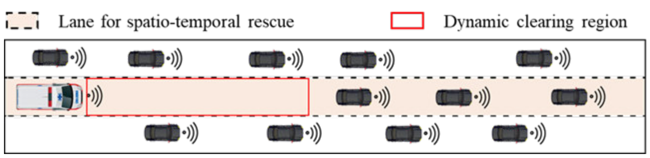


Fig. 5. Schematic diagram of emergency Spatial Priority Strategy

C. MPC Controller

In this section, EVP method in the connected environment is designed based on model predictive control (MPC) framework, which contains three main steps: model prediction, feedback correction and rolling optimization. The core idea of MPC is to make real-time prediction based on the rolling of prediction steps so as to achieve the purpose of dynamic adjustment and optimization [15]. The process of EVP method considering the Spatial-temporal priority strategies is shown in Fig.6.

Compared to the red truncation strategy, the application of green extension strategy will not change the absolute phase difference corresponding to the green light starting position at each intersection within the arterial signal coordination control system [4]. Therefore, the green extension strategy is preferred in the algorithm. Δr_b represents the compressible red time. t_{q_l} represents the predicted time for queue dissipation on the subjective lane l. After reconstructing the trajectories of HVs in the road segment, IDM can be further used to predict the trajectories of surrounding vehicles [16]. Assume that there are n_i vehicles in lane i when the EV enters the isolated intersection. Then, the travel time t_{n_i} for each social vehicle in lane i can be predicted by IDM after obtaining their accelerations. In specific, if the leading vehicle in lane i can pass through the intersection at free-flow speed, its acceleration can be predicted by Eq. (12).

$$a_i(t) = A_i \left[1 - \left(\frac{v_i}{v_f}\right)^{\delta}\right]. \tag{12}$$

Then, dynamics equations are established to model the driving behavior of EVs under the proposed MPC framework. The vehicle dynamics equations of EVs are shown in Eq. (13) and (14).

$$V_{t+1} = V_t + a_t \times b \tag{13}$$

$$X_{t+1} = X_t + V_t \times b + \frac{1}{2} a_t \times b^2 \tag{14}$$

Thereinto, b denotes the sampling interval, X_t denotes the vehicle position at time t, X_{t+1} denotes the vehicle position at time $t+1$, a_t is the acceleration at time t, and V_t denotes the vehicle velocity at time t. Then the operating state-space equation is expressed as:

$$\begin{bmatrix} X_{t+1} \\ V_{t+1} \end{bmatrix} = \begin{bmatrix} 1 & b \\ 0 & 1 \end{bmatrix} \begin{bmatrix} X_t \\ V_t \end{bmatrix} + \begin{bmatrix} \frac{b^2}{2} \\ b \end{bmatrix} a_t \tag{15}$$

The acceleration a_t of the EV is the control variable, and the position X_t and the velocity V_t are state variables, respectively. Since the primary target of emergency rescue is to improve the efficiency of EVs, the optimization function and the safety constraints of EVs in MPC controller is shown in Eq. (16) and (17).

$$F = min \sum\nolimits_{t=t_0} (V_t - V_{t+1})^2 \tag{16}$$

$$s.t. \begin{cases} a_{min} \le a_t \le a_{max} \\ a_{min} = -4\ m/s^2,\ a_{max} = 3\ m/s^2 \\ s_0 \ge 5 \end{cases} \tag{17}$$

Thereinto, t_0 represents the initial moment, and the initial velocity of the EV is close to the free-flow velocity V_{free}, which is 18 m/s in this study. a_{min} and a_{max} represent the acceleration constraint of the EV, $s_0 \ge 5$ represents the minimum safety gap of the EV. Furthermore, all state variables in a pre-set time domain and the controlled variable a_t are combined to construct the vector y', and calculate the expected priority time for the EV.

Moreover, define c as the control time, ΔT as the maximum control time domain of EVs, p_n as the last predicted time domain before the emergency vehicle passes the intersection stop line. Then the control time c can be calculated by Eq. (19).

$$c = \left[\frac{p_k}{q}\right], \quad q = 1, 2, ..., \Delta T; k = 1, 2, ..., n \tag{19}$$

Subsequently, Eq. (15), (16), and (17) can be transferred to a quadratic programming type function and solved by Active Set Method (ASM) [17].

