Traffic & Transportation

Cooperative Lane-Changing Optimisation of Connected and Autonomous Vehicles in Freeway Merging Area

Xuling LIU[1], Xiaoning ZHANG[2]

Original Scientific Paper
Submitted: 26 Aug 2024
Accepted: 21 Mar 2025

[1] 2230413@tongji.edu.cn, School of Economics and Management, Tongji University, Shanghai, China
[2] Corresponding author, cexzhang@tongji.edu.cn, School of Economics and Management, Tongji University, Shanghai, China

Publisher:
Faculty of Transport and Traffic Sciences, University of Zagreb

ABSTRACT

In freeway merging areas, vehicles exhibit flexibility in lane-changing manoeuvres to facilitate merging. However, the lack of effective communication among vehicles leads to inadequate coordination between mainline and ramp vehicles at the merge point, increasing the likelihood of traffic congestion. The technology of connected and autonomous vehicles allows information interaction and cooperation between vehicles, which can effectively solve this problem and improve the efficiency of vehicle merging. This study proposes a merging optimisation framework for connected and autonomous vehicles, dividing the merging area into cooperative lane-change and trajectory optimisation areas. To simulate and manage connected and autonomous vehicles' behaviour, the research employs VISSIM for scenario creation and leverages both VISSIM COM and Python for control purposes. In the cooperative lane-changing area, the optimal number of lane-changing vehicles is determined by considering traffic distribution in the inner and outer lanes downstream of the confluence area. Subsequently, the sequence and combination of these vehicles are established based on connected and autonomous vehicles' cooperative lane-changing mode analysis. Within the trajectory optimisation area, the model refines each vehicle's speed and acceleration, guiding connected and autonomous vehicles to merge smoothly and safely at the confluence point. The simulation results show that the optimisation framework for the freeway merging area proposed in this study performs well. As the level of demand increases, the scenario with control demonstrates superior performance in terms of enhanced trip efficiency, diminished total delay time and a reduction in the number of stops.

KEYWORDS

freeway merging area; connected and autonomous vehicles; cooperative lane-changing; trajectory optimisation; simulation.

1. INTRODUCTION

In freeway merge zones, vehicles enjoy flexibility in lane changes to merge, but this can lead to congestion with high traffic volumes. The lack of congestion information and lane change coordination exacerbates the problem. Connected and autonomous vehicles (CAV) technology offers a solution through enhanced information exchange and collaboration. Optimising cooperative lane changes in CAV environments is complex, but integrating advanced communication and precise motion control is anticipated to significantly enhance traffic flow efficiency and safety in merge zones.

Connected and autonomous vehicles offer the possibility of enhanced coordinated strategies for freeway merging zones through real-time communication and precise motion control. Research on the control of CAVs has been widespread, and many cooperative driving strategies have been proposed [1]. Studies related to cooperative driving strategies mainly focus on vehicle control and optimisation in merging zones, such as constructing a trajectory optimisation model based on longitudinal vehicle dynamics and using PMP algorithms to determine the optimal control inputs for smooth merging [2], and optimising the time window for merging vehicles through a linear programming collaborative decision model [3]. The aim of these studies is mainly to improve the traffic efficiency and safety in the merging area and to ensure that vehicles can enter the main freeway smoothly and safely.

Collaborative lane changing of CAVs is a complex but crucial task that involves interactions between vehicles, information exchange and decision-making processes. CAVs can effectively enable collaborative lane changing between self-driving cars by utilising advanced communication technologies (e.g. 5G NR-V2X) [4], inter-vehicle communication (V2V and V2I) [5, 6] and model predictive control (MPC) [7]. It has been shown that by employing collaborative driving strategies and vehicle lane-changing models, the total delay and the number of stops can be effectively reduced while increasing the outflow rate of downstream merging bottlenecks under different traffic demand conditions [8].

The main research object of this paper is a multi-lane freeway merging area. For the multi-lane mainline merging zone, there are several problems at present. First, the unbalanced distribution of traffic in the outer lanes can cause merging efficiency problems, which can be mitigated by upstream active lane change control. Second, the upstream lane change control requires the cooperative operation of multiple vehicles, otherwise, it can cause severe traffic congestion at the merging point as well as downstream. Meanwhile, the congestion buildup downstream in turn causes more serious impacts upstream. Furthermore, the control of active lane changing should dynamically adjust the number of lane changing vehicles according to the real-time traffic flow to meet different traffic demand situations. Finally, in order to make the on-ramp vehicles merge into the outer lane traffic at a better point in time and space, the study also needs to optimise the trajectory data of the traffic flow, so that the whole strategy can be connected and cooperate, and then improve the operational efficiency of the whole traffic.

This study addresses the existing challenges in multi-lane freeway merging areas and the limited research combining vehicle-specific collaboration methods and lane-changing optimisation strategies. This study proposes a merging optimisation framework and lane-changing control strategy based on a CAV environment, effectively addressing difficulties in vehicle cooperation and untimely lane-changing control. The framework dynamically adjusts the lane-changing behaviours of vehicles in real-time and optimises trajectories, significantly enhancing operational efficiency and safety in intelligent traffic management. The proposed framework significantly enhances the operational efficiency and safety of the merging area, while also offering innovative methods and technical support for intelligent traffic management.

The remainder of this paper is structured as follows. Section 2 briefly reviews the literature, and Section 3 details the proposed methodological framework. First, Section 3.1 introduces the cooperative lane-changing strategy, and Section 3.2 formulates the trajectory optimisation model. Section 4 examines a case study of a two-lane freeway merging area, and Section 5 presents the conclusions of this paper.

