J. Shanghai Jiao Tong Univ. (Sci.), 2023, 28(1): 150-160
https://doi.org/10.1007/s12204-023-2577-z

Straight-Going Priority in Hierarchical Control Framework for Right-Turning Vehicle Merging Based on Cooperative Game

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Abstract: With the development of connected and automated vehicles (CAVs), forming strategies could extend from the typically used first-come-first-served rules. It is necessary to consider passing priorities when crossing intersections to prevent conflicts. In this study, a hierarchical strategy based on a cooperative game was developed to improve safety and efficiency during right-turning merging. A right-turn merging conflict model was established to analyze the right-turning vehicle characteristics of the traffic flow. The proposed three-layered hierarchical strategy includes a decision-making layer, a task layer, and an operation layer. A decision-making-layer cooperative game strategy was used to determine the merging priority of straight-going traffic and right-turning flows. In addition, a task-layer cooperative game strategy was designed for the merging sequence. A modified consensus algorithm was utilized to optimize the speed of vehicles in the virtual platoon of the operation layer. Traffic simulations were performed on the PYTHON-SUMO integrated platform to verify the proposed strategy. The simulation results show that, compared with other methods, the proposed hierarchical strategy has the shortest travel time and loss time and performs better than other methods when the straight-going traffic flow increases during right-turning merging at the intersection. The proposed method shows superiority under a significant traffic flow with a threshold of 900 vehicle/(h · lane). This satisfactory application of right-turning merging might be extended to ramps, lane-changing, and other scenarios in the future.
Key words: cooperative game, right-turning merging, coordinated decision-making
CLC number: U 121 **Document code:** A

0 Introduction

Regarding the merging conflict between right-turning and straight-going vehicles, the Road Traffic Safety Law in China stipulates that going-straight vehicles have priority over right-turning vehicles. However, at some intersections with unbalanced traffic, it is difficult to provide enough space for right-turning vehicles to pass through the straight-going-direction traffic flow. For example, the north–south entry lane of the intersection is larger than the east–west entry lane, and the east–west direction is less efficient than the north–south direction. Vehicles driving in the east–west direction are more likely to queue than those in the north–south direction. The irregular driving behavior of right-turning vehicles in the east–west direction would inevitably cause potential conflicts and increase traffic safety hazards. With the development of intelligent network technology and vehicle-to-road communication, vehicle-to-vehicle (V2V), and vehicle-to-infrastructure (V2I) technologies[1-3], information interaction has developed rapidly, enabling vehicles to cooperate and eliminate potential conflicts[4-6]. Solving the right-turning merging conflict has social significance in improving the safety and efficiency of vehicle merging at intersections.

Research on connected and automated vehicle (CAV) merging has mainly focused on optimization model, cooperative control method, and vehicle platoons to enhance the efficiency, economy, and uniformity of CAVs when passing through the merging area.

In terms of optimal control of the model, Mohebifard and Hajbabaie[7] proposed a methodology for optimizing the trajectory of CAVs in roundabouts using a two-dimensional point-mass model. The optimization problem includes vehicle dynamics and collision avoidance constraints, with an explicit representation of vehicle paths. Wu et al.[8] used the method of outer boundary projection and dimensionality reduction by minimizing the total delay of the intersection and optimizing the

Received: 2021-12-20 **Accepted:** 2022-03-25
Foundation item: the National Key Research and Development Program of China (No. 2020YFB1600400)
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travel route and time to enter the intersection for each autonomous vehicle. Qian et al.[9] developed a method for optimizing the departure times, travel routes, longitudinal trajectories of CAVs, and signal timings at intersections to achieve a stable traffic state. Zhang et al.[10] proposed a framework based on a convolutional neural network to predict the total time consumption of different passing orders. The optimal passing order with the lowest time consumption was selected as the optimal solution. Time optimal control can then be performed on the CAVs. Zhao et al.[11] established a hierarchical ecofriendly cooperative ramp management system, in which, macroscopically, a stratified ramp metering algorithm was deployed, and a model predictive control-based algorithm was designed for the precise speed control of individual CAVs. Wang et al.[12] developed a selection algorithm for a merging controller to determine the merging sequence based on the initial states of vehicles in a cooperative area. The optimized longitudinal trajectory of the on-ramp vehicles was addressed by solving the Hamiltonian function. Chen et al.[13] proposed a hierarchical control approach for CAVs to achieve efficient and safe merging operations.

