



On the Impact Analysis of Emergency Vehicles Preemption on Signalized Intersections with Connected Vehicles

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Abstract. In recent years, vehicle-to-infrastructure (V2I) and vehicle-to-vehicle (V2V) communication are the leading technologies in intelligent transportation systems. With V2I and V2V, new strategies are enabled to better facilitate emergency rescue and traffic emergency management. Since signalized intersection is the major source of delay and congestion, how to prioritize emergency vehicles (EVs) at intersections becomes an indispensable research topic and has drawn extensive studies. Albeit that emergency vehicles should be granted absolute priority, the influence of EVs on the intersection was rarely studied, especially when aggressive preemption strategies are adopted. To this end, this paper is devoted to evaluating the impacts of EVs on the control of signalized intersections, as an effort to better emergency management. Mixed-integer linear programming models are developed to optimize the intersection control before and after the pass of EVs, respectively. Case studies indicate that, by assuming the EV will take exclusively one lane at the intersection, the average delay could increase by 11.28% along with a capacity decrease of 6.63% .

Keywords: Emergency vehicle · Connected vehicles · Intersection control

1 Introduction

With the rapid development of urbanization, urban transportation systems are becoming increasingly congested, bringing a series of side effects such as air pollutions, noise, and traffic accidents. Traffic accidents, in particular, endanger the life and property of the general public. Each incident poses a challenge to the emergency management capacity of the transport agency. According to research, half of the serious injuries can be treated if treated in a timely manner within 30 min of an accident. In medical science, the 30 min are called “prime time” [1].

In traditional intersections, emergency vehicles cannot have access to real-time information, such as queue length and signal, which hinders the key decision-making of speed control and route choices. It is common that a large queue exists at the intersection when

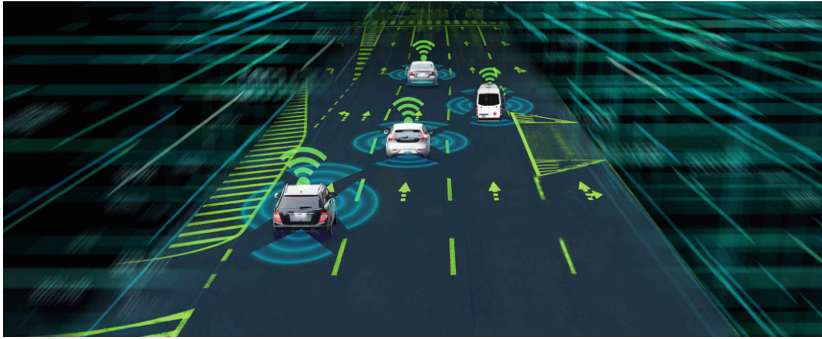


Fig. 1. Emergency vehicle travel in smart connected environment

emergency vehicles arrive due to the lack of communication and cooperation. In the environment of the smart connected vehicles, real-time sharing of vehicles and road information, can be realized through V2V and V2I to enable smarter EV preemption as well as intersection control.

In this area, a large body of research focused on the development of emergency vehicle priority systems. An emergency vehicle priority system ensures the passage of emergency vehicles through priority signal control, route guidance and social vehicle diversion [2]. The use of TPNS in the modeling emergency vehicle priority system was studied to ensure that emergency vehicles can pass through intersections quickly [3]. There are also dynamic preemption strategies that tend to balance different objectives [4].

In recent years, Intelligent Connected Technology is also of great significance to emergency rescue and traffic emergency management control. Intersection signal coordination optimization, enabled by smart connected technology, can accurately obtain the vehicle trajectory information and feed it to the controller for better optimization performance. Intersection collisions are studied in the context of CVIC, so that vehicles can safely and quickly pass through the intersection without collision with other vehicles [5–7]. A lane advance strategy based on integer linear programming (ILP) algorithm was proposed to achieve the absolute priority of emergency vehicles by clearing lanes for approaching emergency vehicles [8].

In order to solve the problem of low traffic efficiency at intersections, two experimental scenarios were designed, using intelligent networked vehicles to guide multiple ordinary vehicles [9]. A * algorithm is used to solve the intelligent interconnected vehicle sequencing problem and find the shortest path quickly [10]. The influence of whether to force lane change on execution time in intelligent networked vehicle environment was discussed [11].

Most of the current research on emergency vehicle preemption gives priority to emergency vehicles based on a limited number of road detectors. The detectors are however costly, cumbersome to set up, and unreliable, especially under unfavorable weather. At the same time, under the control environment of traditional intersection, emergency vehicles cannot have access to the exact information of intersection, such as queue length, traffic information. Frequent acceleration and deceleration at crowded urban intersections make it even more challenging to dissipate queues when emergency vehicles arrive.