2. LITERATURE REVIEW

In freeway merging areas, maintaining smooth and safe traffic is crucial, and optimisation strategies for cooperative vehicle lane changing play a key role. These strategies can be rule-based, such as the “first in, first out” (FIFO) principle for merging order [9], or algorithm-based, using optimisation algorithms to determine merging sequences and reduce waiting times, thereby improving traffic flow efficiency [10]. There is also the coalitional game-based approach for collaborative decision-making in multi-lane merges, which, despite being effective, can be overly conservative [11]. To address this, researchers are exploring optimisation algorithms like AI and deep reinforcement learning to handle complex traffic dynamics, enhance decision-making and increase traffic efficiency and safety [12].

In recent years, CAV technologies have opened up new opportunities for cooperative lane changing in freeway merging areas, enhancing traffic efficiency and safety through real-time communication and motion control [1]. Studies like Ding et al. have successfully reduced delays and stops in merging areas using linear programming for cooperative decisions [3]. Zhu et al. improved efficiency by creating merge gaps for convoy formation [13]. Advances such as multi-agent reinforcement learning have further optimised traffic flow performance. Xie et al. introduced a nonlinear optimisation solution for step-by-step vehicle control in merging areas, boosting both safety and mobility [14]. Wu et al. applied deep neuroevolutionary models and graph convolutional networks for more effective intelligent traffic control [15].

Research indicates that self-driving vehicles enhance traffic flow by following more closely and reducing congestion [8, 16, 17]. Infrastructure support, facilitated by vehicle-to-everything (V2X) communication technology, is vital for cooperative driving behaviours, enabling both vehicle-to-vehicle and vehicle-to-infrastructure interactions [18, 19]. Cooperative autonomous driving has proven beneficial across various transportation scenarios [20]. Jing demonstrated further improvements in merging zone efficiency and safety through hierarchical control and cooperative strategies [21]. Therefore, this study aims to deal with the multi-lane merging situation of self-driving vehicles in a vehicular network environment.

In summary, prior research has shown that many algorithms and strategies can improve the efficiency of the freeway merging process. However, relatively few studies have investigated the interaction of collaborative lane changing and combined it with lane changing optimisation strategies in CAV environments. In this study, we optimise the vehicle lane-changing behaviours and travel trajectories in multi-lane freeway merging areas by proposing a collaborative lane-changing strategy and a trajectory optimisation model in the CAV environment, to improve the efficiency of vehicle merging in the merging area.

3. FREEWAY MERGING FRAMEWORK

Lane changing in a CAV leverages real-time data exchange, such as position and speed, between vehicles and infrastructure via wireless communication. This study examines a two-lane freeway with an entrance ramp, featuring mainline and merge ramp traffic. The model assumes centralised control of CAVs, instantaneous lane changes without lateral control considerations, and disregards communication delays and packet loss for simplification and optimisation purposes.

Figure 1 depicts a schematic of a two-lane freeway merging area, including an inner lane, an outer lane and a ramp. A roadside communications and computing centre (RCCC) is established to receive information from CAVs regarding their vehicle ID, lane ID, position, speed and acceleration. This information is utilised by the RCCC to regulate the speeds and control the acceleration and lane-changing behaviour of all vehicles in the merging area. The collaborative lane changing zone and trajectory optimisation zone are located at [500, 750) and [250, 500) upstream of the merge zone, respectively.

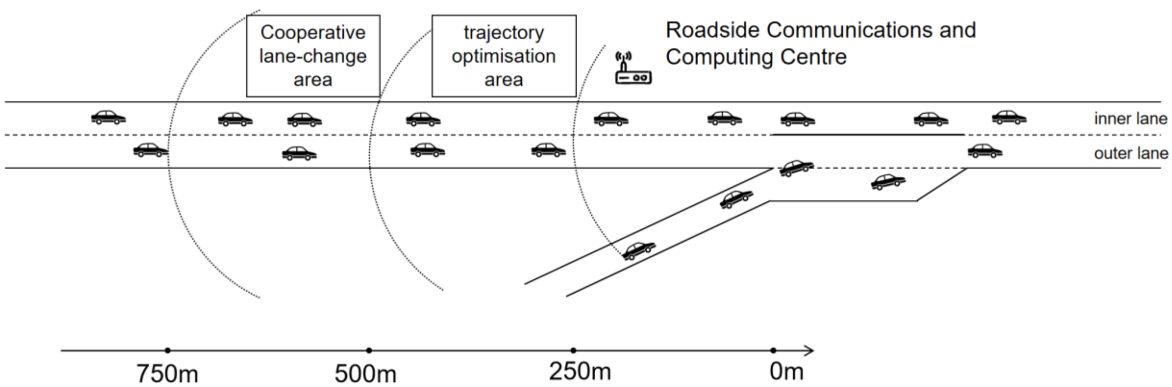

Figure 1 – Optimisation framework

In this optimisation framework, the merging area is divided into two areas: the cooperative lane-change area and the trajectory optimisation area. In the cooperative lane-change area, only the RCCC ordering vehicles to pass can perform lane-change operations in the lane-change area, and other areas do not allow arbitrary lane changes. In the trajectory optimisation area, mainline traffic vehicles and ramp vehicles adjust their trajectories according to the corresponding optimal control model. After passing through the trajectory optimisation area, the vehicle travels at the optimised speed and acceleration in the trajectory optimisation area, and finally passes through the merging area smoothly at a uniform speed.

3.1 Cooperative lane changing

In the cooperative lane-change area, it is necessary to accomplish: (1) determining the number of vehicles that need to change lanes in the outer lanes; (2) calculating the optimal lane-changing order and lane-changing combinations; and (3) the RCCC issuing lane-changing commands to direct the vehicles to collaborate in changing lanes. After determining the number of lane changes in the outer lane, the delay time resulting from CAV collaboration can be calculated according to different collaboration methods. Based on the ordering of delay times, the sequence and combination of lane changes for vehicles in the outer lane can then be determined.

Finally, the RCCC gives the lane change command according to the lane change program and guides the vehicles to change lanes collaboratively.