Vehicle merging is based on a cooperative control algorithm that can abstract merging vehicle clusters into one-dimensional and two-dimensional. Two-dimensional sequences are based on centralized coordination and must make decisions based on global merging information. Rios-Torres and Malikopoulos[14] established an optimization framework and analytical closed-form solution that facilitates the online coordination of vehicles in merging zones, which addressed the problem of optimally coordinating CAVs at merging roadways to achieve smooth traffic flow without stop-and-go driving. Gu et al.[15] established double deep Q-network (DDQN) with a dual-agent algorithm to obtain a stable traffic signal control policy. Tachet et al.[16] provided a capacity-optimal slot-based intersection (SI) management system in a two-road crossing configuration based on a generalized classical queuing theory. The results indicated that transitioning from a traffic light system to an SI can double the capacity and significantly reduce delays. Kumaravel et al.[17] developed a decentralized two-level optimization framework to solve interconnection and automatic vehicle sequence problems through unsignalized intersections. Afterwards, an optimization framework was proposed[18], which included the formulation of optimal scheduling algorithms and time-optimal control to improve the time and energy consumption of the on-ramp synergistic merger on the expressway. However, the two-dimensional method has a heavy computational burden. To solve this problem, some scholars converted two-dimensional vehicle clusters into one-dimensional sequences, which are expressed as the concept of virtual platoons. Morales Medina et al.[19] proposed an algorithm for merging vehicle control using the concept of virtual vehicles. This algorithm generates virtual vehicles by mapping vehicles from one lane to another to achieve smooth convergence between vehicles. Subsequently, the virtual platoon concept was extensively investigated. Xin et al.[20] proposed the formation control of intelligence vehicles in highway environment, and adopted a method which combined the artificial potential field and the virtual leader to control vehicles. To solve the problem that existing reservation-based autonomous intersection control models do not globally optimize the vehicle passing sequence and that the model is nonlinear, which leads to the low efficiency of the solution, Jiang et al.[21] established a vehicle schedule optimization model of an autonomous intersection based on a virtual platoon. This model achieved efficient global optimization of the vehicle passing sequence. Caiazzo et al.[22] used the car networking paradigm and equivalent virtual platoon concept to develop a novel distributed longitudinal diffusion protocol and a control strategy based on a distributed lateral potential function that can coordinate multiple platoons to prevent vehicle collisions. Xu et al.[23] proposed a distributed control framework called the virtual platoon method. The conflict-free topology was built based on the relationship between the traffic order of each vehicle, enabling the vehicles to stagger through the intersection. Chen et al.[24] developed an approach to rotation-based CAV distributed cooperative control based on virtual rotation that transfers the merging problem to a virtual car-following problem to reduce the complexity and dimensions of the cooperative CAV merging control. Wang et al.[25] considered the ideal formation as the goal and proposed a formation method based on the elliptical potential field of the virtual leader, considering the road environment constraints and the vertical and horizontal safety distance of the formation.

In addition, other researchers have attempted to solve the merging problem using game theory. Liao et al.[26] proposed a ramp-merging technique based on the game theory for the optimal merging and coordination of CAVs in mixed traffic. The approach determines the dynamic merging sequence and the corresponding vertical/lateral control. Akti et al.[27] constructed an adaptive cruise control model based on vehicle-following for longitudinal motion modeling, in which vehicles close to the merged area were controlled using a speed coordination algorithm. Koopmann et al.[28] made the best possible and clear decision regarding cooperative maneuvers based on the method for the game theory decentralized control, which could improve traffic efficiency while maintaining road safety. Min et al.[29] developed a centralized method based on the game theory to control all vehicles during ramp merging without collision and optimized the overall fuel consumption and total travel time. Hu et al.[30] proposed an intelligent vehicle decision-making method based on a master–slave game by constructing a game model combined with the right of way and introducing target items such as cooperation factors to design the corresponding income function and maximize decision-making income. Yang et al.[31] proposed a conflict resolution coordination method for connected autonomous vehicles in merging areas of expressways based on a cooperative game theory by considering factors such as vehicle time demand intensity, vehicle type, and driving intention. Xu et al.[32] presented a game-based policy for the signal control of an isolated intersection and the rerouting of vehicles at this intersection using V2I technology to balance the traffic flow on the road network.

These methods mainly focused on vehicles merging in scenes, such as intersections and ramps, and ignored traffic characteristics for right-turning merging at intersections. Many of these methods use first-come-first-served rules, neglecting the priority among vehicles. Therefore, this study focused on solving the conflict between the merging of right-turning CAVs, considering vehicle priority. Although straight-going vehicles have priority over right-turning vehicles, irregular right-turning vehicles affect the straight-going traffic flow, causing traffic bottlenecks at intersections. The proposed hierarchical strategy can make right-turning vehicles merge into the straight-going traffic flow as much as possible to pass through the intersection. In addition, the proposed approach can improve the traffic efficiency and safety of straight-going traffic flow, ensuring that vehicles turning right can merge. Compared to other recent studies on intersection merging, the significant contributions of this study are as follows.

(1) By considering the Xiaozhai Intersection as an example, a right-turning conflict simulation model was established on the PYTHON-SUMO integrated platform. Based on this model, the differences between the merging of right-turning vehicles and vehicles in other scenarios were summarized.

(2) A hierarchical strategy was developed for right-turning merging considering the straight-going priority based on a cooperative game theory. Based on the impact of the right-turning vehicles merging into the straight-going traffic flow and the urgency of the right-turning traffic flow, a cooperative game method was developed to determine whether a right-turning vehicle merges. By considering the mobility and safety of conflicting vehicles, a cooperative game theory was developed to determine the merging sequence, and a consensus algorithm was proposed to adjust the driving state of the vehicles in the virtual platoon. The proposed strategy improved the traffic efficiency and safety of the straight-going traffic flow under right-turning vehicle merging.

(3) Actual scenarios were selected and analyzed to validate the proposed strategy, indicating improved safety and efficiency compared with other methods. The proposed hierarchical strategy has the shortest travel time/loss time during right-turning merging and performs best with a high traffic volume in terms of safety.