This to some extent leads to aggressive preemption strategies, even with connected and automated vehicles [12, 13]. However, few studies investigated the influence of such preemption strategies. To this end, the present paper is devoted to evaluating the influence of EV preemption strategies on the intersection performance under optimal control.

2 Methodology

In this study, we assume to grant the emergency vehicles the highest priority so that they can pass through the intersection without delay. In the smart connect environment, a lane at an intersection can be cleared and used exclusively for EVs. When a lane is occupied by emergency vehicles, as shown in Fig. 1, the signal control plan is adjusted to optimize the intersection capacity for normal vehicles. In summary, we seek to evaluate the impacts on signalized intersections while ensuring the priority of emergency vehicles. The signal timing optimization and the collaborative control of the emergency vehicle are coordinated and modeled in a mixed-integer linear programming framework (Fig. 2).

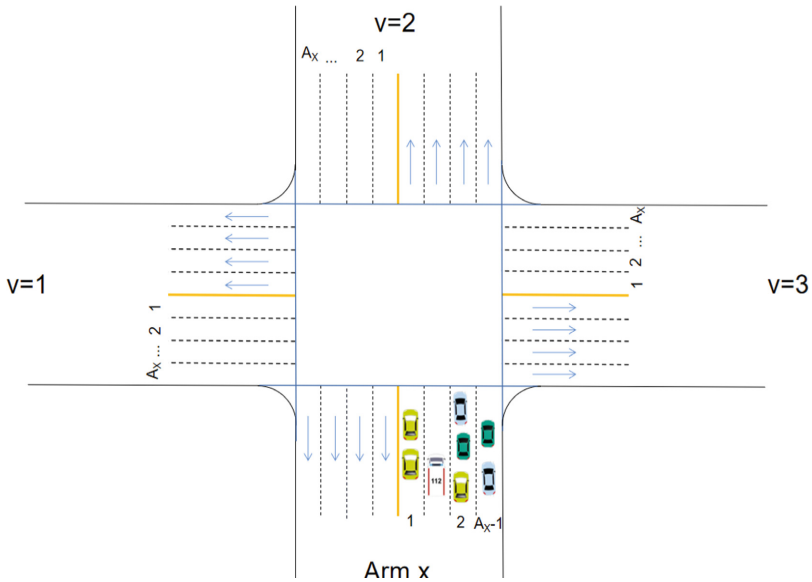


Fig. 2. Emergency vehicle occupancy

In view of the characteristics of the smart connected vehicles, the following assumptions are made.

1. All vehicles are intelligent connected vehicles.
2. All common vehicles voluntarily clear one lane for emergency vehicles through V2V and V2I communication.
3. We assume perfect communication.

4. Pedestrian-related factors (e.g., pedestrian-vehicle conflicts) are ignored to focus on the studied problem (Tables 1 and 2).

Table 1. The set of input parameters

Notations	Descriptions
T_s	Traffic arms
A_x	Approaching lanes
B_x	Exit lanes
m	From arm x to arm c through lane q
γ	A collection of incompatible movements
γ_s	A collection of incompatible signal groups
F_{m1m2}	An interval of incompatible movements
$D_{x,v,q}$	The binary variable determines the allowable movements at the lane
λ	Common flow multiplier
$O_{x,v}$	Traffic demand matrix at intersections
$O_{x,v,q}$	The assigned flow is distributed from arm x to arm c
$S_{x,q}$	Saturation flow of lane q in arm x
$r_{x,v,q}$	The radius of the turning trajectory
$f_{x,v,q}$	Flow ratio
$\bar{S}_{x,q}$	Saturated flow in a straight moving lane
$\Psi_{x,v}$	Green start time
$P_{x,v}$	Green duration
$\beta_{x,q}$	The start of the green display received on lane q in arm x
$\Omega_{x,q}$	The duration of the green display received on lane q in arm x
$g_{x,v}$	Minimum green duration
$N_{x,q}$	Maximum acceptable saturation of lane q in arm x
η	The total number of arms from x to c
M	Any large number
c	Cycle length
δ	Reciprocal of the cycle length
\cap	Successor function
e	The difference between effective green time and actual green time
x	Arm x can be numbered as 1, 2, 3, 4
v	Number clockwise with respect to x
q	Lane number