Cooperative lane changing

In order to determine the number of CAVs that need to change lanes, this study introduces a formula for calculating the number of lane changes between the outer and inner lanes to balance the traffic flow of the two lanes downstream of the merging point. The traffic flow of the outer lane is denoted as q_{out}, the traffic flow of the inner lane is denoted as q_{in} and the ramp traffic flow is denoted as q_{ramp}. Assuming that the downstream flows of the two lanes of the mainline are set equal, the number of lane changes λ is:

$$\lambda = \frac{q_{out} + q_{ramp} - q_{in}}{2} \tag{1}$$

Equation 1 can determine the number of vehicles changing lanes in the outer lane, but the result of the calculation may be less than 0 and non-integer, which is chosen to be rounded upwards in this study. The number of vehicles changing lanes at the same time cannot be larger than the number of vehicles in the outer lanes or the number of vehicles that can be accommodated in the inner lanes, so the minimum value can be taken, as in *Equation 2*; where Q is the maximum number of vehicles that can be accommodated in the inner lane cooperative lane-change area.

$$\lambda = min\left\{\frac{q_{out} + q_{ramp} - q_{in}}{2},\ min\{q_{out},\ Q - q_{in}\}\right\} \tag{2}$$

Cooperation lane-changing approaches

The collaborative lane change optimisation model allows for strategic lane adjustments by CAVs upstream on the mainline, creating space for ramp vehicles to merge efficiently. Lane changing, a critical manoeuvre for vehicles to optimise travel paths or times, involves finding and safely entering a gap in the target lane, with the vehicle adjusting its speed to maintain a safe distance from others.

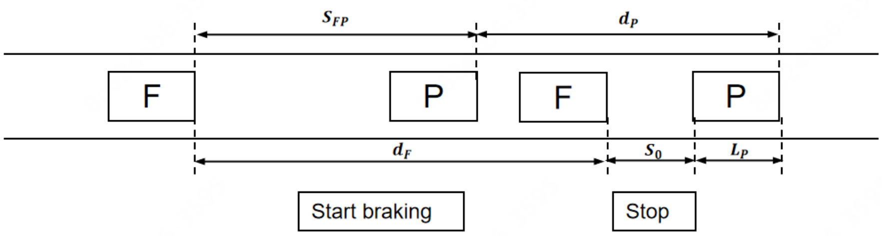

Figure 2 – Adjacent vehicle following safety spacing model

The safety spacing of vehicles in this study adopts the absolute safety distance model [22], as shown in *Figure 2*. *P* is the preceding vehicle and *F* is the following vehicle. When the preceding vehicle *P* starts braking, and after a period of time, both *P* and *F* are in the parking state, the spacing needs to be always greater than or equal to the minimum safe distance. Therefore, the mathematical expression of the safety condition using the absolute safety distance model is:

$$\begin{aligned} S_{FP} &= d_F + S_0 + L_P - d_P \\ &= v_F t_r + \frac{v_F^2}{2a_F} + S_0 + L_P - \frac{v_P^2}{2a_P} \\ &= S_0 + L_P + v_F t_r + \frac{v_F^2}{2a_F} - \frac{v_P^2}{2a_P} \end{aligned} \tag{3}$$

where S_{FP} is the initial spacing between the preceding and following vehicles, d_F is the sum of the reaction distance and braking distance of the following vehicle, d_P is the braking distance of the preceding vehicle, S_0 is the minimum stationary safety distance of the vehicle and L_P is the length of the preceding vehicle. t_r is the desired reaction time of the vehicle when braking, and v_F、a_F、v_P and a_P are the speed, braking deceleration of the following vehicle, speed, braking deceleration of the preceding vehicle, respectively.

According to whether there are front and rear vehicles in the target lane, whether the front and rear vehicles satisfy the critical safety distance, and whether the target vehicle and the front and rear vehicles in the target lane satisfy the minimum safety distance, the cooperative lane changing of vehicles upstream of the mainline can be categorised into the following scenarios:

Scenario 1: The front and rear vehicles in the target lane satisfy the critical safety distance. The target vehicle and the front and rear vehicles in the target lane satisfy the minimum safe distance.

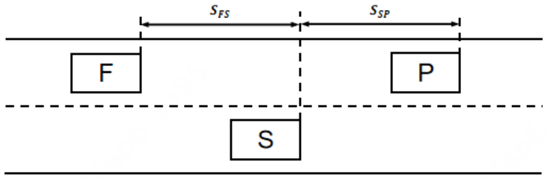

Figure 3 – Scenario 1

At this point, the target vehicle and the front and rear vehicles in the target lane should be satisfied:

$$S_{SP} \geq S_0 + L_P + v_S t_r + \frac{v_S^2}{2a_S} - \frac{v_P^2}{2a_P} \tag{4}$$

$$S_{FS} \geq S_0 + L_S + v_F t_r + \frac{v_F^2}{2a_F} - \frac{v_S^2}{2a_S} \tag{5}$$

Denote P as the initial spacing between the front and rear vehicles in the target lane, and P_{safe} as the critical safe spacing for lane changing in the target lane, when it satisfies:

$$P = S_{FS} + S_{SP} \geq P_{safe} = 2S_0 + L_S + L_P + (v_F + v_S)t_r + \frac{v_F^2}{2a_F} - \frac{v_P^2}{2a_P} \tag{6}$$

Thus, the target vehicle can directly change lanes without the collaboration of the front and rear vehicles in the target lane to change lanes.

Scenario 2: The front and rear vehicles in the target lane satisfy the critical safe distance. The target vehicle does not meet the minimum safe distance from the preceding vehicle in the target lane.