1 Hierarchical Strategy for Right-Turning Merging of Vehicles

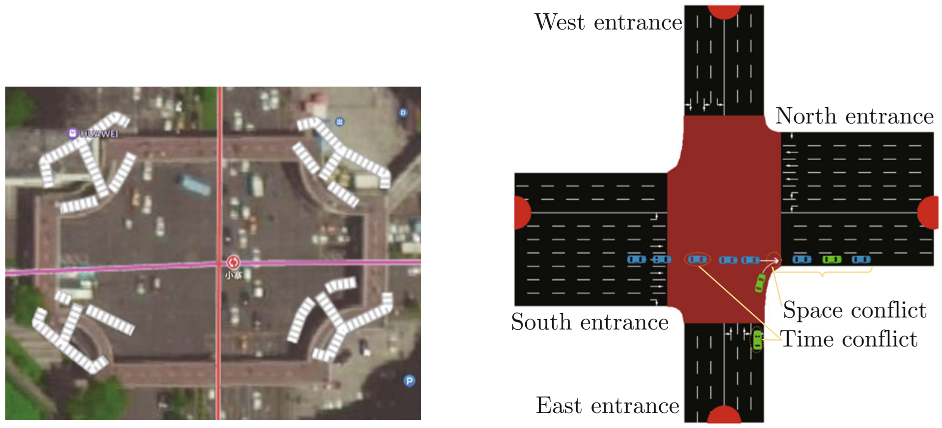
This section presents a proposed strategy based on the cooperative game theory for right-turning vehicles that merge at an intersection. A right-turn-merging conflict model was established to form the possible vehicle merging sequence of approaching right-turning vehicles at intersections. Next, we determined whether the right-turning vehicles merged based on the cooperative game at the decision-making level and determined the right-turning vehicle in the merging flow sequence based on the cooperative game in the task layer. In the operation layer, the driving behavior of the vehicles in the virtual formation was guided based on a consistent algorithm.

1.1 Established Conflict Model

This study was conducted in an Internet of Things (IoT) environment where a roadside device was positioned at each intersection. This device can receive vehicle information at the intersection surroundings and transmit traffic information of the intersection to vehicles. Roadside equipment at intersections can obtain real-time information on all vehicles using V2I equipment, and all CAVs can share real-time vehicle status information through V2V equipment. The Xiaozhai Intersection (Xi'an, China) is used as an example to illustrate congestion and conflict problems at a signalized intersection, as shown in Fig. 1. The reason is that the Xiaozhai Intersection, as one of the largest business districts in Xi'an, has a heavy traffic flow.

Figure 2 shows an intersection with the roadside equipment, with entrances in four directions: N, W, S, and E, representing the north, west, south, and east directions, respectively. Herein, $c_{m,n,k}$ represents the vehicle information, which including the vehicle's ID c, entrance direction m, lane location n, and steering information k; $m \in \{\mathrm{N}, \mathrm{W}, \mathrm{S}, \mathrm{E}\}$; $n \in \{1, 2, \cdots\}$; $k = 1$, 2, 3 represent go-straight, left-turning, and right-turning, respectively. By taking the south entrance road as an example, this study focused on adjusting the acceleration of conflicting vehicles to eliminate potential conflicts in time and space between the east entrance vehicles and other vehicles going to the same target lane. The specific expressions are as follows:

(1) When the vehicle from the east entrance enters the information-exchangeable zone, CAVs can transmit their state information to the roadside equipment at the intersection and obtain the information of the



(a) Satellite map (b) Road network in SUMO

Fig. 1 Conflict of right-turning vehicles merging at Xiaozhai Intersection, Xi'an, China

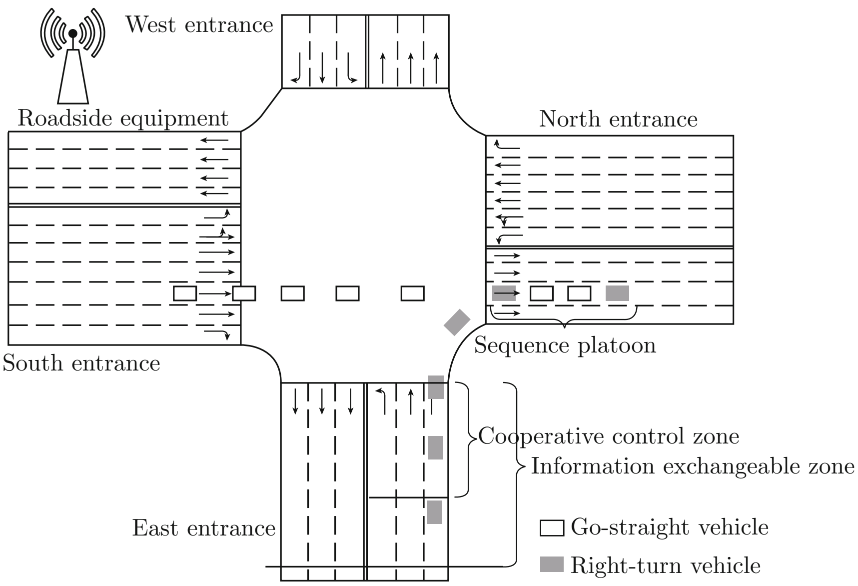


Fig. 2 Right-turning vehicles merging in east entrance at Xiaozhai Intersection

vehicle that passes through the intersection using this equipment.

(2) The roadside equipment can determine and predict the state of the vehicle passing through the intersection using the acquired vehicle state information, ensuring that the vehicle does not conflict with other vehicles in time and space when passing through the intersection in the current state. For conflicting vehicles, the cooperative game method determines the merging sequence of the vehicles in the cooperative control zone and platoon through the intersection.

Therefore, when conflicts between two vehicles exist in different directions at an intersection, the two vehicles play a cooperative game. The cost function is calculated by selecting the overall optimal strategy for the intersection, that is, the strategy adopted by the game. Before the vehicles join the merging, the conflicting vehicle can repeat the game to ensure that the overall queue sequence obtained by the game is optimal. The sequence determined from the game uses the consensus algorithm to form an orderly vehicle platoon by adjusting the acceleration of the vehicles to ensure the efficiency and safety of conflicting vehicles passing through the intersection. Table 1 lists the relationship between right-turning vehicles and platoons, where $c^{\text{ego}}_{\text{E},n,3}$ denotes a right-turning vehicle, $c^{\text{conflict}}_{\text{S},n,1}$ denotes a straight-going vehicle that conflicts with $c^{\text{ego}}_{\text{E},n,3}$, and $c^{\text{ahead}}_{\text{S},n,1}$, $c^{\text{behind}}_{\text{S},n,1}$ represent the front and behind vehicles of $c^{\text{conflict}}_{\text{S},n,1}$, respectively.

