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Emergency vehicle lane pre-clearing: From microscopic cooperation to routing decision making

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ABSTRACT

Emergency vehicles (EVs) play a crucial role in providing timely help for the general public in saving lives and avoiding property loss. However, very few efforts have been made for EV prioritization on normal road segments, such as the road section between intersections or highways between ramps. In this paper, we propose an EV lane pre-clearing strategy to prioritize EVs on such roads through cooperative driving with surrounding connected vehicles (CVs). The cooperative driving problem is formulated as a mixed-integer nonlinear programming (MINP) problem aiming at (i) guaranteeing the desired speed of EVs, and (ii) minimizing the disturbances on CVs. To tackle this NP-hard MINP problem, we formulate the model in a bi-level optimization manner to address these two objectives, respectively. In the lower-level problem, CVs in front of the emergency vehicle will be divided into several blocks. For each block, we developed an EV sorting algorithm to design optimal merging trajectories for CVs. With resultant sorting trajectories, a constrained optimization problem is solved in the upper-level to determine the initiation time/distance to conduct the sorting trajectories. Case studies show that with the proposed algorithm, emergency vehicles are able to drive at a desired speed while minimizing disturbances on normal traffic flows. We further reveal a linear relationship between the optimal solution and road density, which could help to improve EV routing decision makings when high-resolution data is not available.

1. Introduction

Emergency vehicles (EVs), such as fire trucks and ambulances, are essential components in modern Emergency Medical Service (EMS) systems. Once called, a functional EV would deliver necessary equipment and rescue personnel to the accident and provide first aid. Existing studies have clearly demonstrated that the fatality rate of patients is highly affected by the response time of EVs, which is usually defined as the time interval between the receipt of call and arrival on scene (Blackwell and Kaufman, 2002; Blanchard et al., 2012; Meng and Weng, 2013). Therefore, reducing and guaranteeing the response time of EVs has become one of the main goals in developing EMS systems. For instance, the US National Fire Protection Association's (NFPA) 1710 standard requires that all units must arrive at incident sites within eight minutes (Flynn, 2009); the

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medical community also takes the first hour as the “golden hour” of trauma patients (Newgard et al., 2010). To meet such standards, numerous treatments have been applied to improve the performance of EVs. Since signalized intersections could introduce huge travel delays, the most commonly adopted technique for EV prioritization is traffic signal priority control, in which the arrival of EVs would trigger a temporary signal phase plan that prioritizes the pass-through of EVs (He et al., 2014; Guler and Menendez, 2014). However, on normal road segments such as the road between adjacent intersections, it is also very often that EVs are hindered by surrounding vehicles and forced to decelerate or even stop. Even worse, unlike at signalized intersections with explicit timing plans, such hindrances on highway segments depend on time-varying traffic flow conditions and can hardly be predicted or estimated in advance, leading to huge uncertainties in travel time. However, this problem has not been addressed in the literature. To this end, the present paper focuses on the problem of EV prioritization at highway segments, which are defined as extended sections between intersections or ramps on freeways or urban roads in this research.

Travel time uncertainties on highway segments could also degrade other significant EV related operations, e.g., EV allocation planning and routing path planning. In EV allocation planning problems, the objectives are usually to cover as many potential accident sites as possible within certain response time standards, which falls into the more general location planning problem in operations research (Church and ReVelle, 1974; Li and Ouyang, 2010; An et al., 2013; Wang et al., 2013; Bell et al., 2014; Wang et al., 2018). In such problems, link travel time is a fundamental input, while total travel time per mission serves as the measure of effectiveness (Gendreau et al., 2006; Liu et al., 2019). Moreover, routing problems especially EV routing seek to find the time-based shortest path, which entails quantified travel time of road links (Salazar-González and Santos-Hernández, 2015). Most studies in this area simply assume the link travel time to be constant or follow theoretic distributions (Ansari et al., 2015; Ingolfsson et al., 2008; Lou et al., 2011; Geroliminis et al., 2009; He et al., 2019), which cannot represent the reality accurately. In practice, the actual travel time of the same road can be very random at different time of a day or the same time of different days, due to unpredictable hindrances and blockages from surrounding vehicles. Such deviations from ideal assumptions of travel time may heavily undermine the performance of allocation and routing planning models. Even though several studies have considered travel time uncertainties and proposed robust models accordingly (Daskin, 1983; Meng et al., 2005; Bell, 2009; Chen and Zhou, 2010; Bell et al., 2012; Liu et al., 2016; Varga et al., 2020), the solutions can only relieve the situation on routing level indirectly but cannot fundamentally solve the problem, especially in tackling the hindrances from time-varying traffic flows on highway segments. The unprecedented development of connected vehicles (CVs) makes it possible to narrow or even eliminate travel time uncertainties if certain interventions are applied (Qu et al., 2020; Zhou et al., 2019; Murray-Tuite, Phoowarawutthipanich, Islam, Hdieb).

On highway segments, the current practice is that once hearing the siren of an emergency vehicle, all vehicles are supposed to pull over on roadside to clear one lane for the arriving EV. The major problem of this approach is that there is no guarantee on the travel speed of EVs. Even though all drivers are willing to prioritize the coming EV, there are possibilities that they are not able to clear the lane in time. Since vehicles make lane-changing decisions independently, it is highly likely that they may hinder each other, like choosing the same lane-changing gap, which leads to deceleration and thus blockage to the emergency vehicle. In this area, Hannoun et al. (2018) proposed an integer linear programming (ILP) model to facilitate EV traveling through a road segment. The ILP model seeks to find the fastest path inside the road link by assigning pull-over positions to normal vehicles as far away from the EV as possible. However, existing studies show that lane-changing maneuvers and stop-and-go behaviors could introduce oscillations and capacity drop (Weng and Meng, 2011; Chen et al., 2014), indicating that the current pull-over practice imposes substantial disturbances on the normal traffic flow.

In principle, the task of vehicles prioritizing emergency vehicles on highway segments can be considered as a vehicular reorganization problem, with the objective of one cleared lane. An orderly fulfillment of such reorganizations entails high-level cooperation between drivers that are only feasible nowadays through multiple sets of coordinated traffic signals (Xuan et al., 2011; Wu et al., 2016). The difficulties of such self-organization of drivers are partially due to the lack of communication and the absence of a centralized control algorithm. Considering the promising development of connected vehicles, what is missing is an efficient control algorithm for EV lane pre-clearing that could give explicit orders and optimal trajectories for CVs to follow. Note that in the present paper, we assume that all drivers would comply with such trajectories and prioritize EVs based on emergency protocols.

To this end, in this study, we propose a cooperative control strategy for EV prioritization at highway segments in connected environments. Specifically, we intend to design optimal trajectories for both EVs and surrounding vehicles, so that EVs could drive with the desired speed uninterruptedly as well as minimizing the influence on normal traffic. This work contributes to the state-of-the-art in the following aspects: (i) explicit EV priority solutions on highway segments are proposed that do not entail pull-over; (ii) The proposed method is able to guarantee the desired speed of emergency vehicles in feasible traffic conditions[1] ; (iii) The influence of EVs on the normal traffic flow is minimized; (iv) The proposed method could also help in EV routing problems by identifying and suggesting better paths with higher operational EV speed, with only aggregated traffic density data.

The remainder of this paper is arranged as follows. Section 2 reviews related studies in the literature. Section 3 will introduce the assumptions and modeling process. Section 4 provides the solving algorithm for the proposed model.

[1] A feasible condition refers to a traffic condition in which there is enough road space for normal vehicles to clear one lane for the EV through merging maneuvers, and the threshold for such feasible conditions will be introduced later on Page 12.

Section 5 presents a case study based on field data and a comparative study against an existing model to demonstrate the proposed algorithm. Section 6 further explores the merits of the proposed strategy in EV routing problems. Section 7 concludes the paper with discussions.

2. Literature review

2.1. Traffic signal priority control

Traffic signal priority (TSP) control is a commonly adopted technique to give special treatments to various traffic modes for different objectives, such as emergency vehicles, buses, light rail vehicles, and pedestrians. Generally, TSP strategies can be divided into two categories: passive priority and active priority. Passive priority usually refers to long-term offline treatments based on historical data (Christofa and Skabardonis, 2011). Typical examples are coordinated signal systems implemented in an area with substantial transit usage, which are tuned based on the speed and timetable of transit vehicles instead of normal passenger cars. In this area, Estrada et al. (2009) proposed an evolutionary algorithm to optimize the travel time of bus users while avoiding substantially increasing the delay of other passenger cars. Hu et al. (2015) investigated the TSP problem in the connected vehicle environment and developed a model aiming at minimizing passenger delay, under the rule that TSP is only granted when the transit vehicle is behind the timetable. Ji et al. (2019) proposed a mixed-integer linear model to simultaneously optimize tram trajectories and signal timing plans along a tram line. Due to the low volume and frequency of emergency vehicles, the above-mentioned treatments are barely adopted for EV prioritization in practice.

