

Implementation and experimental validation of a multivehicle cooperation method at intersections

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ABSTRACT: With the increasing complexity of urban traffic flow, intersections have become critical bottlenecks for improving overall traffic efficiency. In previous research, we established a modeling framework for multivehicle conflict decoupling and proposed a traffic optimization decision-making method for intersection scenarios. In this study, we present the experimental results of multivehicle conflict decoupling modeling and traffic optimization decision-making methods. The proposed method is implemented on the miniature testbed of Tsinghua Research Center for Intelligent and Connected Vehicles and Transportation to validate its effectiveness, and the implementation details are thoroughly presented. Experimental results demonstrate that in a single experiment, the proposed multivehicle conflict decoupling modeling framework outperforms the benchmark algorithm in average travel time, total delay, and overall traffic uniformity. In the mixed traffic environment, the average number of laps and average speed are higher, and the standard deviation is lower, than those under fixed-time traffic signal control and have significantly reduced the travel delay, providing a theoretical basis for collaborative decision-making in mixed traffic. These experimental findings demonstrate the significant potential of the multivehicle conflict decoupling modeling framework and traffic optimization decision-making method. The approach can be applied to intersection scenarios with different penetration rates of intelligent connected vehicles (ICVs), enabling effective conflict resolution, enhancing traffic safety, and improving overall traffic efficiency.

KEYWORDS: connected and autonomous vehicles (CAVs); miniature experiments; mixed traffic; multivehicle conflict; traffic optimization

1 Introduction

As a primary constraint on urban traffic flow, the idling and stop-and-go movements of surrounding vehicles significantly contribute to congestion, accidents, and energy inefficiency. Therefore, intersection conflict optimization is the key to improving the overall traffic environment (Chen et al., 2022; Gao et al., 2025). Serving as a platform for vehicle connectivity and autonomous driving technologies, connected and autonomous vehicles (CAVs) offer an effective approach to enhancing intersection safety, increasing traffic efficiency, and lowering energy consumption (Chen et al., 2021; Hao et al., 2024; Parashar et al., 2025).

Early studies have shown that the passing sequence of intelligent connected vehicles (ICVs) plays a crucial role in improving intersection traffic mobility (Li and Wang, 2006; Meng et al., 2018). Xu et al. (2018) proposed a typical decision-making method based on the depth-first spanning tree (DFST) for distributed intersection conflict decoupling, which provides a foundational strategy for resolving vehicle conflicts at intersections. In addition, Chen et al. (2022) constructed a multivehicle conflict model using directed conflict graphs and undirected coexistence graphs. Subsequently, an enhanced DFST

approach and a minimum clique covering technique were developed to tackle the multivehicle conflict decoupling problem. These methods were designed from the perspectives of local and global optimization, respectively, with a corresponding heuristic solution also proposed. The approximate optimal traffic sequence solution for large-scale vehicles can be obtained with low algorithm complexity. The layered framework is often used to realize CAV coordination, to achieve transverse and longitudinal joint optimization of vehicles and to improve traffic efficiency. Jin et al. (2013) further proposed a first-come, first-served (FCFS) method to determine the passing sequence of ICVs at intersections. In this approach, the basic unit of application is no longer a single ICV but a queue of ICVs. Roadside computing equipment is used to make scheduling arrangements based on this unit. Another centralized optimization approach minimizes a selected overall traffic-efficiency index. Guney et al. (2020) used particle swarm optimization to solve a similar problem. Moreover, the centralized optimization approach faces challenges for real-time implementation due to its high computational complexity. From the perspective of algorithm mechanism for solving the conflict decoupling problem, Miculescu et al. (2014) demonstrated in detail the conflict problem at the intersection of two branches

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based on the voting system and analyzed the stability of the ordering, which has high theoretical value. Heuristic methods can produce sufficiently good results quickly in a limited time. A heuristic approach is an auction-based approach for solving the conflict decoupling problem of ICVs. Wei et al. (2018) designed an approach based on game theory to find the scheduling method with the least conflict. Wu et al. (2019) developed a reinforcement learning-based method to generate conflict-free strategies. Niels et al. (2024) proposed an optimization-based signal-free intersection management method that integrates pedestrian signal phases to coordinate vehicles and pedestrians. The approach can significantly reduce vehicle delays, increase intersection capacity, and balance vehicle and pedestrian waiting times.

The studies mentioned above primarily focus on fully autonomous intersection scenarios, assuming 100% market penetration of autonomous vehicles. In reality, replacing all human-driven vehicles (HDVs) with CAVs could take several decades (Zhao et al., 2024). Early research in this context has largely concentrated on estimating queue lengths (Feng et al., 2015; Priemer and Friedrich, 2009) or traffic situations (Salman et al., 2017). These studies managed to describe the driving behavior of HDVs and CAVs, but HDVs are still not actively considered in CAV control. In recent years, Zhao et al. (2018) proposed the idea of a mixed platoon (MP). Consisting of four vehicles, MP control was verified in a small-scale simulation. On this basis, Liang et al. (2019) further proposed the concept of cooperative control between traffic signals and CAVs in mixed traffic, and Chen et al. (2021) proposed the standard "1 + N" MP structure to handle random mixed traffic flow. Malcolm et al. (2025) proposed a FCFS lane-free automated intersection management algorithm that prioritizes vulnerable road users in urban environments. Fan et al. (2024) proposed an adaptive speed optimization control model using mixed-integer linear programming to manage connected automated vehicles at signalized intersections in mixed traffic environments. The approach predicts traffic conditions and provides optimal speed recommendations to improve traffic efficiency. Fang et al. (2025) proposed a multi-agent deep reinforcement learning-based cooperative control model called multi-agent reinforcement learning (MAREL)-CTV to coordinate connected and automated vehicles and controllable traffic signal lights. The approach leverages pretrained networks and expert datasets to improve control efficiency and reduce the control burden. In addition, CAVs' speed trajectory will inevitably impact the vehicles driving behind the same lane, thus affecting the overall traffic efficiency. It has been shown that considering overall traffic in CAV planning and control can improve traffic performance. This is achieved through speed control of CAVs, known as lagrangian control. The effectiveness of this approach has been demonstrated across various scenarios (Guan et al., 2025). However, the above studies have only verified the algorithm through simulation, and the vehicle model used is still far from reflecting real-world conditions.

In terms of real vehicle verification, CAVs are generally not allowed to drive freely on nonspecific roads in mixed-traffic environments. Some researchers have carried out algorithm verification on small experimental platforms. Ahn et al. (2020) validated the effectiveness of a CAV supervision control algorithm using experimental vehicles. Chalaki et al. (2020) employed a scaled-down testbed to assess the real-time performance and effectiveness of a multivehicle cooperation algorithm. Dong et al. (2023) developed the mixed cloud control testbed (MCCT), a microexperimental platform based on the digital twin concept, whose vehicle platoon experiments demonstrated its flexibility and

scalability. Pahlavan et al. (2012) and Axelsson et al. (2014) provided an open vehicle simulation platform for modeling the cyber-physical aspects of vehicle systems. Gulliver emphasizes vehicle-to-vehicle communication, whereas MOPED targets low-level control of an individual scaled vehicle. The Duckietown platform, developed by MIT, is open and economical and consists of infrastructure such as small autonomous vehicles, roads, signs, traffic lights, and obstacles to provide a convenient platform for educators and researchers (Paull et al., 2017). Kloock et al. (2021) built the cyber-physical mobility Laboratory (CPM). This laboratory is an open-source development platform for CAVs, emphasizing connected decision-making, trajectory planning, and control. Go-CHART is a four-wheel slip-steering robot equipped with onboard sensors and both onboard and external computers that is capable of replicating much of the sensing and computing capabilities of a full-size autonomous vehicle (Kannapiran and Berman, 2020). Cambridge developed Minicar and its fleet control architecture, creating an experimental testbed that enables the implementation of advanced driver models and autonomous control strategies, allowing their effectiveness to be tested in real, physical multilane environments (Hyldmar et al., 2019). Ulhas et al. (2024) built CHARTOPOLIS, a small-scale driving test platform, to provide a safe, controlled physical environment for evaluating autonomous vehicle controllers in a cost-effective manner.

Due to limitations in real-vehicle experiments, mixed traffic environments involving HDVs and self-driving vehicles are mostly not allowed on licensed sections of the road, especially in high-penetration hybrid traffic scenarios, which are difficult to achieve in most cases. Moreover, the abovementioned experimental platforms still have problems such as a limited number of road terrains for simulating lanes and intersections, difficulties in characterizing heterogeneous vehicle behaviors in mixed traffic, and sensing noise and communication delays, resulting in inaccurate simulation. In this study, a miniaturized experimental testbed is used to verify the multivehicle conflict decoupling modeling and traffic optimization decision-making method in connected and mixed traffic scenarios, and the implementation details are thoroughly presented.

Specifically, our contributions are as follows:

- 1) The multivehicle conflict decoupling method is verified on a microexperiment platform in a fully connected environment. Directed conflict graphs are employed to represent intervehicle conflict relationships, and undirected coexistence graphs are used to represent intervehicle coexistence relationships (Chen et al., 2022). The relationship between the spanning tree and vehicle passage sequence is also established. Experimental results show that the improved depth-first spanning tree (iDFST) and minimum clique cover (MCC) algorithms outperform benchmark algorithms in terms of average travel time, total travel delay, and traffic uniformity.