1.2 Decision-Making Layer

All vehicles that enter the information-exchangeable zone can be determined using the roadside equipment at the intersection and the vehicles' information can be stored with a unique identifier. In addition, a vehicle is

Table 1 Relationship between right-turning vehicles and platoons

Number of right-turning vehicles	Number of platoons	Merging sequence
1	1	(1) $c^{\text{conflict}}_{\text{S},n,1}$ $c^{\text{ego}}_{\text{E},n,3}$ $c^{\text{ahead}}_{\text{S},n,1}$ (2) $c^{\text{behind}}_{\text{S},n,1}$ $c^{\text{ego}}_{\text{E},n,3}$ $c^{\text{conflict}}_{\text{S},n,1}$
2	2	(1) $c^{\text{conflict2}}_{\text{S},n,1}$ $c^{\text{ego2}}_{\text{E},n,3}$ $c^{\text{ahead2}}_{\text{S},n,1}$ $\cdots$ $c^{\text{conflict1}}_{\text{S},n,1}$ $c^{\text{ego1}}_{\text{E},n,3}$ $c^{\text{ahead1}}_{\text{S},n,1}$ (2) $c^{\text{behind2}}_{\text{S},n,1}$ $c^{\text{ego2}}_{\text{E},n,3}$ $c^{\text{conflict2}}_{\text{S},n,1}$ $\cdots$ $c^{\text{conflict1}}_{\text{S},n,1}$ $c^{\text{ego1}}_{\text{E},n,3}$ $c^{\text{ahead1}}_{\text{S},n,1}$ (3) $c^{\text{conflict2}}_{\text{S},n,1}$ $c^{\text{ego2}}_{\text{E},n,3}$ $c^{\text{ahead2}}_{\text{S},n,1}$ $\cdots$ $c^{\text{behind1}}_{\text{S},n,1}$ $c^{\text{ego1}}_{\text{E},n,3}$ $c^{\text{conflict1}}_{\text{S},n,1}$ (4) $c^{\text{behind2}}_{\text{S},n,1}$ $c^{\text{ego2}}_{\text{E},n,3}$ $c^{\text{conflict2}}_{\text{S},n,1}$ $\cdots$ $c^{\text{behind1}}_{\text{S},n,1}$ $c^{\text{ego1}}_{\text{E},n,3}$ $c^{\text{conflict1}}_{\text{S},n,1}$
	1	(1) $c^{\text{conflict2}}_{\text{S},n,1}/c^{\text{conflict1}}_{\text{S},n,1}$ $c^{\text{ego2}}_{\text{E},n,3}$ $c^{\text{ego1}}_{\text{E},n,3}$ $c^{\text{ahead1}}_{\text{S},n,1}$ (2) $c^{\text{conflict2}}_{\text{S},n,1}$ $c^{\text{ego2}}_{\text{E},n,3}$ $c^{\text{ahead2}}_{\text{S},n,1}/c^{\text{conflict1}}_{\text{S},n,1}$ $c^{\text{ego1}}_{\text{E},n,3}$ $c^{\text{ahead1}}_{\text{S},n,1}$ (3) $c^{\text{conflict2}}_{\text{S},n,1}/c^{\text{behind1}}_{\text{S},n,1}$ $c^{\text{ego2}}_{\text{E},n,3}$ $c^{\text{ego1}}_{\text{E},n,3}$ $c^{\text{conflict1}}_{\text{S},n,1}$ (4) $c^{\text{behead2}}_{\text{S},n,1}$ $c^{\text{ego2}}_{\text{E},n,3}$ $c^{\text{conflict2}}_{\text{S},n,1}/c^{\text{behind1}}_{\text{S},n,1}$ $c^{\text{ego1}}_{\text{E},n,3}$ $c^{\text{conflict1}}_{\text{S},n,1}$
⋮	⋮	⋮

expressed as

$$\boldsymbol{x}_c = (\boldsymbol{p}_c, \boldsymbol{v}_c), \tag{1}$$

where $\boldsymbol{x}_c$ is the state of Vehicle c, including the position $\boldsymbol{p}_c$ and the vehicle speed $\boldsymbol{v}_c$.

The status information about a vehicle includes its position and speed. In the second-order model, the dynamic characteristics of a vehicle can be expressed as

$$\left.\begin{aligned} \dot{\boldsymbol{p}}_c &= \boldsymbol{v}_c(t) \\ \dot{\boldsymbol{v}}_c &= \boldsymbol{u}_c(t) \end{aligned}\right\}, \tag{2}$$

where $\boldsymbol{u}_c(t)$ is the vehicle acceleration and is also the control input of the system. The roadside equipment determines and analyzes vehicles with potential conflicts using the acquired vehicle information and establishes a game model for potential conflict vehicles. Taking right-turning vehicles at the east entrance of the intersection as an example, we introduce the specific implementation of the decision-making, task, and operation layers.

The decision-making layer mainly determines whether the right-turning vehicle merges into a straight-going traffic flow. This can be expressed as a game problem of conflict between the right-turning vehicle and the straight-going vehicle. The specific description is as follows: ① The game participants include $c^{\text{ego}}_{\text{E},n,3}$ that is a right-turning vehicle, and $c^{\text{conflict}}_{\text{S},n,1}$ that is a straight-going vehicle conflicting with $c^{\text{ego}}_{\text{E},n,3}$. There is a potential conflict in time and space between $c^{\text{ego}}_{\text{E},n,3}$ and $c^{\text{conflict}}_{\text{S},n,1}$. It should be noted that two vehicles with potential conflicts have a shared target lane. ② The action strategy space of the game is expressed as $A_1 = \{\text{merging}, \text{not merging}\}$. ③ The cost function of the game participant under different action strategy is denoted by C_1.