On the contrary, active priority strategies provide more direct solutions which could detect the presence of emergency vehicles or buses through optical, acoustic, special inductive loop, or Global Positioning System (GPS) (Nelson and Bullock, 2000). In TSP systems, once a request is received, the traffic signal controller would switch to a prespecified or adaptive control plan and give green phases accordingly. In this area, Qin and Khan (2012) proposed and compared real-time control and optimal control strategies for EV preemption, with the purpose of ensuring the operating speed of EVs as well as minimizing the impacts on normal vehicles. Simulation results showed that the proposed strategy overcomes commonly used existing approaches. Huang et al. (2015) developed a Petri net-based approach for the preemption of emergency systems, by modeling the problem as a discrete event system. Based on the Petri net model, a control strategy was also proposed with verified liveness and reversibility. Anderson and Daganzo (2019) evaluated the performance of one conditional signal priority (CSP) strategy which only sends requests when service reliability can be improved. Simulation results demonstrated the benefit of the CSP strategy due to a reduced number of requests.

The minor difference between EV and transit prioritization is that emergency vehicles are legally and morally granted with a higher priority level than transit vehicles. Therefore, EV prioritization usually entails an immediate switch of traffic signal while transit vehicles are prioritized with extended green time, offset adjustments, and phase insertion (He et al., 2011; Ma et al., 2010; Skabardonis and Geroliminis, 2008; Smith, Hemily, Ivanovic). Other researchers also investigated various EV/transit priority strategies in terms of influences on the operation of coordinated signals (Nelson and Bullock, 2000; Wu and Guler, 2019), emission considerations (Han et al., 2016), combined design with pre-signals and queue jump lanes (Guler et al., 2016; Truong et al., 2017).

2.2. Merge control

The operation of clearing one lane for the emergency vehicle is analogous to merging operations around ramps and work zones in that they have the same critical mission, namely, changing lanes within a limited time/space. In this area, one major research stream is to control merging behaviors through ramp metering where extensive studies have been conducted with various methods (Zhang and Levinson, 2004; Cassidy and Rudjanakanoknad, 2005; Srivastava and Geroliminis, 2013). Papageorgiou et al. (1991, 2008) proposed a feedback control algorithm entitled ALINEA for ramp metering design which is robust to disturbances. Chen and Ahn (2015) developed a variable speed limit control method to provide gradual speed transition and clear existing queues around non-recurrent bottlenecks such as work zones. However, this approach highly relies on the implementation and control of traffic signals, which is not feasible for the EV prioritization problem discussed in this paper.

More recent studies take advantage of the emerging connected and automated vehicle technology and explore the opportunity of improving merging performances without traffic signals. Rios-Torres and Malikopoulos (2016a) proposed an optimization framework with closed-form solutions aiming at smoothing traffic flow and reducing stop-and-go disturbances. Simulation results indicated that the proposed model could significantly reduce fuel consumption and travel time. Letter and Elefteriadou (2017) developed a longitudinal merging control algorithm to maximize the average speed of automated vehicles based on roadside communication. Han and Ahn (2018) proposed a stochastic model to reveal the breakdown mechanisms for merging bottlenecks. A proactive control model was then proposed to decrease breakdown probability based on the revealed mechanisms. Ding et al. (2019) proposed a rule-based algorithm to achieve a near-optimal merging sequence for both mainline and on-ramp vehicles. The performance of the proposed model was demonstrated with optimality analysis and also compared with two other control strategies. More through literature reviews can be found in Rios-Torres and Malikopoulos (2016b) and Bevly et al. (2016).

Table 1
Notationlist.

Notations	Descriptions
S	upper-level cost function
s	lower-level cost function
$\mathbf{p_k^e}$	position of the EV at time step k in (x_k^e, y_k^e)
$\mathbf{p_k^i}$	position of normal vehicle i at time step k (x_k^i, y_k^i)
v_e	desired longitudinal speed of the emergency vehicle (m/s)
$v_l(i, k)$	lateral speed of connected vehicles (m/s)
$v_h(i, k)$	longitudinal speed of connected vehicles (m/s)
v_{cv}	average longitudinal speed of normal vehicles in the preceding block (m/s)
V	relative speed between the EV and the average speed of normal vehicles (m/s)
L	distance between the EV and preceding normal vehicles when the designed trajectories are conducted (m)
$c(\mathbf{p_k^i}, \mathbf{p_k^{i+1}})$	cost of vehicle i moving from movement step k to step $k+1$
n_k	number of normal vehicles occupying the emergency lane in time step k
Δt	duration of the unit time step (s)
ξ	length of the buffer zone, which is the safe distance that should always be maintained between the EV and normal vehicles (m)
A	coefficient matrix for all constraints
B	matrix of boundary values for all constraints
a, b, c, d	coefficients of linear regression functions

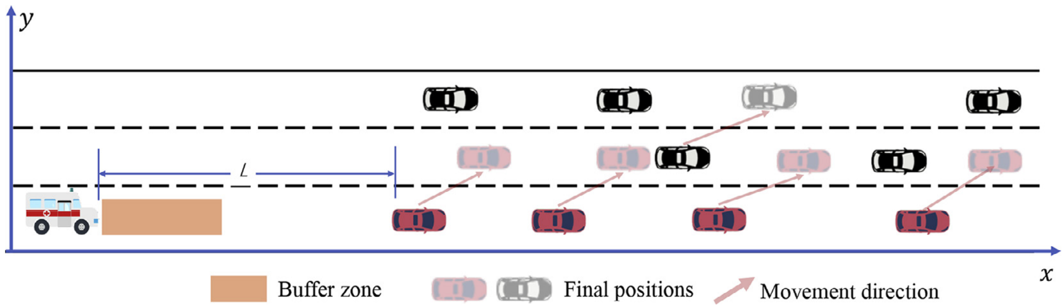

Fig. 1. An illustration of the EV lane pre-clearing problem.

3. The cooperative control model for EV lane pre-clearing

3.1. Notation

For the simplicity of tracking notation, we summarize all of the notation in Table 1.

3.2. Problem statement and assumptions

In the present study, we seek to find the optimal trajectories for normal vehicles to clear one lane for one emergency vehicle on highway segments, given the desired speed of the EV, the locations and speed of normal vehicles. A typical scenario is illustrated in Fig. 1, where an EV is driving towards a vehicle fleet. Instead of the pull-over approach, we propose that the EV could also maintain its desired speed if surrounding normal vehicles drive cooperatively and follow the scheduled trajectories. In the present study, the following assumptions are made with consideration to the promising development of connected vehicle technologies:

(1) The emergency vehicle intends to drive at a constant desired speed and will not change lane. Prevailing technologies such as advanced driver-assistance systems (ADAS) could help drivers better accomplish this task.
(2) Preceding vehicles consist of connected vehicles that are able to share and receive trajectory data in a real-time manner through vehicle-to-vehicle (V2V) or vehicle-to-infrastructure (V2I) communication. We further assume delay and error free communication to focus on the core problem of vehicle cooperation in this paper.
(3) All surrounding vehicles are able and willing to comply with the trajectories that are designed and transmitted in real-time.
(4) We also assume that feasible solutions exist for the EV clearance, that is, there are enough vacant spaces in the studied highway segment to clear one lane for the EV. Extreme conditions such as traffic jam are beyond the scope of this study[2].

[2] We will further explain how to identify feasible conditions later in the paper

3.3. Model formulation

For convenience, the problem is formulated in a discrete-time manner which is commonly adopted in trajectory design problems. In such conditions, the trajectory design problem can be considered as a bi-level optimization problem, where the lower-level task seeks to minimize the disturbances on normal vehicles when clearing one lane for the EV, based on which the upper-level task attempts at minimizing the interference on the EV. The generalized formulation for the bi-level optimization problem is as follows.