III. RESULTS AND DISCUSSION

A. The description of Simulation scene

To verify the effectiveness of EP-MPC, Simulation of Urban MObility (SUMO) software is used to simulate the traffic flow in the isolated intersection with two-way four-lane roads. Each inlet contains a straight-left turn lane and a straight-right turn lane. All the simulated vehicles are generated with random parameters and a certain percentage of them are selected to represent CVs (i.e., the trajectories can be output by SUMO). The length of experimental road segment is 800m. A two-phase fixed signal scheme with a cycle of 120s and an averaged green time (i.e. 60s) is applied.

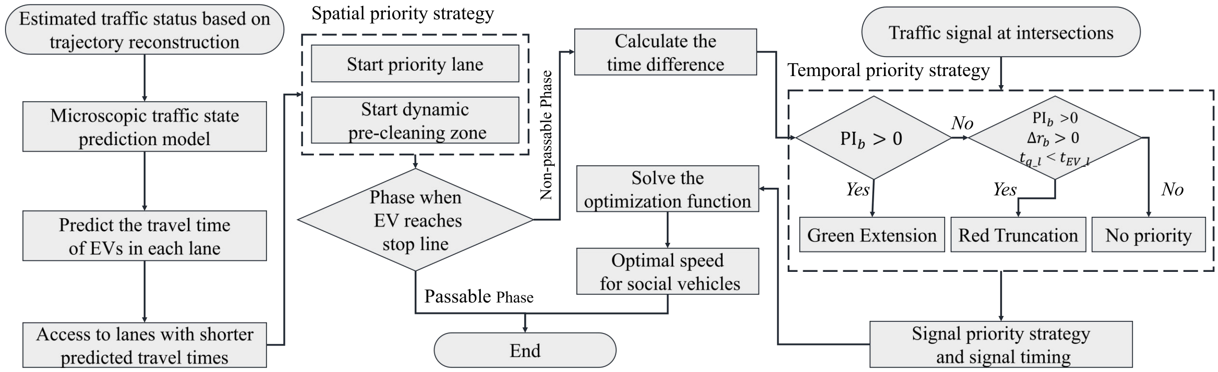


Fig. 6. The process of EVP based on the MPC controller

$$y' = \begin{bmatrix} X_{t_0} & V_{t_0} & nX_{t_0+b} & V_{t_0+b} & \dots & X_{t_0+b\times c} & V_{t_0+b\times c} & a_{t_0} & \dots & a_{t_0+b\times c-b} \end{bmatrix} \tag{18}$$

B. Results of the proposed method

The simulation step is set to 0.1 s. The parameters of the Intelligent Driver Model (IDM), which are employed for estimating and predicting microscopic traffic states, are pre-calibrated based on empirical data. The specific values are as follows: maximum acceleration $A_i = 2.6$, acceleration exponent $\delta = 4$, comfortable deceleration $b_i = 4.5$, minimum gap to stationary objects $s_{0e} = 3$, desired velocity $v_f = 15$, desired time headway $T_i = 1$, and minimum desired gap to moving objects $s_{0s} = 2.5$.

TABLE I
RESULTS OF EMERGENCY VEHICLE UNDER DIFFERENT VOLUME

	Proposed Method		Passive priority strategy		No Priority	
	Travel time	Delay	Travel time	Delay	Travel time	Delay
300	86	537.3	93	643.2	103	178.6
450	94	382.1	99	450.4	112	292.7
600	97	677.8	103	742.3	122	486.2
750	102	1150.9	105	1300.4	137	979
900	105	1819.7	111	2128.7	144	1705.9

Then, the proposed method is evaluated against two baseline approaches: (1) Passive priority strategy, (2) No priority strategy. Performance comparisons are conducted by measuring travel time and intersection delay under various traffic flow density scenarios, with a constant connected vehicle (CV) penetration rate of 50%.The results of the simulation experiment are shown in TABLE I, with all values expressed in seconds. As the traffic volume increases, the overall speed of the emergency vehicles decreases, the travel time increases, and the intersection delay increases. Both the traditional algorithm and the passive priority algorithm show the phenomenon of queuing as well as driving at low speed. However, the proposed method can effectively improve the emergency rescue efficiency while better reducing the extra delay caused by signal transition.

C. Sensitivity Analysis

In this study, the effects of CV penetrance rate and traffic volume are further investigated by a sensitivity analysis. The results of trajectory reconstruction under four typical parameter combinations are shown in Fig.7.