In the first round of the game, the strategies established in the two actions compute the cost function C_1 separately, and C_1 can be expressed as

$$C_1 = \alpha I + \beta E, \tag{3}$$

where

$$I(t) = \left|\boldsymbol{p}_{c^{\text{ahead}}_{\text{S},n,1}}(t) - \boldsymbol{p}_{c^{\text{behind}}_{\text{S},n,1}}(t)\right|, \tag{4}$$

$$E(t) = \frac{1}{\left|\boldsymbol{p}_{c^{\text{ego}}_{\text{E},n,3}}(t)\right|}, \tag{5}$$

I represents the impact on the straight traffic flow after the action strategy implementation and can be calculated from the positions of $\boldsymbol{p}_{c^{\text{ahead}}_{\text{S},n,1}}$ and $\boldsymbol{p}_{c^{\text{behind}}_{\text{S},n,1}}$ at the time t, E is the emergency of the right-turning vehicle to pass the intersection and can be calculated from the position of $\boldsymbol{p}_{c^{\text{ego}}_{\text{E},n,3}}$ at the time t, and a and β are constants.

There are two action strategies in this game. One strategy is that the right-turning vehicles merge into a straight traffic flow, and the other is that they do not merge. The cost functions of the two action strategies are calculated separately, and the action strategy represented by the lower cost function value is selected as the result of the game:

$$\min\left\{C_1^{A_1[0]}, C_1^{A_1[1]}\right\}. \tag{6}$$

When $C_1^{A_1[0]}$ is bigger than $C_1^{A_1[1]}$, the right-turning vehicle will be merging in the go-straight vehicle group. When $C_1^{A_1[0]}$ is smaller than $C_1^{A_1[1]}$, the right-turning vehicle will not be merging in the go-straight vehicle group.

1.3 Task Layer

When the right-turning vehicle can enter the straight-going traffic flow, the next round of the game commences. The aim of the second round of the game is to determine the merging sequence of the right-turning vehicle and its conflicting straight-going vehicles. This means that at least one of the south-imported and east-imported vehicles must adjust the acceleration for the merge sequence. The right-turning merging process at intersections based on the multiagent cooperative game is described as follows: ① The game participants include $c^{\text{ego}}_{\text{E},n,3}$ that is a right-turning vehicle, and $c^{\text{conflict}}_{\text{S},n,1}$ that is a straight-going vehicle conflicting with $c^{\text{ego}}_{\text{E},n,3}$. There is potential conflict in time and space between $c^{\text{ego}}_{\text{E},n,3}$ and $c^{\text{conflict}}_{\text{S},n,1}$. It should be noted that two vehicles with potential conflicts have a shared target lane. ② The action strategy space of the game, which is a combination of the action space of each game player, is expressed as $A_2 = \{\text{as the leader, as the follower}\}$. ③ The cost function of game participant under different action strategy is denoted by C_2.

During the game process, two game participants $c^{\text{ego}}_{\text{E},n,3}$, $c^{\text{conflict}}_{\text{S},n,1}$ should be determined as the leader or as the follower, and the action space of the game participants can be expressed as $A_2(c_{\text{E},n,3}) = \{\text{as the leader, as the follower}\}$, $A_2(c_{\text{S},n,1}) = \{\text{as the leader, as the follower}\}$. The strategies obtained in the different action spaces separately calculate the cost function. The cost function comprises two aspects: one measures safety, and the other measures efficiency. If only vehicle safety is considered, the game process will tend to be conservative. The game participants will be willing to slow down as followers rather than enter the intersection as leaders. The movement factor is added to the cost function to balance the safety and efficiency of traffic at the intersection.

Regarding safety, we referred to Ref. [26] by adding the time interval to the cost function and developed a safety assessment method. The risk of each action can be assessed by combining the predicted TTC and the predicted time interval:

$$R = \frac{1}{2}\Big(1 - \tanh\frac{t_{\text{p}}}{t_h} + 1 - \tanh\frac{h_{\text{p}}}{t_h}\Big), \tag{7}$$

$$R = \frac{1}{2}\Big(1 + \tanh\frac{h_{\text{p}}}{t_h}\Big), \tag{8}$$

$$t_{\text{p}} = \frac{G + \Delta G}{v_{\text{f}} + \Delta v_{\text{f}} - (v_{\text{p}} - \Delta v_{\text{p}})}, \tag{9}$$

$$h_{\text{p}} = \frac{G + \Delta G}{v_{\text{e}} + \Delta v_{\text{e}}}, \tag{10}$$

where, h_{p} is the predicted headway of the ego vehicle in the game; v_{e} is speed of the ego vehicle; Δv_{e} is predicted speed change of the ego vehicle; t_{p} is the predicted collision time; t_h is the minimum safe time interval; G is the gap length of ego vehicle and conflict vehicle; ΔG is the predicted gap length of ego vehicle and conflict vehicle; v_{f} is the speed of the following vehicle; v_{p} is the speed of the preceding vehicle, Δv_{f} is the predicted speed change of the following vehicle; Δv_{p} is the predicted speed change of the preceding vehicle. If $v_{\text{e}} + \Delta v_{\text{e}} > v_{\text{c}} + \Delta v_{\text{c}}$, the safe factor of selecting Eq. (7) is used, where v_{c} is the speed of the conflicting vehicle, and Δv_{c} is the predicted speed change of the conflicting vehicle; if $v_{\text{e}} + \Delta v_{\text{e}} < v_{\text{c}} + \Delta v_{\text{c}}$, the safe factor of selecting Eq. (8) is used.