$$\min_{L\in\mathbb{R}^+, K\in\mathbb{R}^+, \mathbf{p_k^i}\in\mathbf{p^i}} \sum_{k=0}^{K} S(v_e, L, \mathbf{p_k^e}, \mathbf{p_k^i}) \tag{1}$$

subject to

$$(\mathbf{p_k^i}, K) = \arg\min_{K\in\mathbb{R}^+, \mathbf{p_k^i}\in\mathbf{p^i}} \sum_{k=0}^{K} s(v_e, L, \mathbf{p_k^e}, \mathbf{p_k^i}) \tag{2}$$

$$y_k^e = y_0^e, \forall k = 0, 1, \ldots, K \tag{3}$$

$$x_{k+1}^e = x_k^e + v^e \Delta t, \forall k = 0, 1, \ldots, K-1 \tag{4}$$

$$\mathbf{p_{k+1}^i} = \mathbf{p_k^i} + [v_k^{i,l}, v_k^{i,h}]\Delta t \tag{5}$$

$$x_k^r = \arg\min x_k^i, \forall i = 1, 2, \ldots, n \tag{6}$$

$$x_k^r - x_k^e \geq \xi, \forall k = 0, 1, \ldots, K \tag{7}$$

$$\mathbf{p_k^i} \neq \mathbf{p_k^i}, \forall i \neq j \tag{8}$$

$$x_0^r - x_0^e = L \tag{9}$$

$$y_K^e \neq y_K^i, \forall i = 1, 2, 3 \ldots n \tag{10}$$

$$\mathbf{p_k^e} := (x_k^e, y_k^e), \mathbf{p_k^i} := (x_k^i, y_k^i), L \geq \xi \tag{11}$$

where Eq. (1) and Eq. (2) denote the generalized upper-level and lower-level objective functions, respectively, which will be specified later in Section 4. The constraints in Eq. (3) and Eq. (4) confine that the EV will drive on the same lane with a fixed speed of v^e. Eq. (5) indicates that normal vehicles are flexible in accelerating, decelerating, and lane-changing. Eq. (6) and Eq. (7) address the safety concern that a safety distance should always be maintained between the EV and its nearest preceding vehicle. Eq. (8) ensures that there will be no conflict among trajectories of different normal vehicles. Eq. (9) defines the initial condition of the problem, while Eq. (10) defines the final condition that no normal vehicle remains on the EV lane. It should be noted that the problem above is a mixed-integer nonlinear programming problem over a finite time horizon in the future, which is NP-hard in general and thus computationally intensive (Burer and Letchford, 2012). Another unique feature of the problem is that the maximal number of time steps K is also a decision variable, which means that the number of decision variables changes with different values of K, making it challenging to directly use commercial solvers for the optimal solution. Therefore, we develop a new solving algorithm for the cooperative control problem.

For convenience, the lower-level problem will be denoted as problem $[M_1]$, and the upper-level problem will be denoted as problem $[M_2]$, as shown in Eqs. (12) and (13), respectively.

$$[M_1] \qquad \min_{K\in\mathbb{R}^+, \mathbf{p_k^i}\in\mathbf{p^i}} \sum_{k=0}^{K} s(v_e, L, \mathbf{p_k^e}, \mathbf{p_k^i}) \tag{12}$$

$$[M_2] \qquad \min_{L\in\mathbb{R}^+} \sum_{k=0}^{K} S(s^*(v_e, L, \mathbf{p_k^e}, \mathbf{p_k^i}), L) \tag{13}$$

where S and s are upper- and lower-level objective functions, respectively. Specifically, in the lower level, $[M_1]$ solves the problem of designing optimal trajectories p_k^i with the minimal cost, which will be introduced in detail in Section 4.1. In the upper-level, $[M_2]$ finds the optimal L^*, i.e., the optimal distance to start sorting that minimizes hindrances to the EV based on the optimal solution of the lower-level problem, which will be elaborated in Section 4.2. Note that $[M_1]$ and $[M_2]$ are both constrained by the constraints from Eq. (3) to Eq. (11).

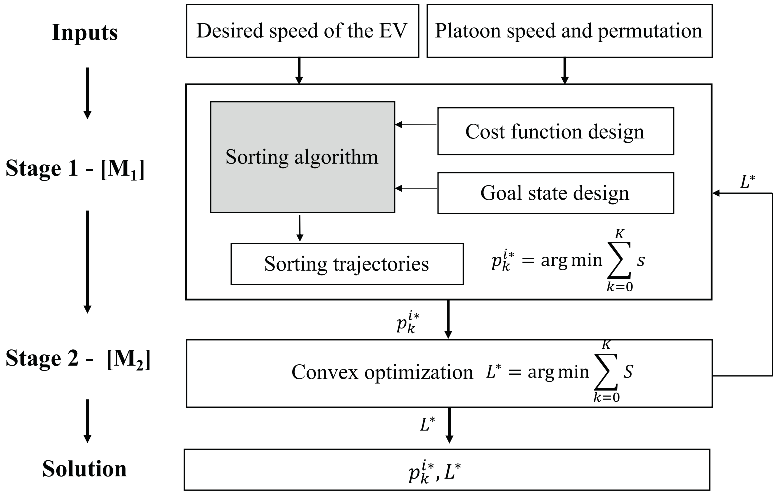

Fig. 2. The solving algorithm framework.

4. EV Lane pre-clearing algorithm

In this section, a solving algorithm for the cooperative control model is proposed. The basic idea is illustrated in Fig. 2. As shown in the Figure, the lower-level problem $[M_1]$ is solved with a local sorting algorithm in Section 4.1, which seeks to find optimal trajectories for normal vehicles, with the purpose of clearing one lane for the EV with minimal cost. The upper-level problem $[M_2]$ will be formulated in a convex way in Section 4.2 to optimize the initiation sorting distance L. The solution of $[M_2]$ will return the optimal L^*, which will be iterated back to stage 1 for convergence tests.

4.1. The EV sorting algorithm for [M*1*]

In this subsection, we develop an algorithm to optimally design trajectories for normal vehicles to clear one lane for the EV, which will be referred to as the EV sorting algorithm. Without loss of generality, we here define a specific formulation of the cost function s for the lower-level problem $[M_1]$ to illustrate explicit solutions as follow:

$$s(v_e, L, \mathbf{p_k^e}, \mathbf{p_k^i}) := R(\mathbf{p_k^i}) \cdot L \tag{14}$$

namely, $[M_1]$ can be denoted as

$$\min_{\mathbf{p_k^i}} \sum_{k=0}^{K} R(\mathbf{p_k^i}) \cdot L \tag{15}$$

subject to:

$$\mathbf{A} \cdot \mathbf{X} \leq \mathbf{B} \tag{16}$$

where R denotes the total operational cost of normal vehicles to complete the clearance of one lane. The cost function s is defined in the sense that disturbances on normal vehicles induced by the emergency vehicle depend on both the time/distance to start clearing the lane and the complexity of corresponding trajectories. The earlier and more complex the clearance operations are, the larger the cost is.

To solve the specified lower-level problem $[M_1]$, we develop an EV sorting algorithm to find optimal trajectories for the clearance with the minimal cost. In the EV lane pre-clearing problem, the goal permutation would be set up as the condition that the EV lane is cleared. Section 4.1.1 will firstly introduce the basic procedure of the general sorting algorithm along with its limitations when directly applied to the EV lane pre-clearing problem. We then develop an EV sorting algorithm to address those limitations in Section 4.1.2.

4.1.1. The general sorting algorithm

The basic procedure for implementing the sorting algorithm is presented in Fig. 3. In sorting algorithms, the studied space consisting of all vehicles is firstly discretized into a grid system, where a vehicle can move from one cell to another in a discrete time-space domain. Then, the cooperative sorting problem is modeled as a path-finding problem in the graphic domain, where each permutation of vehicles represents a node in the graph. The problem is solved by a deterministic A* algorithm with a stepwise strategy, where only one vehicle is allowed to move within each movement step. The purpose of

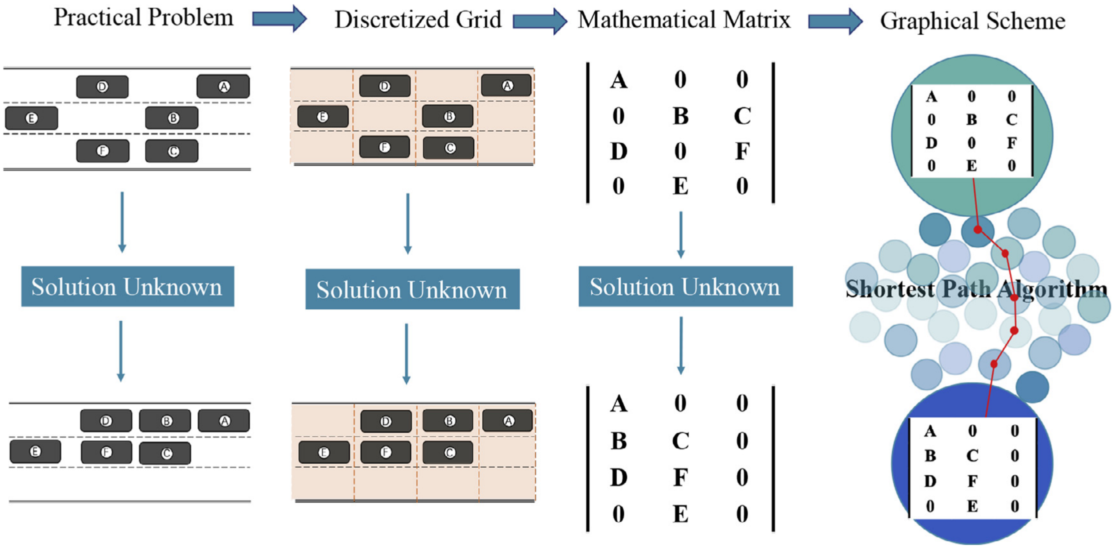

Fig. 3. The sorting algorithm.