- 2) The MP cooperative control framework is validated on a miniature testbed. The results indicate that the framework bridges fixed-timing traffic control and fully connected vehicle cooperation. By actively guiding HDVs to pass intersections, the proposed framework reduces the cumulative velocity standard deviation compared with fully connected algorithms, demonstrating improved traffic regulation performance (Chen et al., 2021).

The rest of this paper is organized as follows: Section 2 describes the scenario explanation. Section 3 provides the multivehicle conflict decoupling and graph theory modeling method and the traffic light-vehicle cooperation method. Section 4

introduces the miniature testbed, and Section 5 analyzes the simulation results. The study is summarized in Section 6.

2 Scenario

This study models a typical signalized intersection with both CAVs and HDVs, as illustrated in Fig. 1, focusing on adaptive traffic signal control under mixed traffic conditions. In this scenario, vehicles entering the intersection constitute a mixed traffic flow of CAVs and HDVs. Here, CAVs can receive sensed signals and execute vehicle control commands, whereas HDVs compute control instructions based on a car-following model. Three conflict relationships between vehicles at intersections are identified: crossing, diverging, and merging. In the figure, the circular dashed line indicates the boundary of the control area, while the white solid line marks the stop line.

In scientific research, it is often necessary to abstract the research object into a physical model and then transform practical problems into mathematical problems for analysis and solution. The abstraction of physical models is based on basic assumptions. Accordingly, the following fundamental assumptions are adopted for the subsequent analysis:

1) Lane-changing behavior near intersections is ignored: Research has found that lane-changing behavior near intersections has a significant negative impact on the traffic efficiency of intersections (Hao et al., 2019). On the other hand, the lane-changing behavior of drivers driving vehicles in road sections also brings unpredictable and difficult-to-solve problems to the decision-making and control of ICVs (Ala et al., 2016). Therefore, similar to most studies in the field of intersection coordination (Malikopoulos et al., 2018; Xu et al., 2017a, 2018), in this study, vehicles do not perform lane-changing operations on sections near intersections.

2) Nonideal communication conditions such as packet loss and delay are not considered because the development of vehicle to everything (V2X) communication technology ensures reliable network communication conditions (Gerla et al., 2014). Dedicated short-range communications (DSRC) (Kenney, 2011) and long-term evolution for vehicles (LTE-V) (Sesia et al., 2011) can both ensure a stable communication distance of more than 800 m with a communication delay of less than 10 ms (Bettisworth et al.,

2015; Demmel et al., 2012). Therefore, this study assumes ideal networked communication, neglecting issues such as communication delay and packet loss. Experimental tests on DSRC and LTE-V devices (Xu et al., 2017b) indicate that at a communication range of 400 m and vehicle speed of 120 km/h, the average packet loss rate remains below 10% and the average round-trip delay is under 20 ms, which satisfies the communication requirements for autonomous driving.

3) ICVs can obtain precise positioning information in real time and track the desired trajectory without error. In terms of real-time kinematic (RTK) technology, differential global positioning system technology (DGPS) and inertial measurement unit (IMU) technology can improve real-time vehicle positioning accuracy to 3–4 cm (Guo et al., 2018). High-precision simultaneous localization and mapping (SLAM) technology provides the possibility for lane-level vehicle localization of ICVs. In terms of vehicle transverse and longitudinal control technology (Bailey and Durrant-Whyte, 2006; Durrant-Whyte and Bailey, 2006), single-vehicle control technology and queue control technology have made considerable progress. Various control methods, such as optimal control, robust control, and sliding mode control, ensure the control accuracy of ICVs during operation (Fei et al., 2024; Li et al., 2024). Therefore, in this study, it is assumed that the positioning and control of ICVs can meet the requirements of algorithm design.

3 Methodology

3.1 iDFST

The analysis of mixed traffic flow can be divided into the MP of steady-state driving and freely driving HDVs. In the following, i and j denote the arrival order of vehicles at the control area. Specifically, i refers to the position of a vehicle within the MP, while j refers to the position of an HDV in free driving. These indices are used consistently in the conflict sets and throughout the analysis of vehicle interactions. Based on these indices, node $\mathcal{V}_i^m$ represents the MP of the first i arriving at the control area, the total number of vehicles in the MP is recorded as m , and node $\mathcal{U}_j$ represents the HDV of the first j arriving at the control area. Similar to pure CAV planning, conflict relationships can also be divided into crossing conflict sets $\mathcal{C}$, driving conflict sets $\mathcal{D}$, confluence conflict sets $\mathcal{V}$, and reachability conflict sets $\mathcal{R}$. Based on the analysis of the vehicle conflict relationship, the conflict directed graph $\mathcal{G}_{N+1}$ can be further defined, and the vehicle conflict relationship can be described from the perspective of graph theory. If N vehicles are driving in the control area, the node set is defined as $\mathcal{V}_{N+1} = \{0, 1, \dots, N\}$ (where node 0 represents the virtual leading vehicle), the directed edge set is defined as $\mathcal{E}_{N+1}^u = \{(i, j) \mid i \in \mathcal{D}_j \cup \mathcal{R}_j\}$, the undirected edge set is defined as $\mathcal{E}_{N+1}^b = \{(i, j) \mid i \in \mathcal{C}_j \cup \mathcal{V}_j\}$, and the combination of the two forms the edge set $\mathcal{E}_{N+1} = \mathcal{E}_{N+1}^u \cup \mathcal{E}_{N+1}^b$. Node sets and edge sets define the conflict directed graph $\mathcal{G}_{N+1} = (\mathcal{V}_{N+1}, \mathcal{E}_{N+1})$.

Take Fig. 1 as an example to analyze the conflict set. The No. 1 and No. 2 vehicles approach from the east in the right turn and left turn lanes, respectively. The No. 3 and No. 4 vehicles approach from the west in the straight and right lanes, respectively. The No. 5, 6, and 7 vehicles approach from the south, with the No. 5 vehicle turning left and the other two turning right. When No. 7 vehicle arrives at the boundary of the control area, because of its late arrival, it cannot pass the intersection with No. 1 vehicle and No. 5 vehicle at the same time.

In the execution of the planning results, to ensure the stability of vehicle driving, the virtual pilot vehicle is usually designed as the front vehicle closest to the intersection (Xu et al., 2018). The

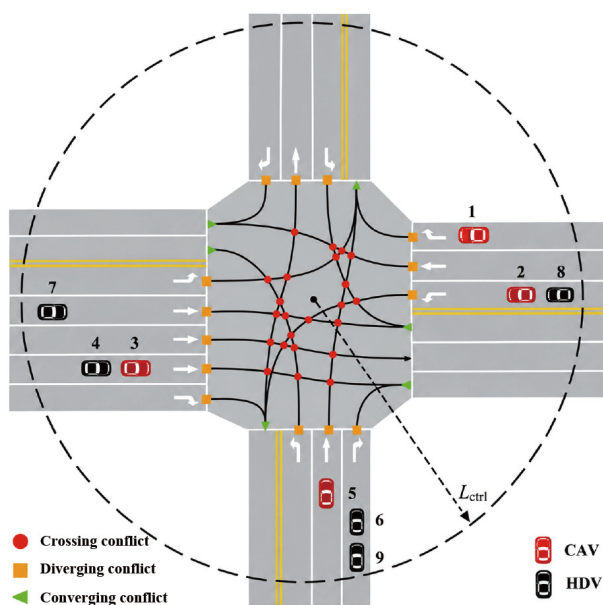


Fig. 1 Complex intersection scenario with mixed-traffic incoming vehicles.

virtual pilot vehicle acts as a No. 0 vehicle, traveling at a constant virtual queue speed v_p . All vehicles closest to the intersection follow the No. 0 vehicle. If the virtual pilot vehicle is not designed, the vehicles closest to the intersection will accelerate to the maximum speed $v_{\max}$ allowed by the road, and the virtual queue cannot be formed, so it is necessary to introduce the aforementioned virtual pilot vehicle to form a stable virtual queue. In Fig. 1, No. 1–6 vehicles have diverging conflicts with No. 0 vehicle, i.e., $\mathcal{D}_k = \{0\}, k = \{1, 2, 3, 4, 5, 6\}$. In addition, when No. 3 vehicle arrives at the control area, there is a cross conflict with No. 2 vehicle. When No. 4 vehicle arrives at the control area, there is a confluence conflict with No. 2 vehicle. No. 5 vehicle has a cross conflict with No. 2 vehicle and No. 3 vehicle. No. 6 vehicle and No. 3 vehicle have confluence conflicts. No. 7 vehicle also has confluence conflicts with No. 3 vehicle, diversion conflicts with No. 6 vehicle, and accessibility conflicts with No. 1 vehicle and No. 5 vehicle. Therefore, the conflict directed graph is constructed, as shown in Fig. 2. Nodes in Fig. 2 represent ICVs in the control area, and the color of nodes represents the direction of traffic flow, as shown in Fig. 3. The black unidirectional edges in Fig. 3 represent diversion conflict and accessibility conflict. Because lane change behavior is not considered, if there is a black unidirectional edge (i, j) between vehicle i and vehicle j , vehicle i cannot reach the stop line before vehicle j . The red bidirectional edge in the figure represents cross conflict and confluence conflict. If there is a red bidirectional edge (i, j) between vehicle i and vehicle j , vehicle i and vehicle j cannot pass through the stop line simultaneously, but the two vehicles can exchange their passing order.