In terms of efficiency, the value of mobility increases the cost of deceleration actions, expressed by

$$M = \frac{1}{2}\left(1 - \tanh\frac{\Delta v_{\text{e}}}{v_{\text{e}}}\right). \tag{11}$$

In summary, the cost function of the vehicle is determined using

$$C_2 = R + M. \tag{12}$$

For the vehicles of game participants, two choices are possible: leader or follower. A two-vehicle play game under two action-space game strategies is considered. One strategy is the right-turning vehicle as the leader and the straight-going vehicle as the follower; the other is the straight-going vehicle as the leader and the right-turning vehicle as the follower. Cost function values for the two strategies denoted by $C_2^{A_2[0]}$ and $C_2^{A_2[1]}$ are calculated, and the action with the minimum value of the cost function under the two strategies is selected. That is,

$$\min\{C_2^{A_2[0]}, C_2^{A_2[1]}\}. \tag{13}$$

The results show that the sequence of two vehicles in conflict passing through the intersection can be determined. If the number of game participants increases, this method can be repeated to obtain the vehicle sequence.

1.4 Operation Layer

Basic conditions exist for a vehicle platoon in IoT environments. Platoon control methods include consistency, graph theory, model prediction, behavior-based, artificial potential field, and following navigation methods. In this section, we present a model for multiagent vehicle platoon control based on a consensus algorithm. By considering the CAVs as a particle model, the state equation of the system can be expressed as

$$\dot{\boldsymbol{x}}_c = \boldsymbol{A}\boldsymbol{x}_c + \boldsymbol{B}\boldsymbol{u}_c, \tag{14}$$

where $\boldsymbol{A} = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}$, $\boldsymbol{B} = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$.

The motion model of the second-order system of the CAVs is established by combining Eq. (2). The controller input, $\boldsymbol{u}_i(t)$, is changed from the speed input to the speed differential, which can also be regarded as the acceleration. Therefore, the input of the second-order system controller is expressed as

$$\boldsymbol{u}_i(t) = -\sum_{j=Q_j}^{N} a_{ij}[(\boldsymbol{x}_i(t) - \boldsymbol{x}_j(t)) + \gamma(\boldsymbol{v}_i(t) - \boldsymbol{v}_j(t))], \tag{15}$$

where i, j are two vehicles' ID; N is the number of vehicles in platoon; γ is the correction coefficient and a positive number, a_{ij} is the matrix element, and Q_j is the residence of the jth vehicle, that is, the set of vehicles that can communicate with the jth vehicle. In the second-order system consensus control algorithm, the input parameter not only considers the available position information but also significantly influences the relative speed information of vehicle. The final requirement for consensus is that the distance between the vehicles is the same, and the speeds of the vehicles are the same; both the magnitude and direction are the same. Therefore, the following condition should be satisfied: $\lim\limits_{t\to\infty} \parallel \boldsymbol{x}_i(t) - \boldsymbol{x}_j(t) - \boldsymbol{r} \parallel = 0$, $\lim\limits_{t\to\infty} \parallel \boldsymbol{v}_i(t) - \boldsymbol{v}_j(t) - \dot{\boldsymbol{r}} \parallel = 0$, where $\boldsymbol{r}$ is the expected distance between the vehicles.

The control input of the vehicle in two-way pilot-following mode is expressed as

$$\left.\begin{aligned} &\dot{\boldsymbol{x}}_j(t) = \boldsymbol{v}_j(t) \\ &\dot{\boldsymbol{v}}_i(t) = -\sum_{j=1}^{n} a_{ij}[(\boldsymbol{x}_i(t) - \boldsymbol{x}_j(t) - \boldsymbol{r}_{ij}) + \\ &\qquad \beta(\boldsymbol{v}_i(t) - \boldsymbol{v}_j(t))] - \\ &k_i[(\boldsymbol{x}_i(t) - \boldsymbol{x}_0(t) - \boldsymbol{r}_i) + \gamma(\boldsymbol{v}_i(t) - \boldsymbol{v}_0(t))] \end{aligned}\right\}, \tag{16}$$

where $\beta > 0$, $\gamma > 0$; k_i is the matrix element, $\boldsymbol{r}_{ij}$ is the expected final distance between the ith and jth following vehicles, and $\boldsymbol{r}_i$ is the expected distance between the ith following vehicle and the pilot vehicle.

The entire game procedure is listed in Algorithm 1 in detail.

Algorithm 1: Vehicle merging sequence based on cooperative game
Input: Vehicles state at intersection, $\boldsymbol{x}_c = (\boldsymbol{p}_c, \boldsymbol{v}_c)$.
Output: Merging sequence which is composed by vehicle ID.

```
if Cooperative control zone detecting vehicle then
  if Potential conflict with right-turning vehicle then
    if I(t) is smaller than minimum safe distance between vehicles then
      Optimizing speed of right-turning vehicle
    else
      From min{C_1^{A_1[0]}, C_1^{A_1[1]}} to obtain the action strategy
      if Right-turning vehicle can merge then
        From min{C_2^{A_2[0]}, C_2^{A_2[1]}} to obtain the action strategy
        Calculating the controller input u_i(t) based on status information of ego and adjacent vehicles
      else
        Repeat optimizing speed of right-turning vehicle
      end if
    end if
  end if
else
  Repeat detection in the cooperative control zone
end if
```

2 Method Comparisons and Generalization Verification

We simulated a scenario on the SUMO platform to validate the proposed method[33]. The control algorithm was implemented in PYTHOM. Figure 3 shows the implementation using SUMO and PYTHON, depicting the transmission, storage, and processing of the data.