this stepwise approach is to reduce the number of explored nodes in each step and thus improve searching efficiency. On the contrary, allowing multiple vehicles to move simultaneously will significantly increase the number of explored nodes in each step and lead to slower search. Therefore, we first adopt the stepwise approach in A* searching and then enable simultaneous movements with a simple integer linear programming method (see later parts of this section). When employing the A* algorithm, the following standard steps are followed:

1) Define an initial state and a goal state. Define the unit cost of changing from one state to its neighbor states.
2) Define a heuristic function H to estimate the generalized cost from the current state to the goal state, and a distance function G to calculate the shortest path found so far from the initial state to the current state. Calculate the estimated cost of the shortest path F if the shortest path goes through the current state by $F = G + H$.
3) Create an open list and put the initial state into the open list. Calculate the F values for all nodes in the open list and select the one with the smallest F value as the current node.
4) If the current node is the goal node, terminate the algorithm and the shortest path is found.
5) Otherwise, put the current node to a closed list and put its adjacent nodes that are not already in the closed list into the open list. Then repeat step 4.

In the A* algorithm, the heuristic function directs a way to search the unexplored parts of the graph so that it is not necessary to generate all nodes of the graph before searching. Instead, the graph is expanded while searching. The resultant shortest path is further optimized with an integer linear programming algorithm to minimize the sorting time by allowing multiple movements within a step. Details of the general sorting algorithm can be found in Wu, Ah, Zhou, Liu, Qu. Note that, after discretization, the threshold of feasible conditions for EV lane pre-clearing can be easily found by simply counting vacant cells on road. Taking Fig. 3 as an example, the threshold of traffic density to implement the proposed method is 2/3.

The general sorting algorithm provides a framework for transforming vehicles from any random permutation to any desired permutation through cooperative driving. However, in the EV lane pre-clearing problem, the general sorting algorithm cannot be directly used. Specifically, the sorting algorithm requires explicit goal states, for both algorithm termination and calculating heuristic functions H. In the EV lane pre-clearing problem, emergency vehicles only need one cleared road lane regardless of vehicular permutations in other lanes, as illustrated in Fig. 4, which is a permutation pattern instead of a specific vehicle permutation. Due to this new feature, the general sorting algorithm cannot be applied in solving the EV pre-clearing problem. To this end, we develop a new solving algorithm.

4.1.2. The EV sorting algorithm

The EV sorting algorithm also adopts the framework shown in Fig. 3, following the procedure of discretization, matrix formulation, and shortest path modeling. However, instead of the standard A* algorithm, we here present a rule-based A* algorithm for finding the shortest path in the graphical domain. In shortest path algorithms, the typical solution for the multiple goals problem is to create a goal set containing all feasible goal nodes. In the EV lane pre-clearing problem, the feasible goal set contains a combinatory number of vehicular permutations. However, enumerating all goal states at every iteration of the algorithm has significant impacts on computation efficiency and therefore should be avoided. To this end, a termination rule is developed and used in replacement of explicit goal states in the algorithm, which is defined as follows:

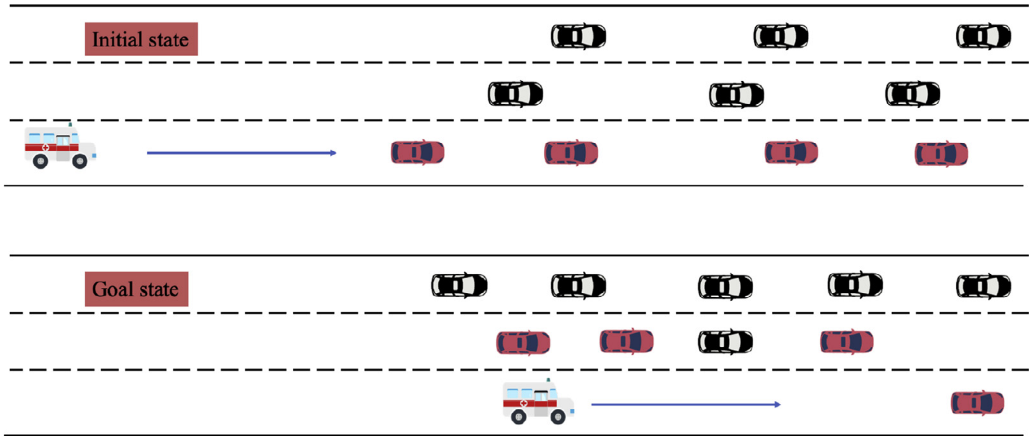

Fig. 4. The initial and goal state in the emergency vehicles priority problem.

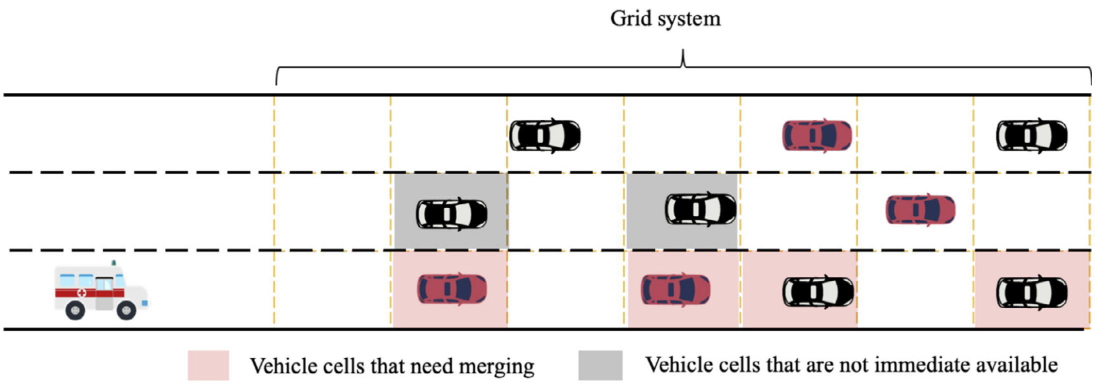

Fig. 5. Illustration for the proposed heuristic function.

Termination rule: In step 4 of A* algorithm, if the EV lane is cleared for emergency vehicles, then terminate the algorithm; otherwise, continue to step 5.

Another challenge of implicit goal states is how to calculate cost functions *H*, *G*, and *F* as most commonly adopted cost functions are based on Manhattan distance or misplaced distance which both entails explicit goal states. To this end, we also follow the rule-based logic and define a new cost function as follows:

$$G(k+1) = G(k) + c(\mathbf{p_k^i}, \mathbf{p_k^{i+1}}) \tag{17}$$

$$H(k) = n_k \min c(\mathbf{p_k^i}, \mathbf{p_k^{i+1}}) \tag{18}$$

$$F(k) = G(k) + H(k) \tag{19}$$

where n_k denotes the number of vehicles occupying the emergency lane in time step k; $c(\mathbf{p_k^i}, \mathbf{p_k^{i+1}})$ denotes the cost of vehicle i moving from movement step k to step $k+1$ which can be defined flexibly for various objectives. In variations of A* algorithms, the heuristic function $H(k)$, by definition, is the estimated distance to goal states from the current state. The value of heuristic function could provide possible directions of goal states, and therefore help to decide the exploring direction in the next iteration. In the heuristic function of Eq. (18), we assume that each vehicle in the emergency lane can successfully merge into adjacent lanes with one movement step.

We use an example in Fig. 5 to further explain how the proposed heuristic function is calculated. For convenience, we here define that $c(\mathbf{p_k^i}, \mathbf{p_k^{i+1}}) = 1$. As shown in the figure, four vehicles need to merge into the middle lane while two adjacent cells are already occupied. Therefore, in this example, the heuristic value in the current movement step j equals $H(k) = 4$. In other words, the heuristic function assumes that all the four vehicles in the emergency lane could successfully merge into the middle lane in the next four steps, regardless of the situation that their adjacent cells may not be immediately available.

Note that, when Hart et al. (1968) propose the A* algorithm, it is proved that if the heuristic function never overestimated the actual cost, then the A* algorithm would find the global optimum solution. Such heuristic functions are called admissible heuristic functions. The proposed heuristic function in Eq. (18) is obviously admissible too.