For the vehicles in the control area, the directed conflict graph $\mathcal{G}_{N+1}$ can be used to describe the conflict relationship between vehicles, the DFST $\mathcal{G}'_{N+1}$ can be obtained to represent the traffic

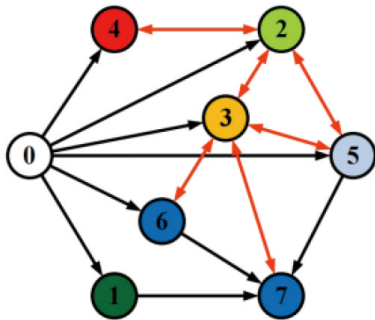


Fig. 2 Conflict directed graph.

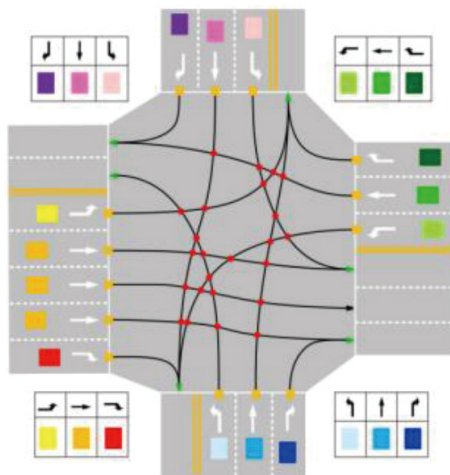


Fig. 3 Incoming vehicles and conflict points.

order, and the depth of the spanning tree is directly related to the traffic efficiency. The spanning tree changes as vehicles continue to enter or leave the control area. Therefore, based on the DFST algorithm proposed by Xu et al. (2017a), the iDFST algorithm can be developed to solve the problem of vehicle passage order generation under dynamic traffic conditions.

In this approach, vehicles are represented as nodes in the spanning tree. The maximum node depth d_{all} corresponds to the overall evacuation time, while the average node depth reflects the average travel time delay. Therefore, the DFST obtained by the iDFST algorithm can generate the conflict-free traffic order of vehicles in the control area. For each new vehicle node i arriving in the control area, the search process for the parent node follows the FCFS principle. Even if there is a bidirectional edge in the conflict-directed graph that can exchange the arrival order of vehicles, the passing order of vehicles is still determined one by one according to the order of vehicles arriving at the stop line. Therefore, when considering the conflict relationship of vehicle j , only vehicles whose vehicle number is less than j in the conflict zone will be considered. If the conflict-directed graph is as depicted in Fig. 2, the spanning tree generated by the iDFST algorithm is shown in Fig. 4a, while the spanning tree obtained by the original DFST algorithm is shown in Fig. 4b. In each spanning tree, the depth of the vehicle node is equivalent to the time it takes the vehicle to reach the stop line. Therefore, for N vehicles in the control area, the spanning tree is equivalent to a feasible solution of a traffic order.

Compared with the DFST algorithm, the improvement of the iDFST algorithm lies in the search for the optimal parent node. In the DFST algorithm, the parent node set of a conflict is treated as the same conflict set $P = P_u + P_b$. Therefore, when judging the conflict relationship of i nodes, only the maximum depth d_k of all conflicting parent nodes is considered. For example, in the conflict-directed Fig. 2, No. 6 vehicle has diverging conflict with No. 0 vehicle and cross conflict with No. 3 vehicle. When determining the conflict relationship of No. 6 vehicle, the DFST algorithm considers the maximum number of layers of the conflict node $d_3 = 2$, so the number of layers of No. 6 vehicle is determined as $d_6 = 2 + 1 = 3$, as shown in Fig. 4b. In the iDFST algorithm, the cross conflict with No. 3 vehicle can be crossed by distinguishing between the crossable bidirectional edge P_b and the uncrossable unidirectional edge P_u , so the number of layers of No. 6 vehicle is determined as $d_6 = 1$, as shown in Fig. 4a. As a result, the iDFST reduced the depth of the No. 6 vehicle from the third layer to the first layer. The iDFST algorithm can always obtain a DFST with a depth smaller or equal to that of the DFST algorithm.

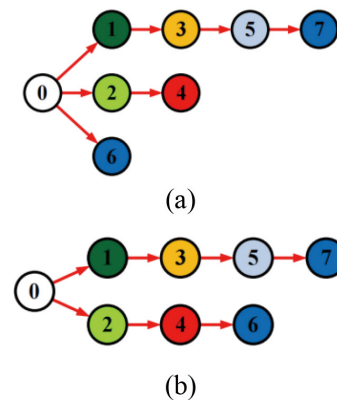


Fig. 4 Two different spanning tree generation algorithms: (a) the spanning tree obtained by the iDFST algorithm; (b) spanning tree generated by the DFST algorithm.

3.2 Minimum clique covering method

Reexamining the traffic scenario in Fig. 1, up to six vehicles can traverse the intersection simultaneously. In other words, given a certain number of vehicles within the control area, minimizing the total depth of the generated tree is equivalent to maximizing the number of vehicles passing through each layer. According to the definition of a coexistence undirected graph, coexistence undirected graph in Fig. 5 can be obtained from conflict directed graph in Fig. 2. Because the edge E_{N+1} in the conflicted digraph represents that the two vehicles have a conflict relationship, the edge in the coexisting undirected graph represents that the two vehicles can pass through the intersection at the same time, that is, they can coexist in the same phase.

A group in a coexistence undirected graph consists of vehicles aiming to pass through the intersection simultaneously. Since the chosen cliques have edges in the phase coexistence undirected graph, the vehicles represented by the clique nodes can traverse the intersection at the same time without conflicts, as illustrated in Fig. 5. $C = \{1, 2\}$ is a clique, but it is not the largest clique. The maximum clique is defined as the clique containing the largest number of nodes in a coexisting undirected graph, for example, where $C = \{1, 4, 5, 6\}$ is the largest clique. In particular, the maximum clique size of an undirected graph G is called the clique number $\omega(G)$. In Fig. 5, $\omega(\bar{G}_N) = 4$. This is the same as the analysis above; that is, for the example traffic scenario in Fig. 1, up to 4 vehicles can pass through the intersection at the same time. In fact, if there are enough lanes occupied by incoming vehicles, as shown in Fig. 4b, the maximum number of cliques s can be $\omega(\bar{G}_N) = 6$.

The minimum clique coverage $\theta(\bar{G}_N)$ of a coexisting undirected graph $\bar{G}_N$ represents the number of minimum cliques that completely cover a coexisting undirected graph. Because a clique in the coexistence undirected graph represents vehicles that can traverse the intersection simultaneously, vehicles within the same clique can be scheduled to reach the stop line concurrently, corresponding to the same level in the spanning tree.

For example, in Fig. 5, the minimum clique coverage number is $\theta(\bar{G}_N) = 3$, and the corresponding clique coverage is shown in Table 1, but the maximum clique $\{1, 4, 5, 6\}$ appears in feasible solution 1 but not in other feasible solutions. In other words, for any intersection scenario, the coexistence traffic relationship of

vehicles can be represented by its coexistence undirected graph $\bar{G}_N$. The number of cliques $\omega(\bar{G}_N)$ represents the number of vehicles that can pass through the intersection at the same time and is directly related to the scene of the intersection, while the minimum clique coverage $\theta(\bar{G}_N)$ represents the minimum overall evacuation time of vehicles and is directly related to the decision algorithm.

In phase coexistence Fig. 5, $\theta(\bar{G}_N) = 3$ means that the minimum depth of the spanning tree is $d_{\text{all}} = 3$. This also shows that the theoretical minimum total evacuation T_{vac} in Table 1 is the same. Therefore, the total evacuation time is equivalent to minimizing the group coverage number $\theta(\bar{G}_N) = 3$. In addition, if the average travel time delay is used as the second indicator of optimal solution selection, t_{ATTD} can be written as Eq. (1) in the graph theory expression.

$$\begin{aligned} \min \sum_{i=1}^k d_i |V_i|, i \in \mathbb{N}^+ \\ \text{s.t.} \quad \sum_{i=1}^k |V_i| = N \end{aligned} \quad (1)$$

If we consider Eq. (1), it is obvious that the set of nodes V_i covered by the minimum clique should be arranged in decreasing order in the spanning tree. On the other hand, when different cliques cover $\theta(\bar{G}_N)$ equally, the subset containing the largest clique should be selected whenever possible. Therefore, in Table 1, feasible solution 1 should be selected, and the corresponding minimum clique covering the spanning tree is $\{1, 4, 5, 6\} \rightarrow \{2, 7\} \rightarrow \{3\}$, as shown in Fig. 6.

The above problem of solving the minimum depth of the spanning tree can be formulated as a minimum clique covering, which is also NP-complete. Therefore, there is a one-to-one correspondence between the minimum clique coverage number $\theta(\bar{G}_N)$ and the total depth d_{all} of the spanning tree, which is the global optimal solution of the problem. The computational complexity and real-time feasibility of the MCC have been systematically and thoroughly discussed in our previous study (Chen et al., 2022). In that work, detailed evaluations of the computational time and scalability of the MCC algorithm under dynamic traffic flow conditions were conducted. A scale-aware algorithm design is adopted to balance optimality and real-time performance. For small-scale scenarios ($N \leq 10$), an enumeration-based exact solution is used to obtain the global optimum. These results serve as theoretical benchmarks to validate the optimality advantage of the MCC formulation and to evaluate the performance gap of heuristic solutions. For larger-scale and practical traffic scenarios ($N > 10$), where exact enumeration becomes computationally infeasible due to combinatorial explosion, a heuristic greedy MCC algorithm is therefore employed. In terms of computational complexity, the proposed

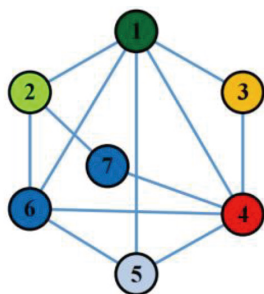


Fig. 5 Coexistence undirected graph.