2.1 Scene Description and Simulation Parameter Settings

The simulated scene was a two-way four-lane intersection. Consider the south entrance to the right-turning merging as an example. The simulation parameter settings are listed in Table 2. In the simulation analysis, we analyzed the average travel time through the intersection during the merging process, the average lost time, and the potential collision number.

For a comparison of method effectiveness, we evaluated the following methods:

(1) Fixed-time control (FTC). The FTC was selected as the benchmark for the other control methods. The

Table 2 Simulation parameters in SUMO

Parameter	Notation	Value	Unit
$N_{\mathrm{L,E}}$	Number of south entrance lanes	3	
$N_{\mathrm{L,S}}$	Number of west entrance lanes	7	
L_{c}	Length of cooperative control zone	100	m
L_{e}	Length of information-exchangeable zone	2 000	m
$a_{\mathrm{a,max}}$	Maximum acceleration of vehicle	2.6	m/s^2
$a_{\mathrm{d,max}}$	Maximum deceleration of vehicle	4.5	m/s^2
$v_{\max}$	Maximum speed of vehicle	14	m/s
ϑ	Speed normal distribution, Norm (mean,deviation)	Norm (0.3, 1.2)	
σ	Driver imperfection	0.5 ± 0.1	
L_{c}	Length of vehicle	5	m
L_{s}	Minimum safe distance	2.5	m

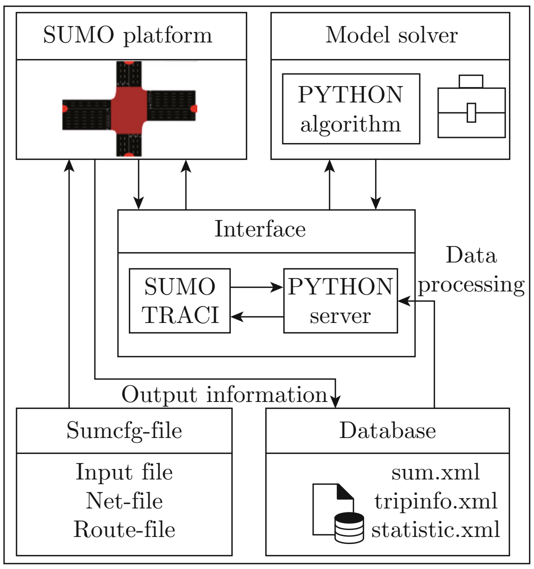


Fig. 3 Flow chart of PYTHON and SUMO co-simulation

signal cycle length of the intersections was 60 s.

(2) Centralized intersection management (CIM). The CIM is an open-source method developed by Raddon[34]. This algorithm demonstrates that automatic intersections are more efficient than intersections with traffic lights[16].

(3) Deep Q-network with reinforcement learning in traffic signal control (RL-DQN). Adaptive traffic signal control based on deep reinforcement learning has shown promising prospects. Gu et al.[15] established a Q-network to achieve stable traffic signal control. The results indicate that the proposed traffic signal control algorithm significantly improves traffic capacity.

(4) Multiagent cooperative game right-turning merging virtual platoon method (MCGRP). The MCGRP method was developed based on the approach by Liao et al[26]. The conflicting vehicle sequence is determined based on game theory, and the platoon is formed using the consensus control algorithm, which can ensure that vehicles successfully pass through intersections.

(5) Double-round multiagent cooperative game in right-turning merging using virtual platoon method (D-MCGRP). This method is an improved version of the MCGRP method. From the algorithm perspective, an additional cooperative game process is added. Thus, the impacts of right-turning vehicles on the traffic flow of the main road and its urgency are considered.

2.2 Analysis of simulation results

Five control methods were used for the intersection scene described above. In these intersection control methods, the average travel time, average lost time, and potential collision number in the simulation process can measure the performance in terms of the efficiency and safety of the right-turning merging. Therefore, except for the different intersection control methods, the vehicle models and flow rates were all evaluated under the same conditions. The straight-going traffic flow was approximately 1 200 vehicle/(h · lane), and the right-turning traffic flow was approximately 60 vehicle/(h · lane).

Table 3 lists the average travel time and average lost time in passing through the intersection within 10 min for the five control methods, where t_{tt} is the total travel time of all vehicles passing through the intersection during the merging process, t_{L} is the total lost time of all vehicles, $t_{\mathrm{a,t}}$ is the average travel time of each vehicle, and $t_{\mathrm{a,L}}$ is the average lost time of each vehicle. The average travel time and average loss time of the vehicle in the FTC control method were inferior to those of the other methods. The MCGRP method outperformed CIM and RL-DQN in terms of the average travel time but is slightly inferior in terms of the average loss time. However, D-MCGRP generally performed better than the other methods in terms of efficiency. The box diagrams for the average travel time and average loss time for the different control methods are shown in Figs. 4 and 5. The mean value of the average travel time of vehicles in the FTC control method was significantly higher than those of the other methods (Fig. 4). However, the average travel time for the D-MCGRP control method was the shortest. The average travel time of the vehicle in the D-MCGRP control method is 25%—75% more concentrated, and the variation in traffic flow is slight. Thus, the efficiency performance of the model is better than those of the other models.