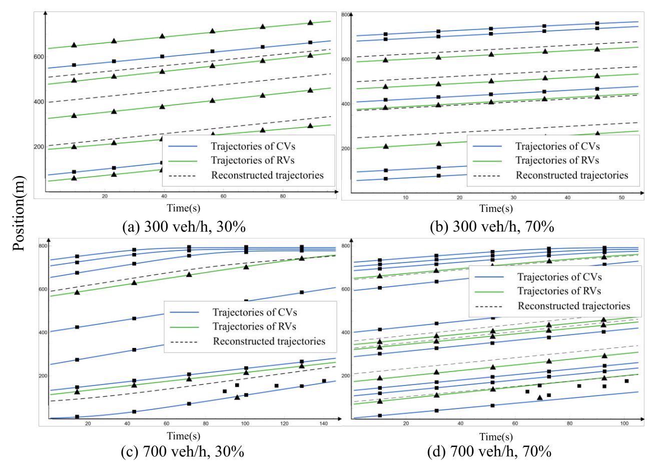


Fig. 7. The results of trajectory reconstruction

It can be experientially seen that when traffic volume and CV penetrance rate increase, the effect of trajectory reconstruction improves consequently. The errors of trajectory reconstruction in different traffic volume (i.e., 300, 450, 600, 750, 900 veh/h) and CV penetration rates (30%, 40%, 50%, 60%, 70%) are shown in TABLE II and TABLE III. Evaluation criterias include Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Root Mean Square Error (RMSE).

In TABLE II, it can be seen that the greater the traffic volume, the better the effect of trajectory reconstruction (i.e., low number error and position error). In TABLE III, with the increase of CV penetration rate, the estimated number error and position error gradually decreased. Overall, the proposed method can obtain a sound trajectory reconstruction effect, even in low CV penetration rate (i.e., 20%).

TABLE II

MAE AND MAPE IN DIFFERENT TRAFFIC VOLUME

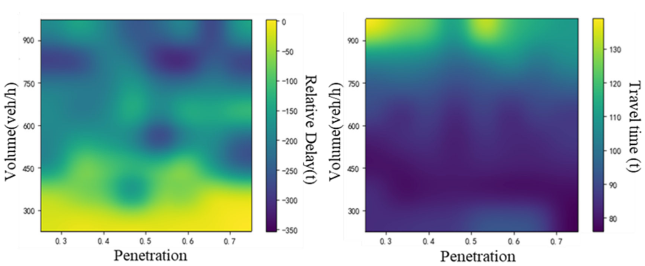
	Number of Inserted HVs		Position of Inserted HVs	
	MAE	MAPE	MAE	RMSE
300	2.61	7.12	4.21	8.13
450	2.11	6.43	4.10	8.04
600	1.81	6.23	3.22	7.35
750	1.73	5.89	2.88	7.12
900	1.31	5.44	2.76	6.11

TABLE III

MAE AND MAPE IN IN DIFFERENT CV PENETRATION RATES

	Number of Inserted HVs		Position of Inserted HVs	
	MAE	MAPE	MAE	RMSE
10%	2.13	7.12	3.44	8.13
20%	1.54	6.33	3.08	7.28
50%	0.97	5.27	2.18	6.14
60%	0.63	4.66	1.55	5.67
70%	0.42	3.22	1.03	5.03

Finally, the emergency rescue efficiency and intersection delays in different CV penetration rates and traffic volume are further obtained by 10-time repeating experiment, and the heatmaps are shown in Fig. 8.



(a) Emergency rescue efficiency (a) Relative delay at intersection

Fig. 8. Heat map of emergency rescue efficiency and intersection delays

Thereinto, Fig. 8(a) shows that as the volume of traffic increases, so does the travel time for emergency vehicles. This is consistent with the characteristics of the macroscopic traffic flow. Besides, as the penetration rate increases, the travel time of the EV decreases as expected. Then, The effectiveness of EP-MPC on intersection delays is further analyzed in Fig. 8(b). The difference between the simulated delay value under proposed method minus that under baseline method for different traffic volume and CV penetration rates scenarios are illustrated in the heat map. With the increase of traffic volume, the simulation results of the proposed method show more superiority.

IV. CONCLUSIONS

The proposed EP-MPC effectively optimizes EV trajectories at isolated intersections in mixed connectivity environments. Simulations in SUMO, under simplified assumptions, validate its superiority. Results show a significant reduction in EV travel time, especially under high traffic volumes. Additionally, the method offers dual benefits: improving EV response time while minimizing impacts on social vehicles. Future work will involve validation using real road networks and traffic data, and extending the method to arterial and network-level scenarios.

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