Table 1 Coexistence undirected group coverage in Fig. 5

Feasible solution	Subset		
	V1	V2	V3
1	{1, 4, 5, 6}	{2, 7}	{3}
2	{4, 5, 6}	{2, 7}	{1, 3}
3	{1, 3, 4}	{5, 6}	{2, 7}
4	{1, 5, 6}	{2, 7}	{3, 4}

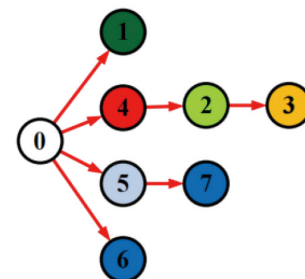


Fig. 6 Spanning tree obtained by the MCC algorithm.

heuristic algorithm has an overall complexity of $O(|E_N| + |V_N|) = O(N)$, which scales linearly with the number of vehicles. Under peak traffic conditions with up to 30 vehicles, the MCC algorithm is capable of meeting the real-time requirements of cooperative control.

3.3 MP modeling

As shown in Fig. 7, the MP has a pilot CAV followed by an n -following HDV. By optimizing its speed trajectory, the CAV enhances the overall traffic efficiency of the MP passing through the intersection.

For the n HDV following behind the pilot CAV, the position and speed of vehicle i at time t are represented as $x_i(t)$ and $v_i(t)$, respectively. The headway distance of vehicle i from vehicle $i-1$ is defined as $\delta_i(t) = x_{i-1}(t) - x_i(t)$. The acceleration of vehicle i can then be expressed as a function of these variables $v_{i-1}(t) - v_i(t)$. Existing HDV-following models mainly include the optimal velocity model (OVM) and the intelligent driver model, among others. Most HDV-following behavior can be expressed using the general form ($i = 1, 2, \dots, n$):

$$\dot{v}_i(t) = F(\delta_i(t), \dot{\delta}_i(t), v_i(t)) \quad (2)$$

This study expects the MP to pass through the intersection at a set steady-state equilibrium speed v^* . At the steady state, $\dot{v}_i(t) = 0, i = (1, 2, \dots, N)$, and thus, for each steady-state equilibrium distance δ^* have

$$F(\delta^*, 0, v^*) = 0 \quad (3)$$

The current state $(\delta_i(t), v_i(t))$ of vehicle i and the equilibrium state (δ^*, v^*) are taken as the state variables, and the deviation between them can be defined as

$$\begin{cases} \tilde{\delta}_i(t) = \delta_i(t) - \delta^* \\ \tilde{v}_i(t) = v_i(t) - v^* \end{cases} \quad (4)$$

The linearized dynamics of (δ^*, v^*) are shown below $i = (1, 2, \dots, N)$:

$$\begin{cases} \dot{\tilde{\delta}}(t) = v_{i-1}(t) - v_i(t) \\ \dot{\tilde{v}}(t) = \alpha_1 \tilde{\delta}_i(t) - \alpha_2 \tilde{v}_i(t) + \alpha_3 \tilde{v}_{i-1}(t) \end{cases} \quad (5)$$

where $\alpha_1 = \frac{\partial F}{\partial \delta}$; $\alpha_2 = \frac{\partial F}{\partial \dot{\delta}} - \frac{\partial F}{\partial v}$; and $\alpha_3 = \frac{\partial F}{\partial \dot{v}}$ represent the parameters linearized around the equilibrium state (δ^*, v^*) .

For the vehicle following model, an overly complex model inevitably increases computational complexity. To balance the relationship between them, the OVM model is used as the following model in the optimal control formulation. Other HDV vehicle following models, such as IDM, can also be used for derivation and subsequent analysis. In the OVM model, the general expression of the HDV follower dynamics becomes

$$\dot{v}_i = \gamma \kappa [V_{\text{des}}(\delta_i) - v_i] \quad (6)$$

In the experiments, the heterogeneity of HDV behavior was explicitly modeled by introducing a random gain $\gamma \in [0.9, 1.1]$. This randomized gain explicitly introduces persistent parameter perturbations into the HDV dynamics, rather than isolated disturbances, thereby providing a meaningful test of the robustness of the proposed control framework under heterogeneous and uncertain human driving behaviors. κ is the sensitivity coefficient of the OVM; V_{des} is the desired speed of the driver at a following distance of δ_i ; and the equation is given by

$$V_{\text{des}}(\delta_i) = V_1 + V_2 \tanh[C_1(\delta_i - L_{\text{veh}}) - C_2] \quad (7)$$

where V_1 and V_2 are velocity-related parameters of the OVM; C_1 and C_2 are model calibration parameters; and L_{veh} is the length of the vehicle. In this case, the coefficients of Eq. (5) can be derived as

$$\alpha_1 = \kappa V_2 C_1 \{1 - \tanh^2[C_1(\delta_i - L_{\text{veh}}) - C_2]\} \quad (8)$$

The three coefficients in Eq. (5) are therefore determined as follows: α_1 is given by Eq. (8), whereas $\alpha_2 = \kappa$ and $\alpha_3 = 0$. The number of the first vehicle, the pilot CAV is 0, and the control input $u(t)$ is acceleration, allowing the longitudinal dynamics of the lead CAV to be given by the second-order form.

$$\begin{cases} \dot{x}_0(t) = v_0(t) \\ \dot{v}_0(t) = u(t) \end{cases} \quad (9)$$

3.4 Mixed optimal control framework

In the optimal control of an $1 + N$ MP, the primary objective is to ensure that the CAV reaches the stop line when the traffic signal turns green while maintaining the CAV and trailing HDV at a stable equilibrium speed v^* . In addition, it is also desirable to minimize fuel consumption throughout the control process, that is, to minimize the amount of control. Accordingly, the cost function can be expressed as

$$J = \varphi(X(t_f)) + \int_{t_0}^{t_f} L(X(t), u(t)) dt \quad (10)$$

where t_0 represents the time at which the CAV enters the control zone; t_f is the time it reaches the conflict zone; $L(X(t_f), u(t))$ indicates the fuel consumption of the MP at time t ; and the Akcelik fuel consumption model is used in this study to calculate the instantaneous fuel consumption. The terminal state cost $\varphi(X(t_f))$ is defined as the deviation from the desired state as

$$\varphi(X(t_f)) = \omega_1 (x_0(t_f) - x_{\text{tar}})^2 + \omega_2 \sum_{i=0}^n (v_i(t_f) - v^*)^2 \quad (11)$$

where ω_1 and ω_2 denote the weighting coefficients for the position deviation of the leading CAV and the velocity deviations of all vehicles in the MP, respectively; $x_0(t_f)$ represents the position of the leading CAV at terminal time t_f ; and x_{tar} denotes the desired terminal position, i.e., the stop line position. In this study, the terminal time t_f is not predefined as a fixed experimental parameter. Instead, it is determined dynamically

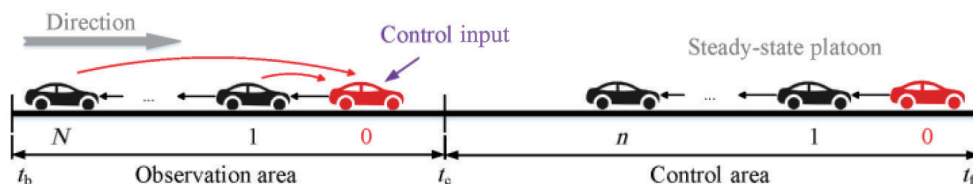


Fig. 7 MP converges to a steady state.

based on the signal timing constraints, the optimal equilibrium speed of the MP, and the geometric relationship between the leading CAV and the stop line. The considered scenario involves a signalized intersection with fixed-time control, where the green duration T_{Green} is known. Given the current distance D_k from the leading CAV to the stop line and the signal phase information, a feasible target green time window is identified and mapped into a corresponding speed interval $[v_{\text{low}}, v_{\text{high}}]$. The target speed is chosen as $v_{\text{high}} = v_{\text{target}}$, provided that the intersection between v_{target} and the feasible speed interval is nonempty. This ensures that the resulting speed trajectory is both meaningful and beneficial for overall traffic efficiency under mixed traffic conditions. Finally, once the target speed v_{target} is determined, the desired terminal time t_f is computed from the distance to the stop line as

$$t_f = \frac{D_k}{v_{\text{target}}} \quad (12)$$

In designing the MP CAV controller, the constraints encompass both process constraints and terminal constraints. For the path constraints, the first consideration is the safety constraint, which ensures that each vehicle in the MP maintains a safe distance d_{safe} from its preceding vehicle:

$$x_i(t) - x_{i-1}(t) - L_{\text{veh}} > d_{\text{safe}} \quad (13)$$

Each vehicle in the MP is subject to speed and acceleration constraints. Let v_{max} denote the maximum speed, and a_{min} and a_{max} denote the minimum and maximum acceleration, respectively. For the terminal constraints, the focus is on the terminal position of the CAV. The deviation of the CAV terminal position $x_0(t_f)$ from the desired position x_{tar} has already been included in the terminal cost function. By combining the above cost functions with the relevant constraints, the optimal control framework for the MP can be formulated as

$$\underset{u(t)}{\operatorname{argmin}} J = \varphi(X(t_f)) + \int_{t_0}^{t_f} L(X(t), u(t)) dt \quad (14)$$

In this study, the high-order nonlinear optimal control problem is converted into a nonlinear programming (NLP) problem using the pseudospectral method. A detailed design can be found in Chen et al. (2021).