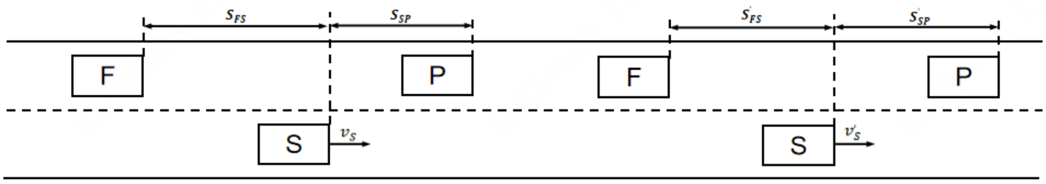

Figure 4 – Scenario 2

At this time, the initial spacing between the front and rear vehicles in the target lane satisfies the critical safety spacing, i.e. it satisfies *Equation 6*. However, the target vehicle does not satisfy the minimum safe distance with the preceding vehicle of the target lane, i.e. it does not satisfy *Equation 4*. At this time, the collaborative scheme is that the target vehicle decelerates forward until the minimum safe spacing with the front and rear vehicles in the target lane satisfies *Equations 4 and 5*.

Assuming that the acceleration of the target vehicle S after deceleration is at least not less than a_{min}, when it decelerates to satisfy the minimum safety distance S'_{SP} with the front and rear vehicles in the target lane, by the velocity formula $v_t = v_0 + at$, the deceleration phase takes time $t = \frac{v_t - v_0}{a}$. By collaborative lane changing, the sum of decelerated displacement $S_{S \to S'}$ of the target vehicle S and the safety distance S'_{SP} of the front vehicle after the collaborative lane change shall be equal to the uniform displacement of the front guide vehicle P in the target lane and the sum of the safety spacing S_{SP} of the preceding vehicle before the collaborative lane change. Similarly, with the target lane-following vehicle, the following conditions are similarly satisfied:

$$S_{S\to S'} = \frac{(v_S')^2 - (v_S)^2}{2a_{min}} \tag{7}$$

$$\frac{(v_S')^2 - (v_S)^2}{2a_{min}} + S_{SP}' = v_P \frac{v_S' - v_S}{a_{min}} + S_{SP} \tag{8}$$

$$\frac{(v_S')^2 - (v_S)^2}{2a_{min}} + S_{FS} = v_F \frac{v_S' - v_S}{a_{min}} + S_{FS}' \tag{9}$$

$$S_{SP}' \geq S_0 + L_P + v_S' t_r + \frac{(v_S')^2}{2a_{min}} - \frac{v_P^2}{2a_P} \tag{10}$$

$$S_{FS}' \geq S_0 + L_S + v_F t_r + \frac{v_F^2}{2a_F} - \frac{(v_S')^2}{2a_{min}} \tag{11}$$

Scenario 3: The front and rear vehicles in the target lane satisfy the critical safe distance. The target vehicle does not meet the minimum safe distance from the following vehicle in the target lane.

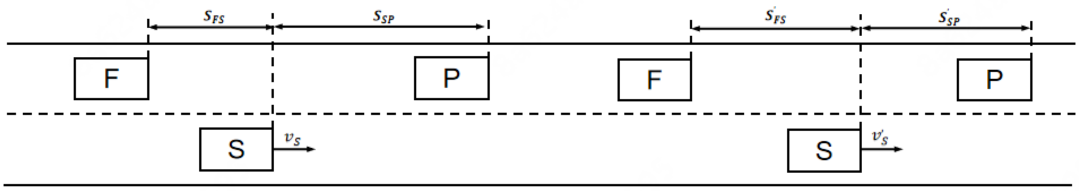

Figure 5 – Scenario 3

At this point, the collaborative scheme at this point is that the target vehicle accelerates forward until the minimum safe spacing between the front and rear vehicles in the lane with the target is satisfied in *Equations 4 and 5*. Assuming that the maximum acceleration of the target vehicle S does not exceed a_{max}, the following conditions should be satisfied after the collaborative lane change:

$$\frac{(v_S')^2 - (v_S)^2}{2a_{max}} + S_{SP}' = v_P \frac{v_S' - v_S}{a_{max}} + S_{SP} \tag{12}$$

$$\frac{(v_S')^2 - (v_S)^2}{2a_{max}} + S_{FS} = v_F \frac{v_S' - v_S}{a_{max}} + S_{FS}' \tag{13}$$

$$S_{SP}' \geq S_0 + L_P + v_S' t_r + \frac{(v_S')^2}{2a_{max}} - \frac{v_P^2}{2a_P} \tag{14}$$

$$S_{FS}' \geq S_0 + L_S + v_F t_r + \frac{v_F^2}{2a_F} - \frac{(v_S')^2}{2a_{max}} \tag{15}$$

Scenario 4: The spacing between the front and rear vehicles in the target lane does not satisfy the critical safety distance, and the target vehicle does not satisfy the minimum safety distance from the lead vehicle in the target lane, but satisfies the minimum safety distance from the following vehicle.

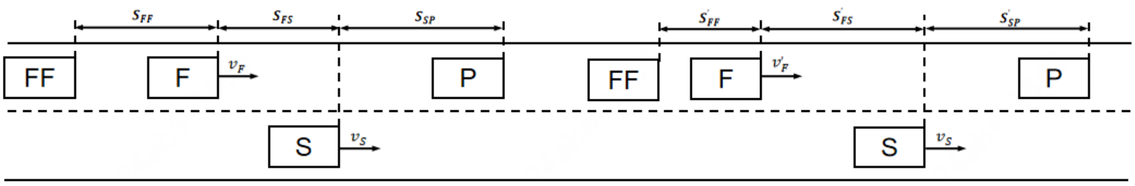

Figure 6 – Scenario 4

At this time, the initial spacing between the front and rear vehicles in the target lane does not satisfy the critical safety spacing, the target vehicle does not satisfy the minimum safety distance with the leading vehicle in the target lane, and it satisfies the minimum safety distance with the following vehicle. The collaborative switching-to scheme in this case is the acceleration of the leading vehicle in the target lane, while the safety spacing between the leading vehicle and its previous vehicle *PP* should be considered, so the following conditions and *Equation 6* should be satisfied after the collaborative switching:

$$\frac{(v_P')^2-(v_P)^2}{2a_{max}}+S_{PP}'=v_{PP}\frac{v_P'-v_P}{a_{max}}+S_{PP} \tag{16}$$

$$\frac{(v_P')^2-(v_P)^2}{2a_{max}}+S_{SP}=v_S\frac{v_P'-v_P}{a_{max}}+S_{SP}' \tag{17}$$

$$S_{PP}'\geq S_0+L_{PP}+v_P't_r+\frac{v_P^2}{2a_p}-\frac{v_{PP}^2}{2a_{PP}} \tag{18}$$