Table 2. The set of decision variables

Variables set		
Binary variables	$D_{x,v,q}$	The binary variable determines the allowable movements at the lane
	$\cap_{x,v,i,d}$	The order in which signal groups (x, v), (i, d) are displayed
Continuous variables	λ	Common flow multiplier
	$\Psi_{x,v}$	Green start time
	$P_{x,v}$	Green duration
	$B_{x,q}$	The start of the green display received on lane q in arm x
	$\Omega_{x,q}$	The duration of the green display received on lane q in arm x
	δ	Reciprocal of the cycle length
	$O_{x,v,q}$	The assigned flow is distributed from arm x to arm c

The developed model is as follows.

$$\text{Maximize } \lambda \tag{1}$$

Subject to

$$\sum_{c=1}^{T_s-1} D_{x,v,q} \geq 1 \quad \forall q = 1, \dots, A_x; \quad \forall x = 1, \dots, T_s \tag{2}$$

$$\lambda O_{X,v} = \sum_{q=1}^{A_x} O_{x,v,q} \quad \forall x = 1, \dots, T_s; \quad \forall v = 1, \dots, T_s - 1 \tag{3}$$

$$MD_{x,v,q} \geq O_{x,v,q} \geq 0$$

$$\forall x = 1, \dots, T_s; \quad \forall v = 1, \dots, T_s - 1; \quad \forall q = 1, \dots, A_x \tag{4}$$

$$1 \geq \psi_{x,v} \geq 0 \quad \forall x = 1, \dots, T_s; \quad \forall v = 1, \dots, T_s - 1 \tag{5}$$

$$1 \geq \rho_{x,v} \geq g_{x,v} \delta \quad \forall x = 1, \dots, T_s; \quad \forall v = 1, \dots, T_s - 1 \tag{6}$$

$$M(1 - D_{x,v,q}) \geq \beta_{x,q} - \psi_{x,v} \geq -M(1 - D_{x,v,q}) \tag{7}$$

$$M(1 - D_{x,v,q}) \geq \Omega_{x,q} - \rho_{x,v} \geq -M(1 - D_{x,v,q}) \tag{8}$$

$$\frac{1}{C_{min}} \geq \delta \geq \frac{1}{C_{max}} \tag{9}$$

$$B_{\eta(x,v)} \geq \sum_{q=1}^{A_x} D_{x,v,q} \quad \forall x = 1, \dots, T_s; \quad \forall v = 1, \dots, T_s - 1$$

$$1 - D_{x,v,q+1} \geq D_{x,d,q} \geq D_{x,v,q+1} \quad \forall d = v + 1, \dots, T_s - 1; \quad \forall v = 1, \dots, T_s - 2 \tag{10}$$

$$\begin{aligned} \forall q = 1, \dots, A_x - 1 \quad \forall x = 1, \dots, T_s \\ m_1 = (x, v, q) \quad m_2 = (i, d, t) \end{aligned} \quad (11)$$

$$\psi_{id} + \cap_{x,v,i,d} + M(2 - D_{x,v,q} - D_{i,d,t}) \geq \psi_{x,v} + \rho_{x,v} + F_{m_1 m_2} \delta \quad \forall m_1, m_2 \in \gamma \quad (12)$$

$$\cap_{x,v,i,d} + \cap_{i,d,x,v} = 1 \quad \forall ((x, v), (i, d)) \in \gamma_s \quad (13)$$

$$\begin{aligned} M(2 - D_{x,v,q} - D_{x,v,q+1}) \geq \frac{1}{S_{x,q}} \sum_{v=1, \dots, T_s-1} (1 + \frac{1.5}{r_{x,v,q}}) O_{x,v,q} \\ - \frac{1}{S_{x,q+1}} \sum_{v=1, \dots, T_s-1} (1 + \frac{1.5}{r_{x,v,q+1}}) O_{x,v,q+1} \geq -M(2 - D_{x,v,q} - D_{x,v,q+1}) \\ \forall q = 1, \dots, A_x; \quad \forall x = 1, \dots, T_s \end{aligned} \quad (14)$$

$$\begin{aligned} \beta_{xq} + e\delta \geq \frac{1}{S_{x,q} N_{x,q}} \sum_{v=1, \dots, T_s-1} ((1 + \frac{1.5}{r_{x,v,q}}) O_{x,v,q}) \\ \forall q = 1, \dots, A_x; \quad \forall x = 1, \dots, T_s \end{aligned} \quad (15)$$

In the constraints listed above, Eq. 1 represents the objective of the optimization, where capacity is positively correlated with traffic demand, and the problem can thus be converted into solving the common flow multiplier. Equation 2 indicates that movement should be greater than 1 in each lane. Equation 3 ensures the normal operation of the intersection as traffic demand increases. Equation 4 defines if lane q indicates no movement, then there is no traffic allocation in the lane. Equation 5 and Eq. 6 define the constraints on green start time $\psi_{x,v}$ and $P_{x,v}$. Equation 7 and Eq. 8 ensure that all traffic movements on a lane q are consistent, with the green starting at the same time as the green received on the lane, and green duration time equals the green on the lane. Equation 9 defines the range of cycle length, ensuring that c is a reasonable value. Equation 10 indicates that the number of exit lanes on lane v should be greater than or equal to the number of lanes x in one movement.