3.5 MP prioritized generation tree algorithm

The conflict relationship between the MP and HDVs is established once the vehicle reaches the control area boundary. Therefore, the vehicle number j in the conflict set of node i is less than i , that is, the following formula is satisfied:

$$i < j, \mathcal{V}_i^m \cup \mathcal{U}_i \in \mathcal{C}_j \cup \mathcal{D}_j \cup \mathcal{V}_j \cup \mathcal{R}_j \quad (15)$$

Then, the conflict digraph $\mathcal{G}_{N+1}$ under mixed traffic can be defined to express the conflict relation between nodes. Conflict analysis is conducted for the traffic scenario shown in Fig. 1. In this traffic scenario, four CAVs numbered 1, 2, 3, and 5 and five HDVs numbered 4, 6, 7, 8, and 9 are considered. After the convergence of the MPs is assessed, four MPs can be formed: One led by CAV No. 1, one led by CAV No. 2 with HDV No. 8, one led by CAV No. 3 with HDV No. 4, and one led by CAV No. 5, with $\mathcal{V}_1^1$, $\mathcal{V}_2^2$, $\mathcal{V}_3^2$, $\mathcal{V}_5^1$, respectively, where the subscript denotes the index of the leading CAV and the superscript denotes the total number of vehicles in the mixed platoon. The superscripts represent the total number of vehicles in the MP. No. 4 and No. 8 vehicles do not need to be considered in the decision due to fixed

vehicle following behavior. The remaining HDVs are free to drive, represented by $\mathcal{U}_6$, $\mathcal{U}_7$, $\mathcal{U}_9$.

After the above nodes are obtained, the conflict relationship between nodes can be determined. $\mathcal{V}_1^1$ enters the controlled area, with no other vehicles in the controlled area, so the conflict set $\mathcal{C}_i$, $\mathcal{D}_i$, $\mathcal{R}_i$ is an empty set since $\mathcal{V}_1^1$ is the vehicle in the lane closest to the intersection. It is affected by the virtual pilot vehicle 0, $\mathcal{D}_1 = \{0\}$. When No. 2 CAV enters the control area because it is similar to $\mathcal{V}_1^1$, and the conflict relationship is the same. It is worth noting that currently, because No. 8 HDV still does not enter the control area, the MP number is $\mathcal{V}_2^1$, and the MP number is $\mathcal{V}_2^1$. The MP number is updated to $\mathcal{V}_2^2$ when No. 8 HDV enters the control area and is judged to be converging. When the No. 3 CAV enters the control area, it becomes the $\mathcal{V}_3^1$ node. It can be judged that it has a cross conflict with the $\mathcal{V}_2^1$ node. Therefore, $\mathcal{C}_3 = \mathcal{V}_2^1$. Then, for No. 3 HDV in the controlled area, node $\mathcal{V}_3^1$ updates $\mathcal{V}_3^2$. By analogy, the conflict relationship between the remaining nodes can be obtained, as shown in Fig. 8.

In Fig. 8, gray denotes the virtual node 0 vehicle, MP node $\mathcal{V}_1^1$, $\mathcal{V}_2^2$, $\mathcal{V}_3^2$, $\mathcal{V}_5^1$ is blue, and the remaining freely driving HDV node $\mathcal{U}_6$, $\mathcal{U}_7$, $\mathcal{U}_9$ is white. The edge between the nodes represents the conflict relationship between each other and can exchange their order through cross conflicts $\mathcal{C}_i$. The confluent conflict $\mathcal{V}_i$ is represented by the red bidirectional edge and cannot exchange through the order of the flow conflict $\mathcal{D}_i$. The reachability conflicts $\mathcal{R}_i$ are represented by black unidirectional edges.

After the conflict digraph is obtained, the MP-iDFST can be designed. The algorithm uses the FCFS principle to arrange the arrival order of vehicles. If the node is a free driving HDV, that is, $\mathcal{U}_i$, then the number of layers occupied by the node is 1, which can be regarded as the depth of single-vehicle processing. The earliest time that the HDV can reach the stop line is determined according to the vehicle dynamics constraints, and the accessibility conflict $\mathcal{R}_i$ constrains its earliest time to reach the stop line. If the planned arrival time is later than the time that it freely travels to the stop line, the time is limited by the red phase of the traffic signal. If the node is a MP, i.e., $\mathcal{V}_i^m$, then the maximum size of the MP is determined by the number of HDVs in the same lane in the rear observation area when the head vehicle CAV i reaches the stop line, and this maximum value is not the final value. Based on the expected arrival time of the CAV, the feasibility of the MP's convergence time must be checked to determine the final platoon size. The procedure for selecting the optimal parent node is similar, with the vehicle count at each node taken into account when evaluating conflict relationships.

Thus, the corresponding DFST can be calculated for the directed conflict shown in Fig. 8. There is no difference between node $\mathcal{V}_1^1$ and MP node $\mathcal{V}_2^2$, which are carried out when there are no conflicting vehicles in the road connected. Therefore, the number of target layers is the first layer. The difference is that

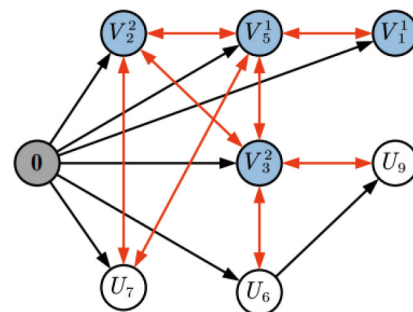


Fig. 8 Conflict diagrams in mixed traffic scenarios.

there is No.8 HDV after No. 2 CAV. Therefore, it occupies two layers of the spanning tree. Nodes V_3^2 and V_2^2 have overlapping conflicts; therefore, they cannot occupy Layers 1 and 2, number of target $d_3 = 3$. The location of the spanning tree of subsequent nodes can be obtained by analogy. The difference is that U_6 and U_8 have an insurmountable diversion conflict, and V_3^2 has a cross conflict, so the number of selected layers must be greater than 1 and cannot intersect with 3, 4. Thus, the number of target layers $d_9 = 2$. The final spanning tree is shown in Fig. 9.

3.6 Mixed traffic signal-vehicle cooperation decision-making method

The traffic signal-vehicle cooperation decision method under mixed traffic is shown in Fig. 10 as an algorithm flowchart. In the

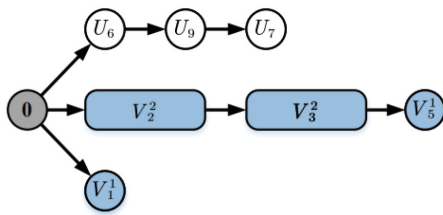


Fig. 9 DFSTs in mixed traffic scenarios.

mixed traffic scenario where CAVs and HDVs coexist, the entering section of the intersection is divided into an observation area and a control area. In the observation area, CAVs are controlled according to the HDV-following model. When a CAV reaches the control area boundary, the number of HDVs is set as the maximum vehicle count in the MP. The convergence time of the MP is then determined based on this number, yielding the feasible convergence time and the corresponding platoon size. HDVs can likewise be managed using an HDV-following model.

After obtaining the MP model and the corresponding convergence time, the conflict relationship between the MP, the MP that has entered the control area and the free HDV is judged, the conflict digraph is obtained, and then the conflict-free passage sequence is calculated. Taking this time as the terminal moment, the MP optimal control problem can be solved, and the optimal control velocity trajectory of CAV can be obtained. By continuously executing this speed trajectory, the optimal control of the MP can be achieved in the control area until the MP reaches the stop line at a steady speed. For the HDV, except for the scene constraints that cannot change lanes, the HDV only follows the vehicle according to the driver-following model. When the HDV can reach the stop line according to the planned number of generated tree layers, the corresponding lane signal light becomes green, and the HDV can pass through the