Scenario 5: The spacing between the front and rear vehicles in the target lane does not satisfy the critical safety distance, and the target vehicle satisfies the minimum safety distance with the preceding vehicle in the target lane and does not satisfy the minimum safety distance with the following vehicle.

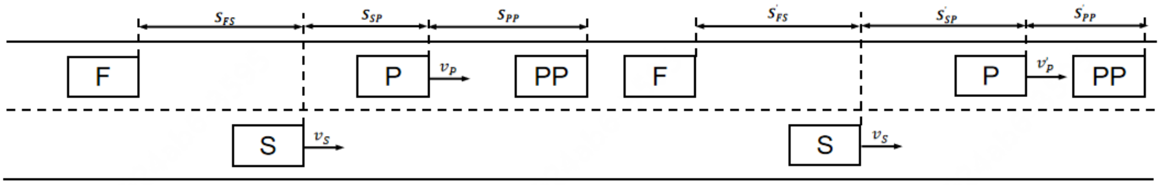

Figure 7 – Scenario 5

At this time, the collaborative change to program in this case is the target lane following car deceleration, while the safety distance between the leading car and its previous car *FF* should be considered, so the collaborative change of lanes should satisfy the following conditions and *Equation 6*:

$$\frac{(v_F')^2-(v_F)^2}{2a_{min}}+S_{FF}=v_{FF}\frac{v_F'-v_F}{a_{min}}+S_{FF}' \tag{19}$$

$$\frac{(v_F')^2-(v_F)^2}{2a_{min}}+S_{FS}'=v_S\frac{v_F'-v_F}{a_{min}}+S_{FS} \tag{20}$$

$$S_{FF}'\geq S_0+L_{FF}+v_F't_r+\frac{v_{FF}^2}{2a_F}-\frac{v_F^2}{2a_F} \tag{21}$$

Scenario 6: The spacing between front and rear vehicles in the target lane does not satisfy the critical safety distance, and the target vehicle does not satisfy the minimum safety distance from both front and rear vehicles in the target lane.

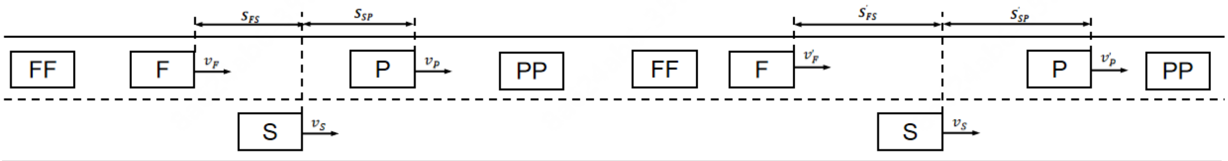

Figure 8 – Scenario 6

In this case, the collaborative lane change scheme is acceleration of the leading vehicle and deceleration of the following vehicle, taking into account both the front *PP* of the leading vehicle and the rear *FF* of the following vehicle. The lane change can be adjusted according to scenarios 4 and 5.

The above analysis can be expressed in *Figure 9* of the collaborative lane changing mode recognition process.

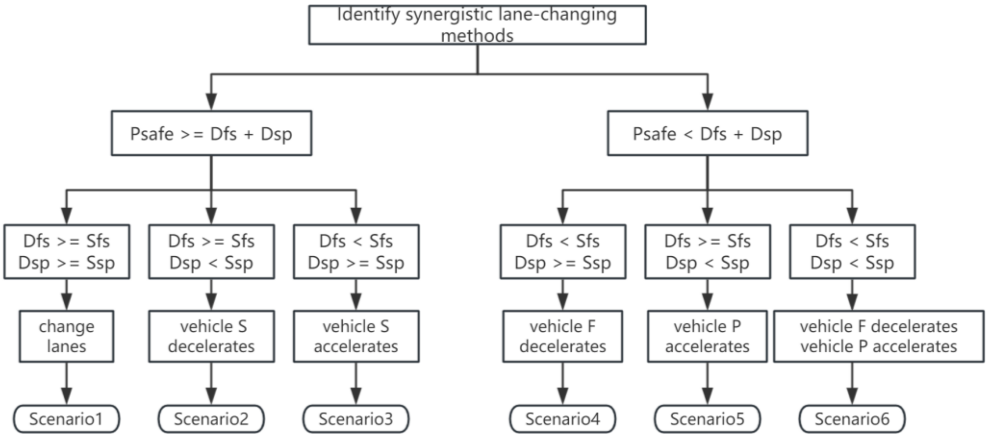

Figure 9 – Recognition flow of the collaborative lane changing method

Optimal lane-changing sequences and combinations

During collaborative lane changing, different collaborative operations result in different vehicle speed reductions or additional time to stop and wait. Therefore, this study selects the previous vehicle with the smallest delay for collaborative lane-changing by evaluating the delay time of the set of lane-change vehicles in the cooperative lane-change area. The delays generated by different scenarios are calculated below:

Scenario 1: The target vehicle changes lanes directly. Since this study assumes that the lane-changing behaviour is instantaneous, the target vehicle does not incur delay in this scenario.