Equation 11 denotes the lane q on the arm x is prohibited from turning onto other arms which do not include arm v when the lane q + 1 on the arm x allows turning onto the arm v to avoid unnecessary traffic collisions between adjacent lanes. Equation 12 defines the movements (x, v, q) (i, d, t) that a set of conflicts γ , and when both movements are allowed, we set the clearing time to avoid their conflicts. Equation 13 indicates the sequence of conflicting signaling groups. Equation 14 restricts the flow factor between adjacent lanes to make them equal. Equation 15 defines that the saturation on the lane q cannot exceed its maximum saturation $N_{x,q}$.

3 Case Study

In this section, we demonstrate the impacts of the EVs on the normal traffic flow at intersections with a series of numerical experiments. In order to solve the model in this paper, we apply it to the four-branch road intersection. By constraint (2)–(15) and

mixed integer programming algorithm, a mixed integer linear programming model is established. Traffic signal optimization before and after the EV arrivals are conducted with the commercial solver Gurobi, respectively. At the studied four-leg intersection, the number of arms is set at 4. Since emergency vehicle traffic occupies one lane, one of the four legs can be reconsidered with 3 approaching lanes. Considering the principle that the number of exit lanes is greater than the number of approaching lanes, the exit lanes of each arm remain 4. The maximum cycle length is set to be 120 s. Assume that the minimum duration of all vehicle movements equals 5 s with a turning radius of 12 m. The maximum acceptable saturation per lane is set at 0.9. The time difference between a valid green and an actual green is set as 1 s, and the clear time for movements with conflicting trajectories is set as 3 s (Table 3).

Table 3. Pre-set values of parameters

Parameter	Interpretation	Value
T_s	Traffic arm	4
A_x	The approaching lane where arm X is located	4 or 3
B_η	The exit lanes where arm η is located	4
C_{max}	Maximum cycle length	120
$g_{x,v}$	Minimum green duration	5
$r_{x,v,q}$	Radius of the turn trajectory	12
$N_{x,q}$	Maximum acceptable saturation of lane q in arm x	0.9
e	The difference between effective green time and actual green time	1
F_{m1m2}	An interval of incompatible movements	3

To demonstrate the results of allocating one exclusive lane for the EV. All simulation scenarios are implemented via the python platform. Specifically, before the arrival of EV, we assume $\lambda = 2.23$ $c = 120$ s, while after the EV arrival, we assume $\lambda = 2.26$ $c = 120$ s.

The results of optimization indicate the maximum capacity of the direction of motion based on the pre-set saturation flow. X is calculated using the ratio of the total assigned flow in the direction of motion to the capacity of the traffic, and then the delay is calculated according to Eq. 16 (Fig. 3 and Table 4).