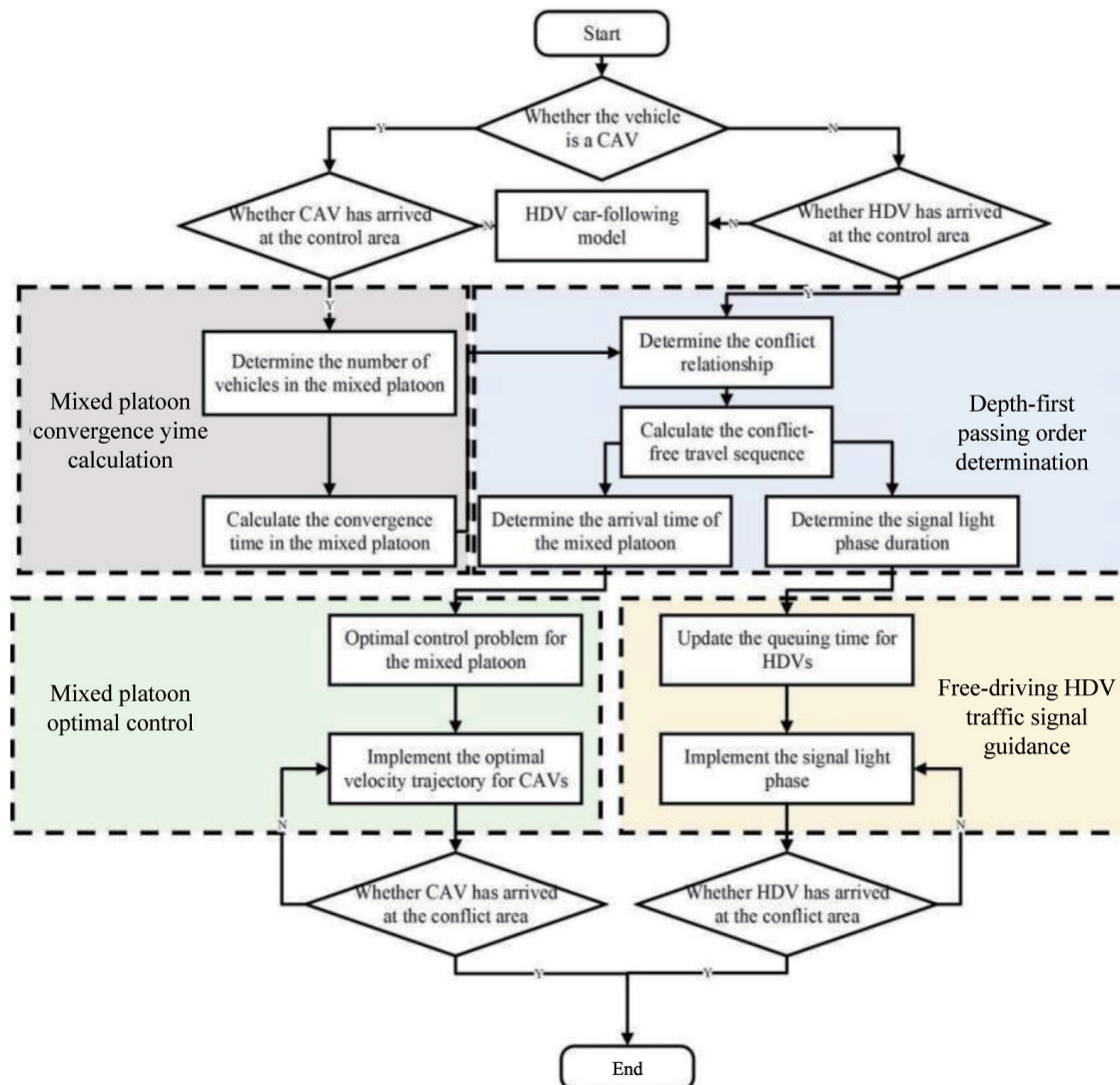


Fig. 10 Traffic light and CAV cooperation in mixed traffic intersection.

intersection without stopping. When the HDV reaches the stop line earlier than the planned time, the signal light is used to make the HDV stop and wait until the required time to pass.

4 Miniature experimental testbed

This study uses a miniature experimental testbed at Tsinghua University, measuring 9 m in length and 5 m in width, as shown in Fig. 11. The intersection includes features such as two-way two-lane roads, four-lane roads, overpasses, parking lots, islands, parking barriers, traffic lights, streetlights, and warning signs. These interactive elements support serial cooperative control and meet the requirements for verifying a variety of intelligent traffic algorithms.

In addition, this study independently built miniature experimental vehicles, as shown in Fig. 12. The miniature test vehicle is 200 mm in length and 130 mm in width, with a wheelbase of 140 mm and a wheel diameter of 60 mm. In terms of sensing, the miniature vehicle is equipped with a 640×480 onboard camera with a sampling frequency of 30 frames per second (FPS). In terms of control, the upper computer uses the Raspberry Pi 4B single-chip microcomputer equipped with the

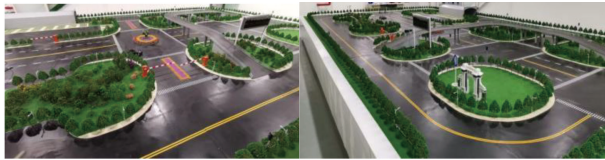


Fig. 11 Miniature experimental testbed platform.

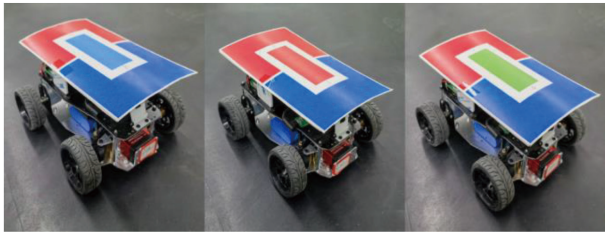


Fig. 12 Miniature experimental vehicles with different colored identification markers.

Ubuntu 18.04.4 long term support (LTS) system, and the main control chip of the lower computer uses the STM32F103RBT6 chip. The overall maximum longitudinal speed of the miniature vehicle is 1 m/s, the maximum steering angle is 40° , the highest control frequency is 20 Hz, and the longest running time is approximately 3.5 h, which fully meets the verification requirements of each scenario of the cooperation algorithm.

The main functions of the experimental platform are shown in Fig. 13. The traffic environment information, such as signal lights, streetlights, parking poles and traffic signs, is uploaded to the virtual data bus through serial ports. The number and speed of the miniature vehicle in the experiment can also be uploaded to the virtual data bus through Wi-Fi, but the position and orientation cannot be directly calculated. Therefore, in this study, several central color blocks of different colors were placed above the vehicle to identify different vehicle identification (ID) information. The blue and red parts were used to distinguish the front and the rear of the vehicle, and the line from red to blue indicates the vehicle's heading direction. An array of four cameras above the miniature testbed can be used to monitor the detection of color blocks and number information of vehicles driving on the miniature testbed. After subsequent image preprocessing, target detection, tracking, and matching, the complete speed and position information of the vehicle can be uploaded to the virtual data bus through user datagram protocol (UDP) communication. After the cloud computing platform obtains the vehicle information, it first performs preprocessing, such as filtering on the signal, executes multivehicle collaborative decision-making, optimizes traffic efficiency, and transmits control instructions back to the virtual data bus. It then sends them to the vehicle side and the testbed through UDP and serial port communications, forming a closed control loop between the vehicle side and the sandbox environment.

Although there are inherent physical scale differences between the miniature testbed and full-scale vehicles, the experimental design follows widely adopted similarity principles in traffic control and multivehicle coordination research to ensure the validity of the conclusions at the mechanism level. Specifically, the miniature platform applies a uniform scaling to key parameters such as vehicle geometry, traveling speed, acceleration limits, and

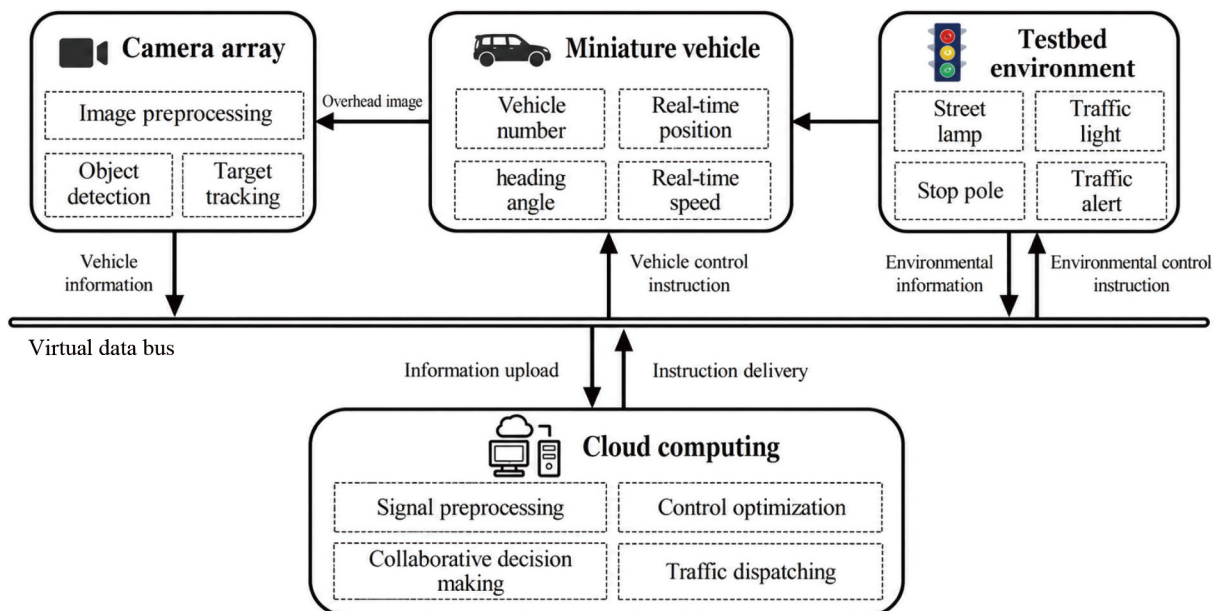


Fig. 13 Functional architecture of the miniaturized testbed.

safety headway, thereby preserving the time-space relationships of longitudinal vehicle dynamics, car-following behavior, and intersection traversal processes. Meanwhile, the signal timing logic, vehicle arrival sequences, conflict relationship identification, and MP cooperative control strategies used in the experiments are fully consistent with those in real intersection scenarios, ensuring that the problem formulation and decision-making logic remain invariant across scales. It should be emphasized that the primary objective of the experiments is to validate the effectiveness of the proposed multivehicle conflict decoupling modeling, passage sequence generation, and MP cooperative control framework rather than to achieve high-fidelity reproduction of single-vehicle dynamics or absolute energy consumption values. The proposed algorithms mainly rely on relative positions, temporal ordering, and conflict topology among vehicles, which exhibit strong scale invariance. Therefore, the miniature testbed is capable of capturing the essential characteristics of multivehicle interactions and cooperative decision-making in real-world environments.