Scenario 2: The target vehicle decelerates and then changes lanes. The target vehicle needs to change lanes by decelerating to a specified position, and this process takes time $\frac{v_S'-v_S}{a_{min}}$.

Scenario 3: The target vehicle accelerates and then changes lanes. The target vehicle needs to change lanes by accelerating to the specified position, this process takes time $\frac{v_S'-v_S}{a_{max}}$.

Scenario 4: After the preceding vehicle in the target lane decelerates, the target vehicle changes lanes. The acceleration of the preceding vehicle P may cause the preceding vehicle's front vehicle PP to be unable to maintain a safe distance from P, thus requiring acceleration. At this time, the preceding vehicle accelerating should transmit an acceleration command to the vehicle in front of it through the vehicle-to-vehicle network to make it accelerate cooperatively, so the time consumed for this process is considered to be approximated as $\frac{v_P'-v_P}{a_{max}}$.

Scenario 5: After the following vehicle in the target lane decelerates, the target vehicle changes lanes. The deceleration of the following vehicle F is likely to result in the following vehicle's rear vehicle FF being unable to maintain a safe distance from F and thus needing to decelerate. In the same case as scenario 5, the following vehicle in the target lane sends a deceleration command to its rear vehicle, and the set of rear vehicles decelerates after receiving the command while ensuring the minimum safety distance, so the time consumed for this process is considered to be approximated as $\frac{v_F'-v_F}{a_{min}}$.

Scenario 6: The target vehicle changes lanes after the preceding vehicle in the target lane accelerates and the following vehicle decelerates. The process is the same as in scenario 4 and scenario 5, and the delay is approximated as $max\left\{\frac{v_P'-v_P}{a_{max}}, \frac{v_F'-v_F}{a_{min}}\right\}$.

By enumerating and ranking the delay times of the CAVs in the lanes outside the cooperative lane-change area, the first vehicle with the smallest delay time is selected as the lane-change combination and the cooperative lane-change is carried out in the order of the delay times as the cooperative lane-change order. This process is coordinated by the roadside communication and computation centre to ensure smooth lane changing.

3.2 Trajectory optimisation

The CAV enters the trajectory optimisation area after completing the lane change operation, at this time, the vehicles in the lanes within the merging area are not allowed to change lanes to the outer lanes, so this study transforms the mainline and ramp merging problem into the mainline outer lane and ramp merging problem, as shown in *Figure 10* below.

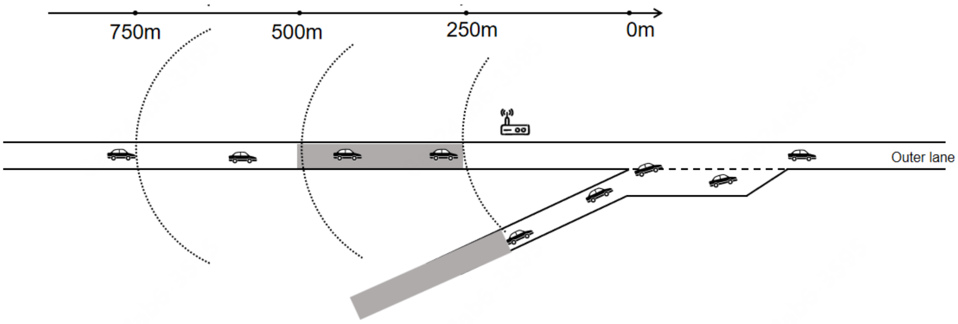

Figure 10 – Simplification of the trajectory optimisation area

In real scenarios, vehicles on freeways and ramps enter continuously and in real time. It is difficult to optimise the trajectories of all vehicles from a global perspective, so 10 seconds is considered the decision interval. At the beginning of each decision-making step, the RCCC first collects information about all vehicles in the trajectory optimisation area, including position, velocity and acceleration. This 10-second interval is further divided into ten 1-second decision steps.

In this study, the optimal control strategy of Xie [14] is improved, and the original optimisation model is changed to a linear time-discrete model, which can effectively improve the computational efficiency. The model maximises the total speed of all CAVs in the current lane-changing cycle by optimising the longitudinal travel speed of each vehicle, and can pass the merging point without collision along the optimised trajectory. The trajectory optimisation model and parameters are described below.

$$max\left(\sum_{i=1}^{2}\sum_{s=1}^{n_i}\sum_{t=1}^{m} v_{i,s,t}\right) \tag{22}$$

$$0 \le v_{i,s,t} \le v_{max}; \forall i,s,t \tag{23}$$

$$a_{min} \le a_{i,s,t} \le a_{max}; \forall i,s,t \tag{24}$$

$$\left|a_{i,s,t} - a_{i,s,t+1}\right| \le a_{max\_diff}\ ; \forall i,s;\ \ t = 1,\cdots,m-1 \tag{25}$$

$$\left|x_{i,s,t} - x_{i,s-1,t}\right| \ge g_{min} \cdot v_{i,s,t}; \forall i,t; s = 2,\cdots,n_i \tag{26}$$

$$\left|x_{1,j,m} - x_{2,p,m}\right| \ge g_{min} \cdot v_{1,j,m}; \forall j,p \tag{27}$$

$$x_{i,s,t} - x_{i,s,t-1} = v_{i,s,t-1} \cdot \Delta t\ ; \forall i,s,t = 2,\cdots,m \tag{28}$$

$$v_{i,s,t} - v_{i,s,t-1} = a_{i,s,t-1} \cdot \Delta t\ ; \forall i,s,t = 2,\cdots,m \tag{29}$$

where i is the lane label, 1 denotes the outer lane and 2 denotes the on-ramp. j denotes the CAV serial number of the off-freeway lane; p denotes the CAV serial number on the on-ramp; s denotes the vehicle serial number without distinguishing between the off-freeway lane and the on-ramp. t is the time-step; m denotes the total time-step, which is taken as the value of 10; and n_i denotes the total number of vehicles in the trajectory optimisation area of lane i. $a_{i,s,t}$ denotes the acceleration of vehicle s in lane i at time step t; $v_{i,s,t}$ denotes the velocity of vehicle s in lane i at time step t; $x_{i,s,t}$ denotes the distance between vehicle s in lane i and the merging point at time step t. v_{max} is the maximum velocity limitation; a_{min} and a_{max} are the maximum and minimum acceleration limitation; a_{max_diff} denotes the maximum change of acceleration in two consecutive time steps; and g_{min} denotes the minimum allowable headway time gap for lane change.