4.2. Convex optimization for [M$_2$]

The EV sorting algorithm mainly focuses on cooperative driving problems within one block, based on which [M_2] addresses how to minimize the hindrances on the approaching EV along a road segment with several vehicle blocks. We formulate [M_2] in Eq. (20) and Eq. (21) to illustrate explicit solutions. In practice, other cost functions can be used for alternative objectives, and specific emergency related factors should also be carefully examined to refine the cost function.

$$S(s^*, L) := s^*(v_e, L, \mathbf{p_k^e}, \mathbf{p_k^{i*}})F_d(v_e, L, \mathbf{p_k^e}, \mathbf{p_k^{i*}}) \tag{20}$$

$$F_d(v_e, L, \mathbf{p_k^e}, \mathbf{p_k^{i*}}) := \sum_{k=0}^{K} \frac{n_k L \Delta t}{L - \Delta t \cdot V \cdot k} \tag{21}$$

$$V = v_e - v_{cv} \tag{22}$$

where v_{cv} denotes the average longitudinal speed of normal connected vehicles in the preceding block (m/s); V denotes the relative speed between the EV and the average speed of CVs (m/s); n_k denotes the number of vehicles occupying the emergency lane at time step k. The physical meaning of Eq. (21) is the cumulative disturbance time of normal vehicles to the emergency vehicle, weighted by their distance to EV. Note that the definition in Eq. (21) is not exclusive[3] We chose the formulation of Eq. (21) due to its convexity, which will be elaborated later in this section. Based on Eq. (7) to (11), L is far larger than $Vk\Delta t$ so that the singularity point is avoided. With the defined S function, [M_2] can be specified as:

[M2]
$$\min \sum_{k=0}^{K} \frac{n_k L \Delta t}{L - V k \Delta t} L R^* \tag{23}$$

subject to:

$$\mathbf{A} \cdot \mathbf{X} \le \mathbf{B} \tag{24}$$

We now prove that the cost function is a bounded convex function, and [M_2] has a unique solution subject to its constraint set in Proposition 1.

Proposition 1. *The cost function in Eq. (23) has a unique solution subject to constraints defined in Eq. (24).*

Proof. S function in Eq. (23) can be derived as Eq. (25). Assume normal conditions when $k \ge 1$.

$$S(L) = \sum_{k=1}^{K} \frac{n_k \Delta t}{1/L - V k \Delta t / L^2} R^* = \sum_{k=1}^{K} \frac{4 n_k V k \Delta t^2}{1 - (2 V k \Delta t / L - 1)^2} R^* = \sum_{k=1}^{K} \zeta(L) R^* \tag{25}$$

Define

$$\zeta(L) = \zeta(\delta(L)) = \frac{4 n_k V k \Delta t^2}{1 - \delta(L)}, \delta(L) = (2 V k \Delta t / L - 1)^2 \tag{26}$$

Since $\delta(L)$ is a single variable function in quadratic form, therefore, we have

$$\delta(aL_1 + (1-a)L_2) < a\delta(L_1) + (1-a)\delta(L_2), \forall a \in (0,1), L_1, L_2 \in [VK\Delta t + \xi, W] \tag{27}$$

ζ is a strictly convex and monotonically increasing function of $\delta(L)$. Therefore, $\zeta(L)$ preserves the convexity of $\delta(L)$. Similarly, it can be derived that

$$S(aL_1 + (1-a)L_2) < aS(L_1) + (1-a)S(L_2), \forall a \in (0,1), L_1, L_2 \in [VK\Delta t + \xi, W] \tag{28}$$

Eq. (28) proves that S is a strictly convex function of L. Furthermore, it can be derived that S is also bounded within the domain of L:

$$\sum_{k=1}^{K} n_k \cdot \frac{4 V \Delta t^2}{1 - (2 V \Delta t / L - 1)^2} R^* \le S(L) \le \sum_{k=1}^{K} n_k \frac{4 V K \Delta t^2}{1 - (2 V K \Delta t / L - 1)^2} R^* \tag{29}$$

With Eq. (29), the upper and lower bound of the optimization function can be further determined by Eq. (30).

$$\sum_{k=1}^{K} 4 n_k \Delta t^2 V R^* \le S \le \sum_{k=1}^{K} n_k \cdot \frac{4 n_k \Delta t^2 V K R^*}{1 - (2 V K \Delta t / W - 1)^2} \tag{30}$$

Therefore, we prove that the objective function in [M_2] is a convex function with a bounded range, namely, it has a single optimal solution.

In fact, considering the formulation of Eq. (25), the last quadratic term will dominate the value of the S function, showing a semi-quadratic form in the Cartesian coordinate system and intuitively having a minimum solution. The exact optimal solution of the problem can be easily solved by any prevailing solver, such as Matlab and R, due to its convexity. □

[3] we can also use other formulations as long as they satisfy the following intuitive rules: a) the cost should be an increasing function of sorting steps K; b) the cost should be a decreasing function of L.

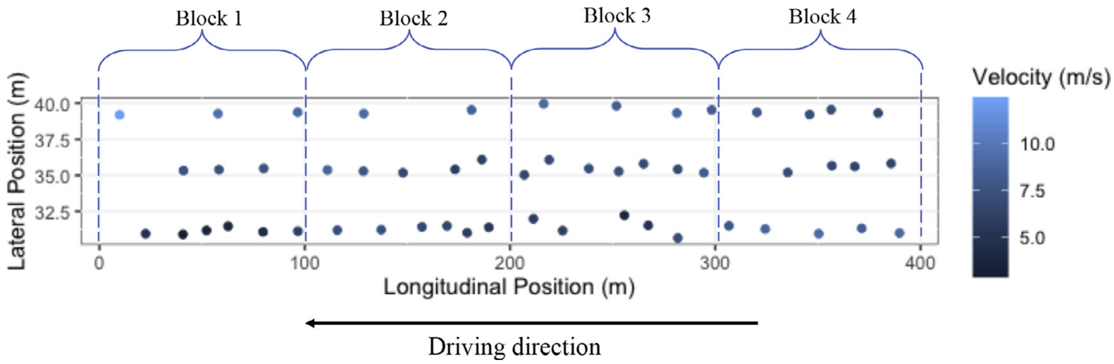

Fig. 6. Vehicle position in HighD dataset.

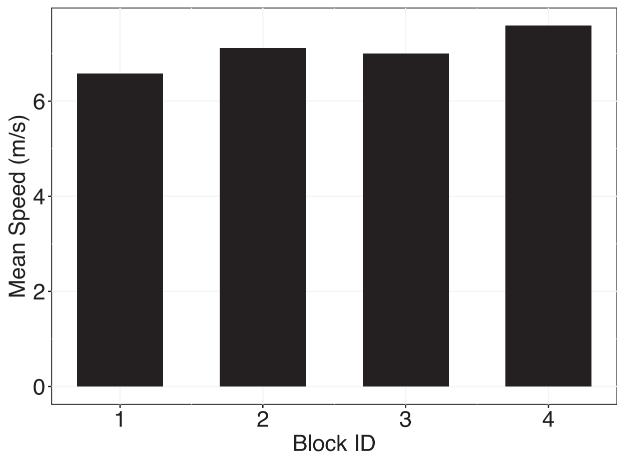

Fig. 7. Mean speed of each vehicle block.

5. Case study

In this section, a case study is conducted with field data to illustrate the implementation and results of the proposed method. The data used in this study is from the ”HighD” dataset collected on German highways (Krajewski et al., 2018). Naturalistic driving data including location and speed were recorded on different highway segments without ramp and weaving sections nearby. The dataset was released in 60 trajectory tracks with each track covering about 420m length of the six-lane bidirectional highway. In this section, we select one direction on a single frame (frame ID: 29246) in the 25th data track.

In the selected frame, there are 54 vehicles randomly distributed in three lanes, driving from east to west on a 400m highway. Their relative positions are shown in Fig. 6, where each dot denotes a vehicle. In this section, we assume that all vehicles on the highway have been segmented into several blocks with a uniform length of 100 m. The influence of different segmentation methods will be discussed later in Section 6. We presume that an approaching EV needs to pass through this highway segment through the shoulder lane from right to left. The current positions and speed of all the 56 vehicles will be used as inputs to generate the sorting solutions. The resultant trajectories will then be sent to all drivers and be actioned upon accordingly.

In each block, the EV sorting algorithm is applied to generate a local sorting plan, which entails discretizing the block into homogeneous cells relative to a background speed. The speed distribution in the selected frame is shown in Fig. 7, and the mean speed for all vehicles equals to 7 m/s. For each block, the block mean speed is defined as the average space speed of all vehicles located in the block. We observe that the difference in average speed among four blocks is very minor. We then assume that all four vehicular blocks have the same space mean speed of 7 m/s.