5 Experimental results and analysis

5.1 Improved spanning tree and minimum clique covering algorithm verification

In this study, east-west two-way four-lane intersections and north-south two-way two-lane intersections were used as intersection scenes. In Fig. 14, six colors are used to mark the tracks of the six vehicles. The star markers on the tracks are the preset boundary of the control area. Since the east-west lane is farther from the stop line and the north-south lane is shorter, the preset boundary of the No. 1 vehicle and No. 3 vehicle are moved back a certain distance on the corresponding track, so that the distance between the No. 1 vehicle and No. 6 vehicle is the same from the stop line.

First, the optimization performance of the proposed iDFST and MCC algorithms is evaluated relative to the DFST algorithm and the recursive optimal control strategy (ROCS) (Yang et al., 2024), in a single-intersection traffic scenario. Starting from the same initial positions until all six vehicles had passed through the intersection, the vehicle speed trajectories are shown in Fig. 15. Unlike ROCS, which relies on sequential trajectory adjustments in dense traffic, the proposed MCC algorithm identifies the maximum concurrent passing sets via clique covering. This global structural optimization eliminates the need for repeated local recursive replanning, leading to the smoother velocity profiles and superior traffic uniformity observed in Fig. 15. Furthermore, it is observed from Fig. 15 that vehicles under the DFST algorithm exhibit a delayed startup response. The lack of a global temporal hierarchy in DFST conflict resolution forces followers to wait for preceding conflicts to be fully cleared before initiating acceleration,

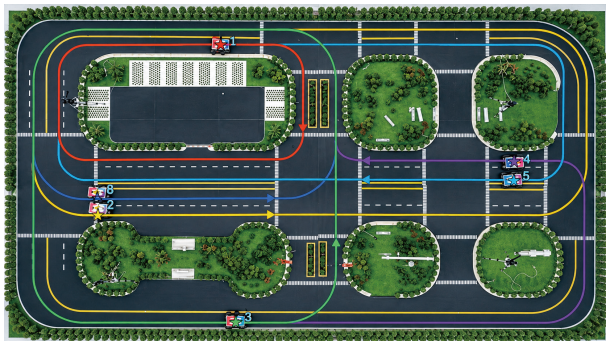


Fig. 14 Experimental intersection scenario.

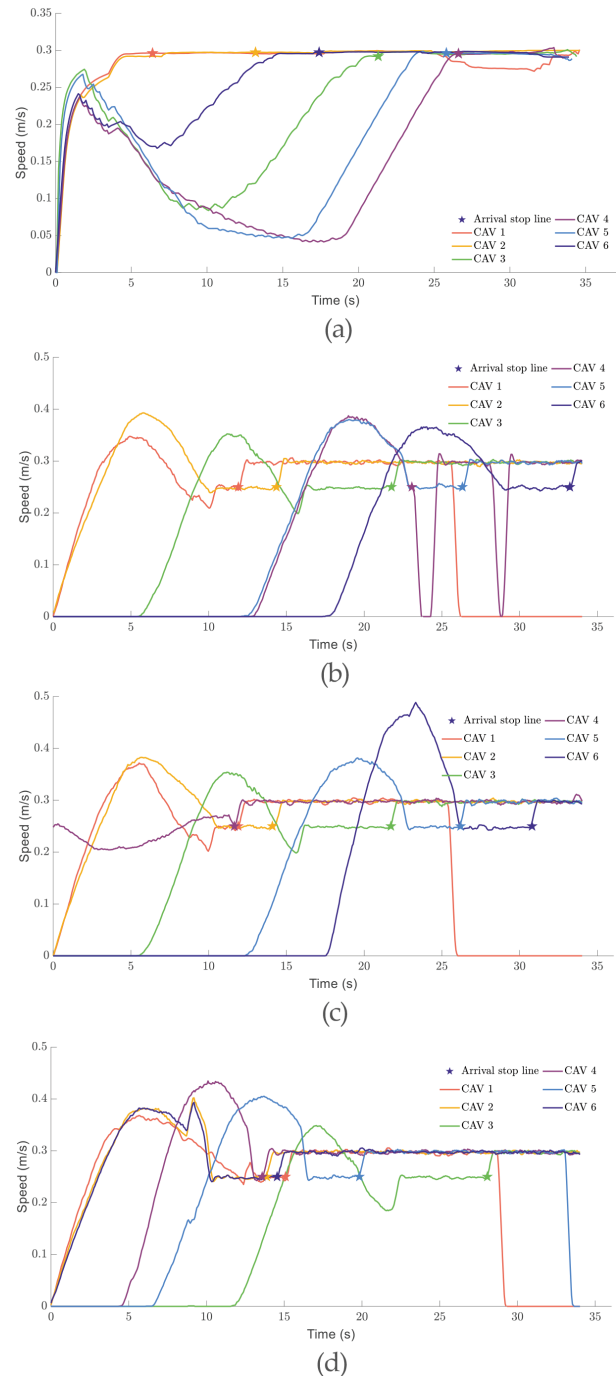


Fig. 15 Vehicle speed trajectory. (a) ROCS algorithm; (b) DFST algorithm; (c) iDFST algorithm; (d) MCC algorithm.

resembling a stop-and-go wave effect. In contrast, the proposed iDFST and MCC methods facilitate an earlier and more synchronized start-up by leveraging preoptimized passage sequences. This effectively minimizes start-up latencies and enhances the instantaneous evacuation efficiency at the intersection.

Statistical results of arrival time are shown in Table 2. iDFST has 10.97% average optimization and 7.31% maximum optimization for arrival time of each vehicle compared with DFST, while MCC has 19.7% average optimization and 15.56% maximum optimization for arrival time of each vehicle with the same starting point. Furthermore, compared with ROCS, the proposed method demonstrates clear advantages in evacuation

Table 2 Vehicle arrival time under different algorithms

Algorithm	No. 1 CAV	No. 2 CAV	No. 3 CAV	No. 4 CAV	No. 5 CAV	No. 6 CAV	Mean value	Maximum value
ROCS	6.40	13.20	21.30	26.60	25.80	17.40	18.45	26.60
DFST	11.91	14.36	21.76	23.07	26.32	33.23	21.78	33.23
iDFST	11.90	14.10	21.72	11.65	26.20	30.80	19.39	30.80
MCC	15.08	13.88	28.06	13.58	19.83	14.54	17.49	28.06

efficiency. Although the ROCS reduces the mean arrival time to 18.45 s, which is shorter than the 21.78 s achieved by the traditional DFST, it remains 5.19 percent slower than the MCC algorithm. In addition, the ROCS achieves a lower maximum arrival time of 26.60 s compared with the 33.23 s of DFST, but it still fails to provide the same level of temporal compactness as the MCC algorithm. In particular, for CAV 6, the MCC algorithm further shortens the arrival time to 14.54 s, which is a significant improvement over the 17.40 s obtained by the ROCS. These results highlight the ability of the MCC algorithm to maximize the parallel utilization of spatiotemporal resources at intersections through the clique-covering mechanism. Maximum optimization is positively correlated with total evacuation time optimization, while average arrival time optimization is positively correlated with average travel time delay optimization. Since the average travel time delay is an average statistical value, to display the real-time traffic efficiency, the total travel delay $\text{Delay}_{\text{total}}$ is taken as the overall traffic efficiency indicator below, as shown in Eq. (16):

$$\text{Delay}_{\text{total}} = \sum_{t=1}^T \sum_{i=1}^N \frac{(v_{\max} - v_i') \cdot T_{\text{step}}}{v_{\max}} \quad (16)$$

where $v_{\max}$ denotes the maximum speed; T_{step} is the sampling time; v_i' is the speed of vehicle i at time t ; T is the total traveling time in the control area; and N is the number of vehicles.