Equations 23 and 24 are the allowable limits for velocity and acceleration values, respectively. *Equation 25* limits the change in acceleration for each vehicle over two consecutive time steps to account for freeway travel safety. *Equation 26* requires that the distance between two consecutive vehicles in the same lane must be greater than the minimum safe distance limit, which is here defined in terms of the minimum permissible headway gap to allow for lane changing. *Equation 27* ensures that any pair of freeway and ramp vehicles can maintain a safe distance at the end of the decision interval (i.e. when t = 10). *Equations 28 and 29* are the system dynamics equations describing the relationship between velocity, acceleration and distance.

4. SIMULATION

4.1 Simulation platform and realisation

To evaluate the effectiveness of the proposed algorithm, this study uses VISSIM version 8.0 to construct the research scenario and perform simulation verification, utilising the platform of the VISSIM COM interface and Python to implement the control logic of CAV.

In this paper, a typical two-lane freeway and an on-ramp network are created as a research scenario in VISSIM. The cooperative lane-change area, trajectory optimisation area and uniform speed driving area all have a default length of 250 m, and the merging area has a length of 200 m. For the simulation of CAVs, a vehicle type has been created based on the VISSIM 100 vehicle to simulate a CAV [23]. These connected self-driving cars incorporate advanced features of autonomous driving technology. For example, their desired speed limit is set to 90 (km/h), while these vehicles are capable of more precise speed control and spacing between vehicles through the COM interface, as well as more efficient integration of traffic flows, thus demonstrating the benefits of self-driving cars in terms of safety and efficiency in a simulated environment. In order to validate the lane-changing optimisation logic in Chapter 3, three control scenarios, four demand levels and three demand assignments were considered in this study [23-25]. The total simulation time for each scenario is 1,500 seconds with a warm-up of 300 seconds. Based on the above demand levels and allocation ratios, the 12 types of traffic flows calculated are shown in *Table 1*.

Table 1 – Mainline and ramp traffic volumes for different demand levels and allocation methods

Demand level (veh/h/ln)	Total volume (veh/h/ln)	Proportion of demand split					
		80-20		65-35		50-50	
		mainline lanes	ramp lane	mainline lanes	ramp lane	mainline lanes	ramp lane
800	2400	1920	480	1560	840	1200	1200
1000	3000	2400	600	1950	1050	1500	1500
1200	3600	2880	720	2340	1260	1800	1800
1400	4200	3360	840	2730	1470	2100	2100

The quantitative parameters in the model are described in *Table 2*. The values of the following parameters were selected mainly with reference to Hu [23] and Ding [24].

Table 2 – Lane-changing optimisation model variables

Parameter	Unit	Value	Description
S_0	s	2.5	Minimum static safety distance of the vehicle
L_P	m	4.64	Vehicle length
t_r	s	0.1	Desired reaction time when braking the vehicle
a_{min}	m/s^2	-3	Minimum acceleration limit
a_{max}	m/s^2	3	Maximum acceleration limit
m	s	10	Total time step
v_{max}	m/s	25	Maximum speed limit
$a_{\max\_diff}$	m/s^2	2	Maximum change in acceleration in two consecutive time steps
g_{min}	s	1.2	Minimum allowable headway gap for lane change

The specific simulation flow is shown in *Figure 11*. Firstly, Python starts the simulation program by calling VISSIM COM, and after loading the VISSIM network file and layout file, the parameters such as the simulation step size, simulation period and random number seed are set. The simulation then warms up for 300 s and enters the evaluation phase, using vehicle driving data from 300 s to 1,500 s for simulation effect evaluation. After entering the single-step simulation phase with a simulation step length of 1 s, if it is scheme 1, no control is made, and the trajectories under all labels at the current moment are extracted directly at the end of each simulation step. If it is a CAV collaborative lane changing scheme and reaches the computation interval of 10 s, the dynamic traffic flow information, i.e. the relevant information of vehicles at the current moment (moment, path, road section, position, speed, etc.), is extracted for the subsequent trajectory data visualisation. In the case of the CAV collaborative lane changing and trajectory optimisation integration scheme, it first enters the next simulation step, and executes the collaborative lane changing model and trajectory optimisation model at the same time. At this time, according to the optimal lane-changing order and combination obtained by the collaborative lane-changing model, the desired lane colour of CAV is set through the COM interface; according to the solution result of the trajectory optimisation model, a 10 s single-step simulation is executed, and the desired speed and colour of CAV vehicles are set through the COM interface. All the traffic flow information is extracted, and coordinate conversion is carried out, to save the vehicle trajectories under the global coordinates. The simulation ends when it reaches 1,500 s, counts each evaluation index of the current scene, and performs data processing and visualisation analysis.