Table 3 Comparison of five control methods

Method	t_{tt}/s	$t_{a,t}$/s	t_L/s	$t_{a,L}$/s
FTC	20 765.50	174.50	3276.07	27.53
CIM	18 667.53	156.87	1147.16	9.64
RL-DQN	18 622.31	156.49	1 210.23	10.17
MCGRP	18 214.14	153.06	1 422.05	11.95
D-MCGRP	18 076.10	151.90	1 155.49	9.71

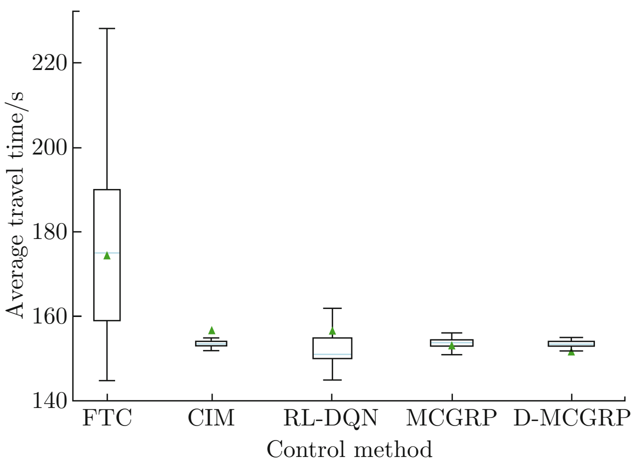


Fig. 4 Average travel time of vehicles for different control methods

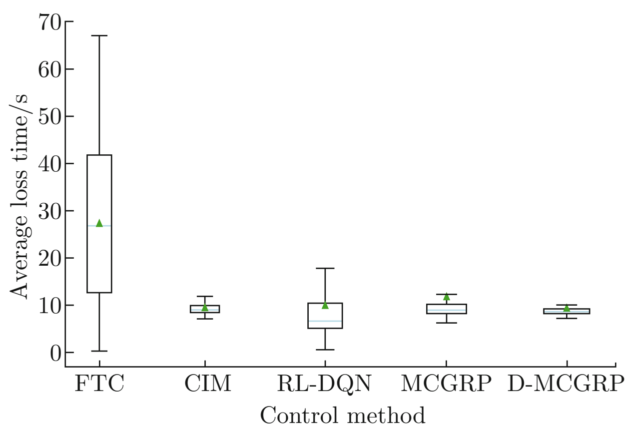


Fig. 5 Average loss time of vehicles for different control methods

Figure 6 shows the potential collision numbers denoted by N_{pc} for the five control methods under different traffic flows denoted by f_t, in which a smooth curve is fitted from the results of multiple experiments. When the traffic flow was lower than 900 vehicle/(h · lane), other control methods, except the FTC, showed minimal differences in the number of potential collisions, and the values were low, indicating that vehicles were safer to drive in the environment. However, as the traffic volume increased, the potential collision number for the FTC, CIM, and RL-DQN methods increased exponentially. In particular, the RL-DQN control method showed a significant increase. In the MCGRP and D-MCGRP control methods, the number of potential collisions increased with the traffic flow but was relatively stable, and D-MCGRP performed better than MCGRP. Therefore, the D-MCGRP control method is safer and has a broader scope of application than the other methods.

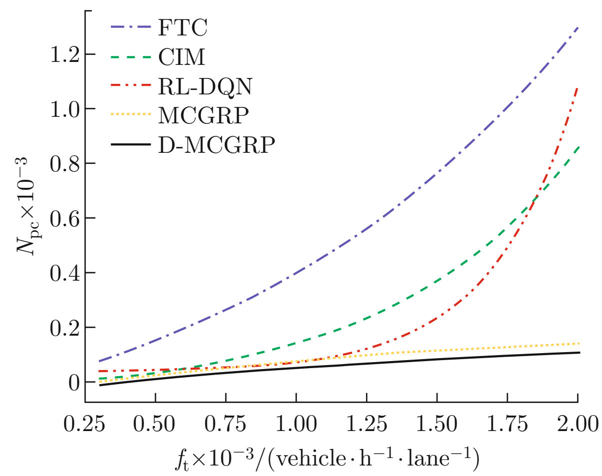


Fig. 6 Potential collision number for different traffic flow

Figure 7 shows the vehicle trajectories during vehicle merging. The overlapping parts of the curves indicate that the vehicles have conflicts in space. After implementing the hierarchical strategy developed, the conflict disappears before right-turning merging.

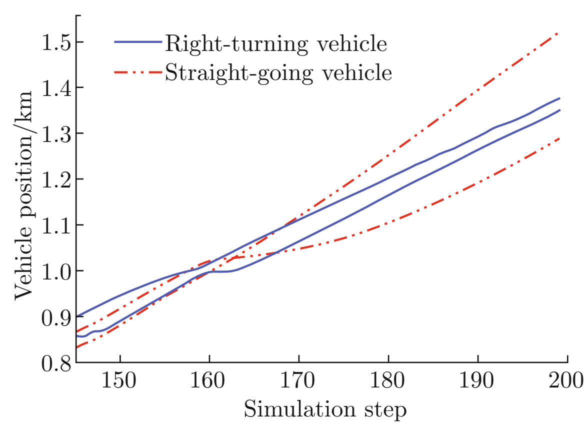


Fig. 7 Position trajectory of vehicles at right-turning merging

3 Conclusion

This study focused on the merging of right-turning and straight-going vehicles so as to improve safety and efficiency in intelligent vehicle-infrastructure collaboration systems. A hierarchical strategy based on a cooperative game was developed to determine the merging sequence of CAVs. The hierarchical strategy comprised two cooperative games. In the decision-making layer, the cost function of the game was designed based on the impact of the right-turning vehicle on the straight-going traffic flow and the urgency of the right-turning traffic flow, which makes right-turning vehicles merge into the straight-going traffic flow with minimal influence on the passing of straight-going vehicles. The task layer was based on the safety and mobility of vehicles during merging. The cost function of this cooperative game was based on safety and mobility during vehicle merging such that the obtained action strategy was optimized for the safety and efficiency of vehicles. Finally, the driving characteristics of the vehicles in the virtual platoon were guided at the operation layer to pass through the intersection smoothly. The hierarchical strategy proposed in this study performs better than other methods. The communication delay between vehicles and roadside equipment at intersections will be considered in future work.

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