Because the miniaturized vehicle is driven by a motor and the change in the particle size of the battery state of charge (SOC) is large, it is difficult to reflect the real-time energy consumption of the vehicle. Therefore, the cumulative speed standard deviation is introduced to evaluate the traffic homogeneity of vehicles passing through the intersection; that is, the standard deviation of the running speed of all vehicles at every moment is calculated, and its cumulative value is calculated. The curve of the mean travel time delay and cumulative speed standard deviation is shown in Fig. 16. In terms of the average travel time delay, the iDFST, ROCS, and MCC algorithms all exhibit varying degrees of performance improvement across the entire experimental range. After all vehicles have passed through the intersection, the total travel time delays of the DFST, iDFST, ROCS, and MCC algorithms are 8.44, 6.46, 7.14, and 4.39 s, respectively. Compared with DFST, iDFST and MCC reduce the total travel delay by approximately 23.4% and 47.9%, respectively, both outperforming ROCS, which achieves a reduction of approximately 15.4%. These results indicate that iDFST already surpasses the recursive-control-based ROCS in delay mitigation, while MCC further achieves the most significant performance improvement. Further analysis shows that the MCC algorithm optimizes the vehicle sequencing strategy, enabling more vehicles to achieve conflict decoupling at intersections in a more compact manner without stopping, thereby substantially improving the overall traffic efficiency. In terms of the cumulative speed standard deviation, the differences in traffic homogeneity among the algorithms are even more pronounced. Because MCC enables as many vehicles as possible to rapidly reach the desired steady speed and pass through the intersection earlier, its cumulative speed standard deviation is the first to stop increasing. After vehicles pass through the intersection under steady-state conditions, the cumulative speed standard

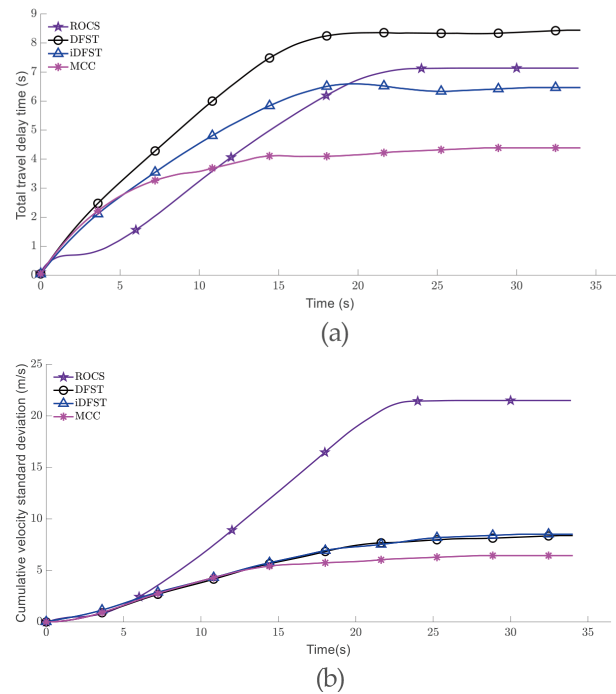


Fig. 16 Comparison of the traffic efficiency optimization effect of different algorithms: (a) total travel delay; (b) cumulative velocity standard deviation.

deviations of the DFST, iDFST, ROCS, and MCC algorithms are 8.39, 8.52, 21.49, and 6.44 m/s, respectively. The results show that iDFST maintains a level of traffic homogeneity comparable to DFST while significantly reducing travel delay, whereas MCC further reduces the cumulative speed standard deviation by approximately 24.4%, demonstrating a clear advantage in speed coordination and traffic homogeneity. In contrast, the markedly larger cumulative speed standard deviation of ROCS indicates that its recursive control strategy tends to induce accumulated speed fluctuations in intersection scenarios. Overall, the MCC algorithm not only achieves the lowest travel delay but also exhibits superior comprehensive performance in improving the homogeneity of vehicle operations at intersections.

5.2 MP modeling and optimal control algorithm verification

To illustrate the optimal control method for the MP under the mixed traffic scenario, the purple trajectories for vehicles No. 3 and No. 4 in Fig. 14 are removed, while an additional vehicle is added to the yellow trajectory of vehicle No. 2 and the dark blue trajectory of vehicle No. 6. In Fig. 14, four vehicle tracks are marked with four colors. To reflect the mixed optimal control, there are two vehicles on two tracks to form mixed traffic, and the boundary of the preset control area is marked at the star of the track. To reflect the optimal control method, one vehicle is added to the yellow track corresponding to No. 2 vehicle and one to the dark blue track corresponding to No. 6 vehicle.

To study the performance of the three algorithms, the first algorithm is a fixed-time traffic signal control algorithm, which is

the all-HDV scenario, and the intersection is controlled by a fixed-time traffic signal control. The second algorithm is mixed traffic-vehicle cooperation, where four CAVs and two HDVs are distributed in four-lane roads, including two lanes. The third algorithm is all-connected-vehicle cooperation, and mixed traffic is equivalent to the iDSFT algorithm, so this algorithm is used to perform intersection conflict decoupling. The experimental results are shown in Fig. 17. The analysis shows that in terms of traffic efficiency, mixed traffic-vehicle cooperation and all connected vehicle cooperation under mixed traffic significantly improved the traffic efficiency within the full control time, and the total travel delay gradually increased with the accumulation of time. At 510 s, the total travel delays of the fixed timing traffic light, mixed traffic vehicle cooperation and all connected vehicle cooperation are 61.8, 31.9, and 13.4 s, respectively. Compared with fixed-time traffic signal control, mixed total traffic travel time delay time can be optimized by 42.8%, and all connected vehicle cooperation can be optimized by 78.6%. For these reasons, the mixed traffic-vehicle cooperation algorithm can make the vehicle pass through the intersection as quickly as possible and improve the traffic efficiency of the intersection. Due to the small number of real vehicles in the experiment, there will be no parking in the environment of all connected vehicle cooperation, so the optimization range is more significant. In the case of more vehicles and larger traffic flow, after the virtual platoon in the control area is completely occupied by vehicles in different directions, the vehicles will wait to stop at the boundary of the control area, which weakens the optimization effect. In addition, in the mixed traffic scenario, in the traffic homogeneity index of traffic flow, due to the same starting point of each vehicle, the all connected vehicle cooperation algorithm enables each vehicle to pass through the intersection as soon as possible, so the standard deviation of cumulative speed rises rapidly. As the fixed-time traffic signal control stops and waits at the intersection in some

directions, the cumulative speed standard deviation increases stepwise. After each vehicle reaches a steady state, the cumulative speed standard deviation of the fixed-time traffic signal control, mixed traffic-vehicle cooperation and all connected vehicle cooperation algorithms is 30.6, 21.6, and 24.1 m/s, respectively, at 510 s. Therefore, compared with fixed-time traffic signal control, mixed traffic-vehicle cooperation and all connected vehicle cooperation can effectively improve the quality of traffic flow homogeneity. Under the coordination of mixed traffic, CAVs actively guide HDVs to pass at the optimal speed, so the homogenization of traffic flow under mixed traffic-vehicle cooperation is better than that under all connected vehicle cooperation.

The corresponding statistical results are summarized in Table 3. According to the statistical results, because the virtual platoon reduces the vehicle parking idle waiting point time, mixed traffic-vehicle cooperation and all connected vehicle cooperation in the mean number of laps and average speed are significantly better than fixed-time traffic signal control, because in simulation the same operating time, the mean number of laps increases by 1.6–1.8 laps, the average speed increases by 0.4–0.6 m/s. Therefore, the two cooperation algorithms effectively improve the traffic efficiency, while the mixed traffic-vehicle cooperation algorithm effectively connects the transition from the fixed-time traffic signal control to the all connected vehicle cooperation, providing theoretical and algorithm support for the application and development of the algorithm under mixed traffic.

6 Conclusions

The experimental results of the multivehicle conflict decoupling modeling and traffic optimization decision-making method are presented. The algorithm is deployed on the miniature testbed of the Tsinghua Intelligent Connected Vehicle Laboratory to validate its effectiveness under real-world traffic flow conditions, and the implementation details are thoroughly described. The experimental results show that the average travel time, total travel delay and traffic uniformity of the proposed iDFST algorithm and MCC algorithm outperform the benchmark algorithm in average travel time, total travel delay, and traffic uniformity in all connected vehicle cooperation. In the mixed traffic environment, the average speed and its standard deviation are better than those under the fixed-time traffic signal control, which provides a theoretical basis for the cooperative decision-making and control method in mixed traffic. The traffic optimization approach is applicable to intersections with varying penetration rates of CAVs, ensuring safety while enhancing traffic efficiency.

Author contributions

Chaoyi Chen: Conceptualization, Methodology, Software, Validation, Writing – original draft. **Liang Chen:** Methodology, Validation, Writing – review & editing, Supervision. **Yuxin Ma and Yuxuan Si:** Validation, Data curation. **Mengchi Cai:** Methodology, Writing – review & editing. **Qing Xu:** Supervision, Project administration, Writing – review & editing. **Keqiang Li:** Supervision.

Replication and data sharing

The source data for this study are available from the corresponding author upon reasonable request.

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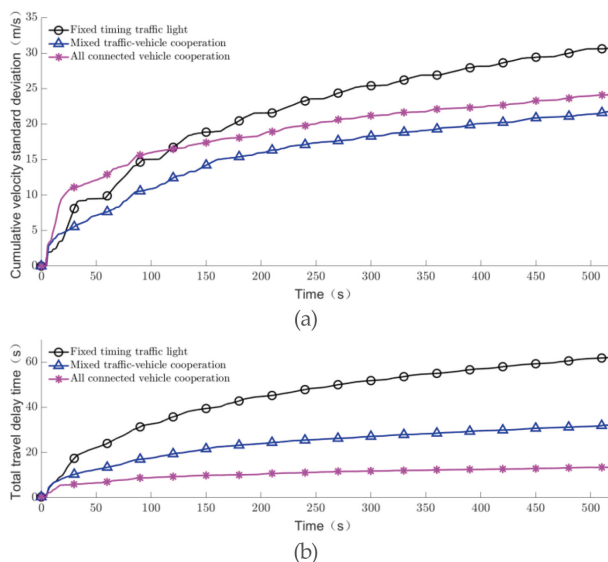


Fig. 17 Comparison of the traffic efficiency optimization effect of different algorithms: (a) total travel delay; (b) cumulative velocity standard deviation.

Table 3 Operation indicators of each vehicle

Algorithm	Mean number of lap	Average velocity (m/s)
Fixed-time traffic signal control	9.50	0.21
Mixed traffic cooperation	11.16	0.25
All connected vehicle cooperation	11.33	0.28

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Declaration of competing interest

The authors have no competing interests to declare that are relevant to the content of this article. The author Keqiang Li is the Editor-in-Chief of this journal.

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