Specifically, the cell width naturally equals the lane width but the cell length is decided mainly considering the critical lane-changing gap in the regarded traffic flow. Existing studies indicate that the critical gap required for lane-changing maneuvers by human drivers is very short when surrounding vehicles have similar speed (Hidas, 2002; Toledo et al., 2003). With cooperative driving strategies, the critical gap could be expected to be even smaller. The field data in this frame shows that the minimum distance between vehicles equals to 9.5 m. Therefore, the cell length of 10m is used for discretization. Other input parameters are: the desired speed of the emergency vehicle is assumed as 22 m/s, resulting in the relative

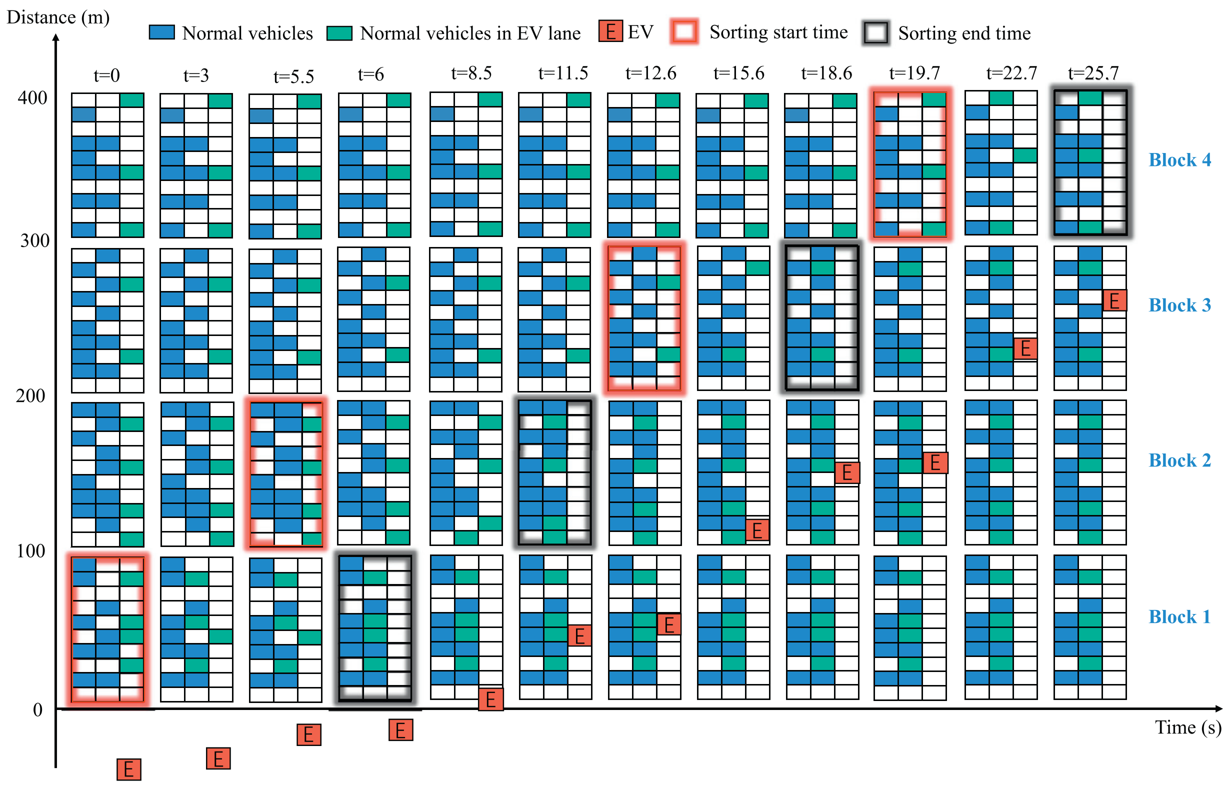

Fig. 8. The result of the EV lane pre-clearing algorithm with the HighD Sample.

speed of 15 m/s to normal vehicles; the unit time Δt for each movement step equals to 3 s; ξ equals to 50 m. Note that the relatively conservative buffer zone of 50 m is used in this case study only to present various optimal solutions. A large safe distance will make Eq. (7) the binding constraint which dominates other constraints. In such conditions, the optimal solution will always be equal to the safe distance.

With the aforementioned setup, the sorting plan for each block can be gained through the method proposed in Section 4.1. The resultant sorting steps for four vehicle blocks are all 2 steps. Subsequently, the initiation sorting time for each platoon can be further calculated through the method proposed in Section 4.2. For instance, block 2 needs 2 sorting steps to clear the EV lane. Therefore, the optimization function of $[M_2]$ can be specified as:

$$S(L) = \frac{96L^2}{L-45} + \frac{72L^2}{L-90} \tag{31}$$

The optimal distance L^* is then found as 152.1m. The optimal distances for block 1, 3, and 4 equal to 135 m, 145.8 m, and 139.4 m, respectively. The exemplified results are also illustrated in Fig. 8. In the figure, blue blocks denote the vehicles in the leftmost and middle lanes while the cyan blocks denote the vehicles in the EV lane. Therefore, those vehicles denoted by cyan blocks will receive merging trajectories generated by the improved sorting algorithm. Meanwhile, surrounding vehicles would drive cooperatively to ensure the merging gap. In this example, the emergency vehicles managed to maintain its desired speed with a reliable priority.

It is also noticeable in the figure that block 2 starts sorting before the sorting in block 1 is completed. The reason is that, the sorting in block 2 is more complicated and therefore needs to initiate earlier accordingly. This interesting phenomenon would otherwise be less possible to happen with only self-organized human drivers which partially demonstrates the efficiency and advantage of the proposed strategy over the current practice.

We also compare the proposed strategy with one state-of-the-art pull-over strategy to illustrate different ideas of facilitating EVs on highway segments. The pull-over group is based on the study of Hannoun et al. (2018), which seeks to facilitate EVs through designing pull-over trajectories as far away from EVs as possible. Similar to the present paper, their model also investigates the problem in a discrete manner with identical cells. However, the very basic ideas of the two studies are different. In their study, normal vehicles need to decelerate and pull-over, during which EV speed is assumed to be not only hindered by vehicles on the same lane but also influenced by vehicles on adjacent lanes. On the contrary, in our study, all normal vehicles could maintain their speed and have no impact on EVs on adjacent lanes. Here, we use the same basic setups as those in their case study (Fig. 4 in their paper), such as initial positions as shown in Fig. 9(b) and EV maximum speed. The final locations of EVs and normal vehicles from two strategies are presented in Fig. 9.

Initial Position					v3		v6		v9		v12		v15		
	EV			v1		v4		v7		v10		v13			
					v2		v5		v8		v11		v14		

(a)

Final Position				v1	v3	v4			v6		v9	v10	v12	v13	v15
					v2		v5			v7	v8		v11		v14
	EV	EV	EV	EV	EV	EV	EV	EV	EV	EV	EV	EV	EV	EV	EV
EV Speed	13.4 m/s			15.5 m/s			17.2 m/s			18.9 m/s			20.4 m/s		

(b)

Final Position					v3	v4	v6		v9	v10	v12		v15		
	EV	EV	EV	EV	EV	EV	EV	EV	EV	EV	EV	EV	EV	EV	EV
				v1	v2		v5	v7	v8		v11	v13	v14		
EV Speed	20.4 m/s														

(c)

Fig. 9. Comparison with Hannoun's model (a) initial position (b) the solution of Hannoun's model (source: Hannoun et al. (2018) (c) the solution of our model.

With the pull-over strategy, as shown in Fig. 9(b), the emergency vehicle starts with relatively low speed and constantly accelerates because all normal vehicles pull over to positions far away from the EV. In this scenario, the EV could pass through the road segment of 252-feet in 4.54 seconds. With the proposed strategy in this study, the EV could always drive in the maximum speed and needs only 3.76 seconds to travel the same road segment. One notable advantage of the pull-over approach is that EVs travel in a static environment, which could make EV drivers feel safer. Even though our model requires EVs to travel in a dynamic environment and thus entails a higher level of cooperation between EVs and non-EVs, traffic safety is guaranteed, and the benefits are significant. Except for higher EV speed, the proposed strategy imposes considerably less disturbances on traffic in terms of both intensity and scale. Specifically, in our model, surrounding vehicles could maintain their speed which is obviously more favourable for non-EV drivers compared with pull-over. In addition, since normal vehicles will maintain speed leading to smaller relative speed to the EV than that in the pull-over scenario, the EV will pass through and thus influence less normal vehicles when traveling through a road segment of the same length. Take Fig. 9 as an example, and further assume that the downstream road segment has constant traffic density, and the EV will continue to travel with the maximum speed of 20.4 m/s in both scenarios with normal vehicles driving in 10.2m/s if not pulling over. In such conditions, the proposed strategy would influence a half number of normal vehicles compared with the pull-over strategy.

6. Application to EV routing problems

In the current practice, EVs usually suffer from time-varying traffic flow conditions, resulting in highly stochastic and unpredictable travel time from the allocation station to accidents. The uncertain travel time not only influences local operations on each road but also makes upper-level routing problems more challenging where link travel time is the fundamental input. The method in this paper makes it possible to simplify routing problems by removing travel time uncertainties and changing it to a deterministic shortest path problem. In consideration of this, we further investigate the inherent features of the problem, as well as how the algorithm should be set up to better support EV routing-related decisions.