$$d = \frac{C(1 - \frac{g}{C})^2}{2(1 - Xg/C)} \tag{16}$$

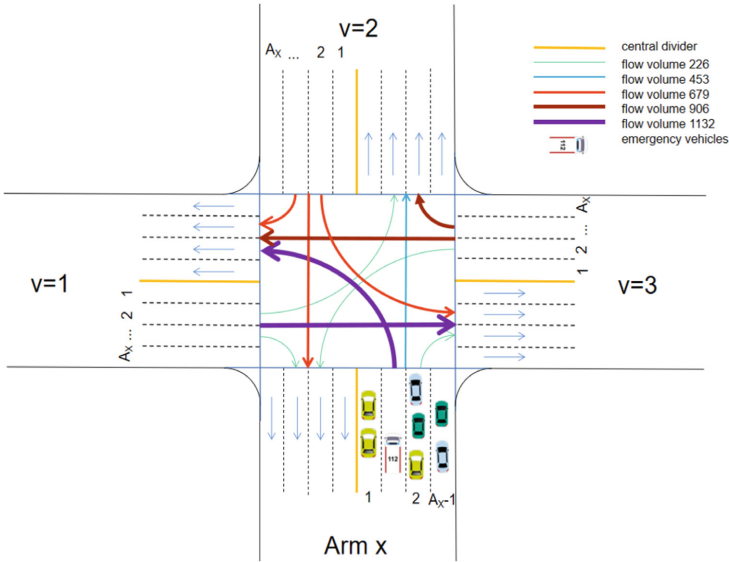


Fig. 3. Flow distribution at intersections

Table 4. Optimal results for one lane occupied by emergency vehicles

From x	To v	Total assigned flow (pcu/h)	Delay (s)	Traffic capacity (pcu/h)	$P_{x,v}$
1	1	1132	38.53	1227	0.33
1	2	452	29.94	739	0.38
1	3	226	25.97	739	0.38
2	1	226	52.05	236	0.13
2	2	1132	38.62	1227	0.33
2	3	226	52.26	236	0.12
3	1	679	34.10	739	0.10
3	2	679	40.23	962	0.26
3	3	679	40.01	986	0.26
4	1	226	52.07	236	0.13
4	2	906	43.22	975	0.26
4	3	906	24.96	991	0.54

In Fig. 4 and Fig. 5, group 1 represents the cases of lane occupancy by emergency vehicles and group 2 indicates the scenario before EV arrival. As can be seen from Fig. 4, delays generally increased due to the EV. Calculations of the overall average delay show that the overall average delay increased by a modest 11.28%. The movement to the right of the north entrance observed the biggest increase in delays at 36.63%. Of these,

delays decreased in four directions, with the largest decrease of 30.94%. Comparisons of the traffic capacity of the two optimization results can be seen in Fig. 5. Following the occupancy of lanes by emergency vehicles, the overall average capacity decreased by 6.63%.

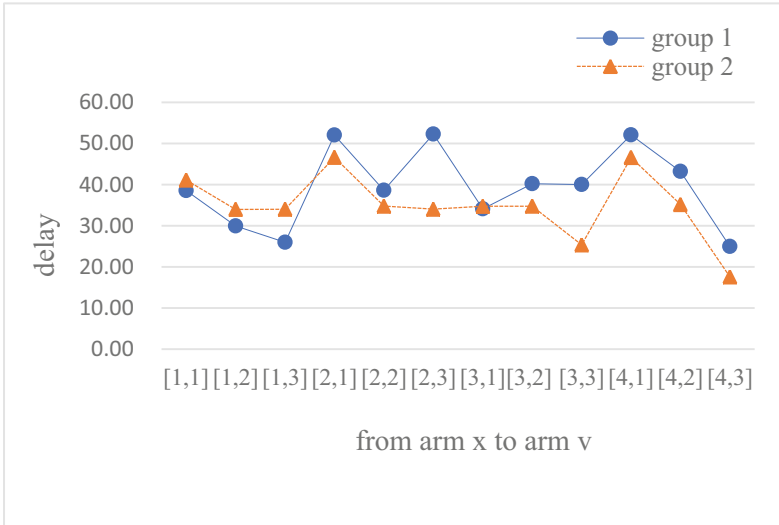


Fig. 4. Delay comparison between two optimizations

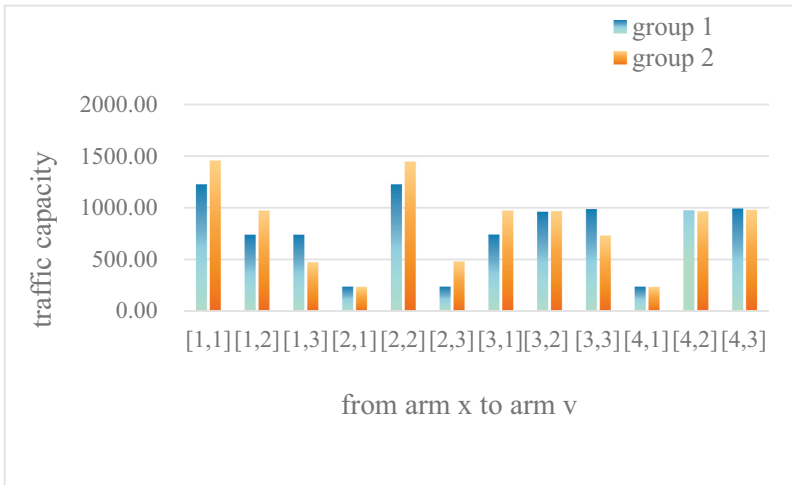


Fig. 5. Traffic capacity comparison between two optimizations

4 Conclusion

In this paper, we developed an optimization framework to evaluate the impact of aggressive emergency vehicles preemption strategies under optimal intersection control. A mixed-integer linear programming model is developed and solved by the Gurobi software. Numerical simulation results indicate that delay and capacity changes vary, with the overall average delay increase by 11.28% and the overall average capacity decrease by 6.63%. Future extension of the present study can be exploring the possibility of incorporating EV route choice with intersection optimization.

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