Theoretically, the optimal distance L^* to initiate sorting could always be solved based on the pre-specified block length setup, desired EV speed, and time-varying CV speed and permutations. However, in practice, the resultant optimal solution L^* may be beyond the communication range of the arriving EV due to unfavorable setups and surrounding traffic flow conditions and thus unfeasible. In such conditions, several key variables have to be adjusted, such as a reduced EV speed, in order to cover the optimal value of L^* into the communication range, which will inevitably compromise EV routing plans. Therefore, the field implementation entails a reasonable estimation of the optimal distance of L^* when making EV routing decisions. However, the necessary inputs of calculating L^*, such as vehicular permutations on a road, are hardly predictable before EV enters that road. This dilemma leads to a challenging problem of how to estimate L^* with limited data instead of perfect high-resolution data. In order to address this issue, we conduct simulations to examine the relationship between

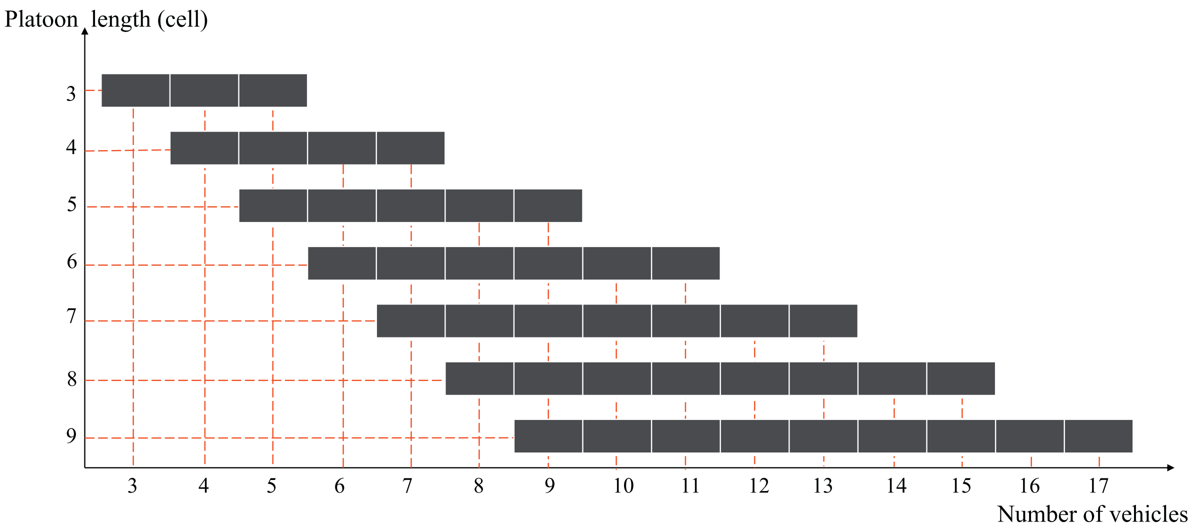

Fig. 10. The simulated scenarios with various block length and traffic density.

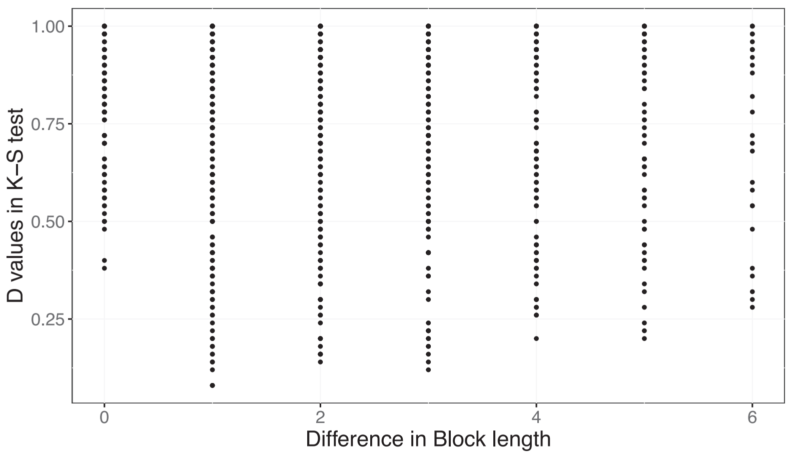

Fig. 11. The relationship between the block length difference and K-S statistics.

the optimal solution and influencing variables including EV desired speed, block length in segmentation, and traffic density, with the purpose of achieving a reasonable estimation of L^*.

Without loss of generality, in all scenarios, we assume a three-lane highway segment without nearby ramps. Vehicle blocks are discretized into a grid system by the method introduced in the present paper. The block length setup ranges from 3 vehicle cells to 9 vehicle cells, incremented by one cell. For each block length, the grid size is fixed but a various number of vehicles were tested to examine the influence of traffic density on the optimal solution. The simulated scenarios are illustrated in Fig. 10. Note that the traffic density in this section is a unitless variable defined by the number of vehicles divided by the number of cells in the block. For each scenario in Fig. 10, 50 different permutations were randomly generated and for each of them, five simulations were run considering the randomness in the ILP procedure. In total, 13,000 simulations in 42 scenarios were conducted.

Based on the results, we found that the optimal solution L^* highly depends on the traffic density but is less relevant to the block length setup. To demonstrate this conjecture, two-sample Kolmogorov-Smirnov (K-S) tests were conducted to examine distributional differences of L^* among all 42 scenarios with various block length setups, desired EV speed, traffic density, and permutations (Meng and Qu, 2012). In total, the results of 861 K-S tests were obtained. Firstly, the relationship between block length and K-S test statistics, D value, which represents the deviations in distribution between the two samples, is presented in Fig. 11. In the figure, no clear statistical correlations could be found between block length setups and D values.

Similarly, the relationship between traffic density and the K-S test statistics is presented in Fig. 12. In the figure, it is obvious that a slight difference in traffic density will result in a large difference in the distribution of the optimal L^*. Several exceptions exist in Fig. 12 where the scenarios have the same density but result in significantly different L^* values. The reason is that in those K-S tests, the block length in one scenario is much larger than the other one, and therefore presents

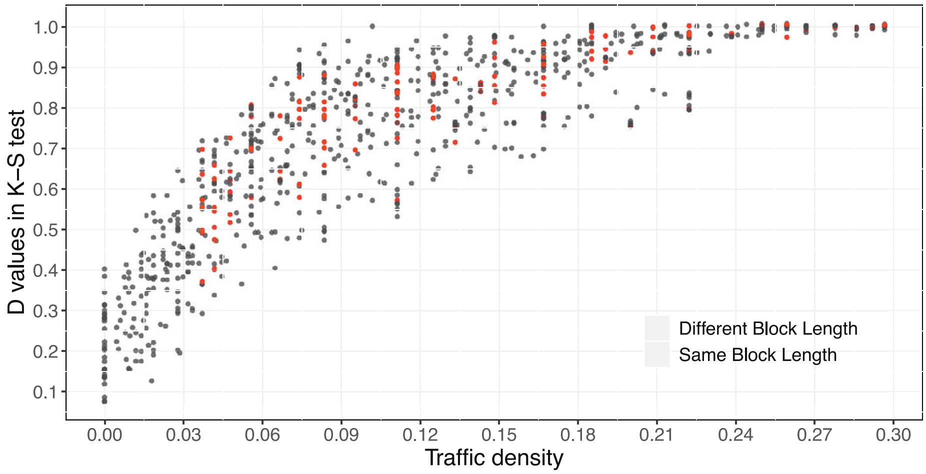

Fig. 12. K-S tests of L^* with different traffic density and block length.

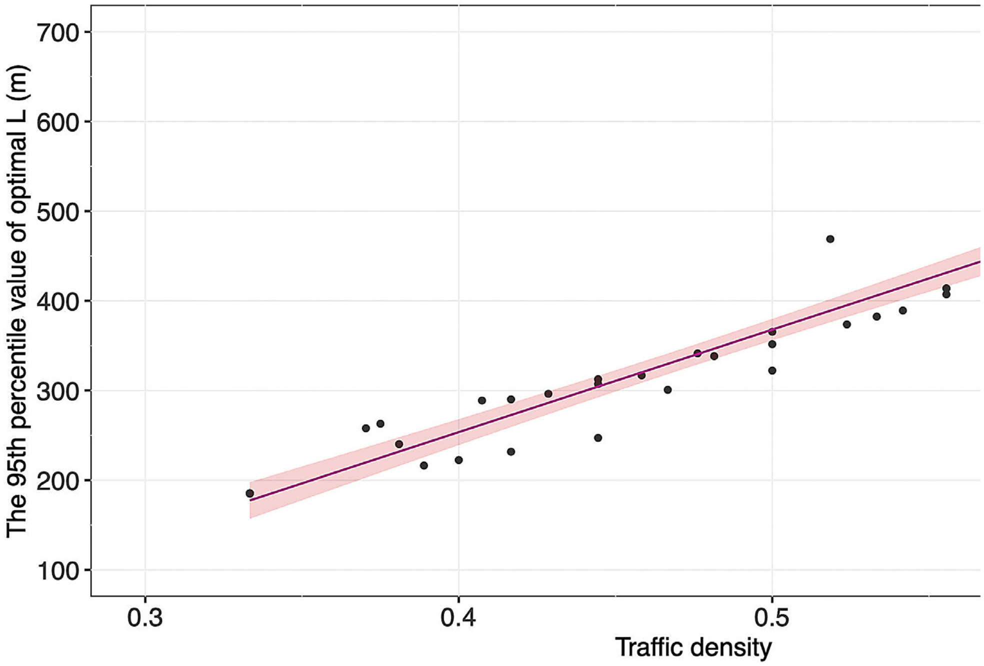

Fig. 13. Linear fitting between the 95th percentile value of L^* and traffic density.

local clustering or dispersing phenomenon. In addition, we also differentiate two groups where the red dots denote K-S test results between scenarios with the same block length, and blue dots denote K-S test results between scenarios with different block lengths. The red group reports a more significant relationship between traffic density and optimal L^*. In other words, when the block length is fixed, the optimal solution L^* is very sensitive to traffic density.

Since travel time percentile value is widely used in travel time reliability studies (Zang et al., 2018), we here adopt the 95th percentile value of L^* as a threshold to ensure that the actual optimal solution can be largely covered within EV communication range. The relationship between traffic density and the 95th percentile value of optimal L is presented in Fig. 13, indicating a linear relationship with a R-square value of 0.9, as shown in Eq. (32). In Fig. 13, the shadow around the fitting line indicates a 95% level of confidence interval. Note that other fitting functions such as quadratic forms can be chosen but we pick the linear fitting for simplification.

$$L^*_{95th} = ak + b + e \tag{32}$$

where a and b are the coefficients obtained through simulation, e is fitting errors, and k is the traffic density. In addition, we can further prove that there exists an explicit fractional relationship between the optimal value of L^* and the relative speed V by the following Proposition.

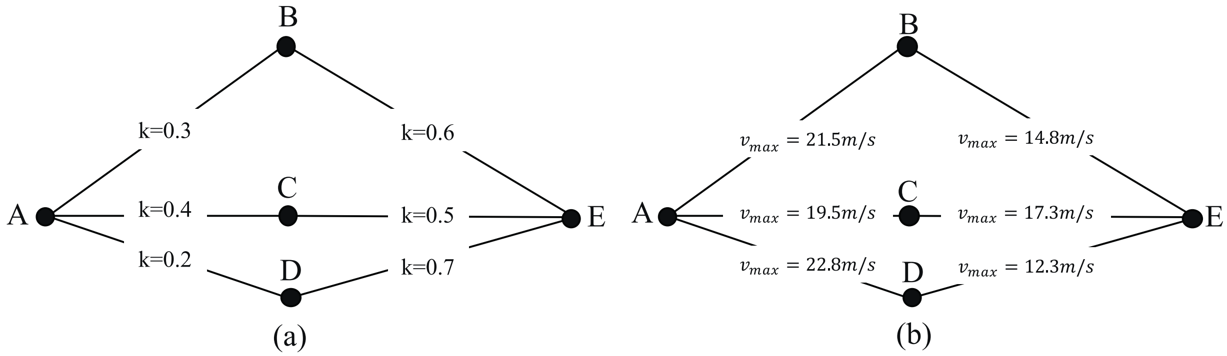

Fig. 14. A simple traffic network with (a) traffic density data; (b) calculated speed limits of EV.

Proposition 2. *The optimal solution L^* is an explicit fractional function of the relative speed V if the traffic density is fixed.*

Proof. Assume that L^* is the optimal solution of Eq. (25) with a relative speed V, so that we have

$$S_{min} = \sum_{j=1}^{N} \frac{4n_j \Delta t^2 \cdot V \cdot j}{1 - (2\Delta t \cdot V \cdot j / L^* - 1)^2} R^* \tag{33}$$

Assume that L^*_{new} is the optimal solution of Eq. (25) with a new relative speed $V_{new} = mV$, so we have

$$S^{new}_{min} = \sum_{j=1}^{N} \frac{4n_j \Delta t^2 \cdot V \cdot j}{1 - (2\Delta t \cdot V \cdot j / L^* - 1)^2} R^* = m \sum_{j=1}^{N} \frac{4n_j \Delta t^2 \cdot V \cdot j}{1 - (2\Delta t \cdot V \cdot j / (L^*_{new}/m) - 1)^2} R^* \tag{34}$$

Therefore, it can be derived that

$$L^*_{new} = \frac{V_{new}}{V} L^* \tag{35}$$

□

Therefore, the relationship between the 95th percentile value of the optimal L can be statistically summarized as the following Equation.

$$L^*_{95th} = (ak + b + e) \frac{v'_e - v_{cv}}{v_e - v_{cv}} \tag{36}$$

If vehicle speed data is not available, such as in traffic planning problems, by applying the theory of linear-shape fundamental diagram where traffic speed is a linear function of traffic density (Greenshields et al., 1935), Eq. (36) can be further derived as:

$$L^*_{95th} = (ak + b + e) \frac{v'_e - ck - d}{v_e - ck - d} \tag{37}$$

where c and d are the coefficients in fundamental diagram; v_e is the EV speed used in simulation and v'_e are an alternative EV speed. In conclusion, the 95th percentile value of the optimal L^* can be reasonably estimated with only traffic density data of each road path. Furthermore, Eq. (37) is informative in choosing the desired speed based on the traffic density of the path, especially when there is a limit in the EV communication range. The physical meaning of a can be interpreted as the incremental distance headway between EV and normal vehicles to start sorting, brought by the increase of traffic density. A large value of a indicates that the optimal solution is highly sensitive to traffic density, and vice versa.

We provide a simple example here to illustrate the merit of the proposed method in routing problems. For convenience, assume that $a = 1133, b = 196, c = -30, d = 30, v_e = 22, e = 0$, and the communication range of EV is 250m. Considering that the EV is driving in a traffic network as shown in Fig. 14(a), where the distance between adjacent nodes all equal to 200m and traffic density is denoted by k. With the strategy in the present paper, speed limits $v_{\max}$ for EV on different road links can be easily calculated as shown in Fig. 14(b), which is more direct and valuable information for routing problems. In this example, the shortest path is $A - C - E$ with the minimum travel time of 21.8s.

7. Discussion and conclusion

In this paper, we propose a cooperative control strategy for local EV priority at highway segments. The basic idea is to clear the lane to be used by EV through cooperative driving with surrounding connected vehicles. In the proposed model, normal vehicles in the target road section are firstly divided into several blocks. For each block, we develop a searching and integer linear programming based algorithm, entitled EV sorting algorithm, to optimally clear one lane for the approaching emergency vehicle. With the resultant local sorting plan, a constrained optimization problem is then formulated to determine when to conduct the sorting trajectories for each block. Case studies indicate that with the proposed algorithm, emergency vehicles are able to proceed with a desired speed, and also minimize the disturbance on normal traffic flows. In addition, simulation analysis is conducted to examine the relationship between optimal solutions and influencing variables. It is found that the optimal solution mainly depends on traffic density. Simulation results also indicate a linear relationship between the optimal control solution and road density, which helps EVs to make better routing decisions.

Note that in this paper, high-level vehicle automation is not necessary for implementing the proposed method. The only requirement is that related vehicles need to be able to receive and comply with the designed trajectories. Considering that emergency vehicles are legally granted with absolute priority, we believe that such assumptions would be feasible in the near feature. In addition, the cost functions defined in Section 4 are not exclusive. The formulations used in the present paper are chosen due to their consistency with reality and convexity. Other cost functions may also work for the proposed framework. One notable limitation of the present study is that we did not consider the uniqueness of various kinds of emergency vehicles. For example, first aid ambulances and back-up units have different priority levels, which may lead to different sizes of buffer zones. Police cars and fire trucks have distinct vehicle dynamics. Those specific features should be carefully considered before the algorithm is implemented in practice.

CRediT authorship contribution statement

Jiaming Wu: Methodology, Formal analysis, Writing - original draft. **Balázs Kulcsár:** Conceptualization, Methodology, Writing - review & editing. **Soyoung Ahn:** Conceptualization, Methodology, Writing - review & editing. **Xiaobo Qu:** Conceptualization, Methodology, Resources, Supervision, Writing - review & editing.

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