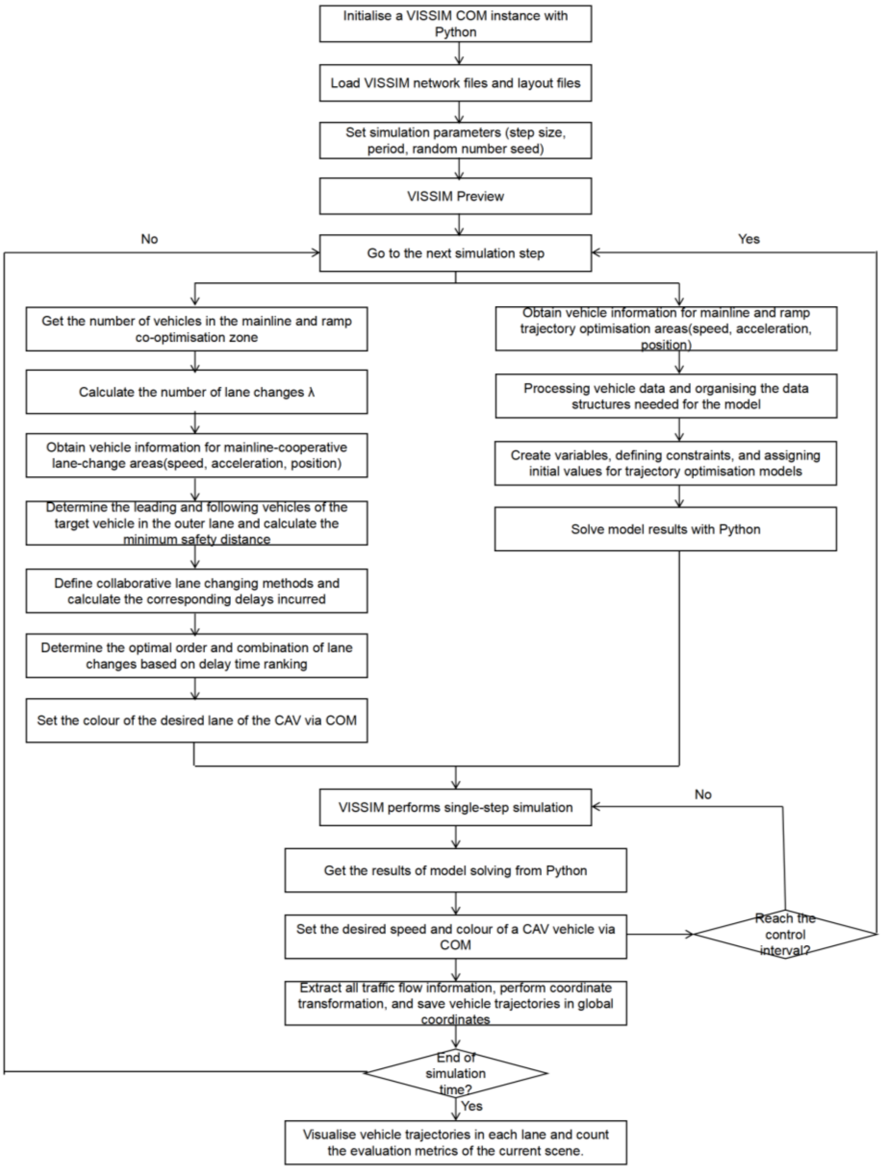

Figure 11 – Simulation flow chart

4.2 Simulation results

In this study, average travel speed, total delay time and number of stops are selected as performance indicators. By setting travel time detection points 50 metres before the cooperative lane-change area and 50 metres after the merging area, this paper counts the average travel time of all vehicles passing through the travel time detection section after the simulation warm-up of 300 s, to calculate the average travel speed of all vehicles. The simulation results of different simulation evaluation scenarios are shown in *Table 3*.

Table 3 – Simulation results

Demand split	Case	Average travel speed				Total delay time				Number of vehicle stops			
		800	1000	1200	1400	800	1000	1200	1400	800	1000	1200	1400
80-20	0	83.79	71.4	67.25	19.04	0.28	2.53	11.42	152.19	0	0	0.61	11
	1	84.13	83.85	72.15	28.93	0.46	0.6	7.62	85.35	0	0	0.38	6.26
	2	84.62	84.15	79.22	43.92	0.22	0.42	8.25	45.01	0	0	0.41	3.98
	1Effect	0.41	17.44	7.29	51.94	64.29	-76.28	-33.27	-43.92	0	0	-37.7	-43.09
	2Effect	0.99	17.86	17.8	130.67	-21.43	-83.4	-27.76	-70.43	0	0	-32.79	-63.82
65-35	0	83.86	83.73	38.58	18.03	0.23	0.31	52.66	163.15	0	0	3.93	13.39
	1	84.15	83.88	39.13	20.99	0.42	0.57	51.08	134.3	0	0	3.49	10.14
	2	83.88	83.77	51.45	42.82	0.3	0.44	28.64	43.5	0	0	2.2	3.38
	1Effect	0.35	0.18	1.43	16.42	82.61	83.87	-3	-17.68	0	0	-11.2	-24.27
	2Effect	0.02	0.05	33.36	137.49	30.43	41.94	-45.61	-73.34	0	0	-44.02	-74.76
50-50	0	84.15	83.79	46.21	23.84	0.17	0.31	36.62	112.54	0	0	2.48	9.16
	1	84.7	83.85	48.99	28.86	0.25	0.61	31.96	85.02	0	0	2.17	6.42
	2	84.41	83.1	68.81	35.68	0.23	0.63	10.03	60.22	0	0	0.66	4.37
	1Effect	0.65	0.07	6.02	21.06	47.06	96.77	-12.73	-24.45	0	0	-12.5	-29.91
	2Effect	0.31	-0.82	48.91	49.66	35.29	103.2	-72.61	-46.49	0	0	-73.39	-52.29

In terms of overall effect, both case 2 and case 1 have some optimisation effect on improving trip efficiency. The gain effects of average travel speed, total delay time and number of stops are positive, negative and negative, respectively.

From the demand level perspective, the increase in the number of vehicles increases the probability of congestion on the freeway as the level of demand within the roadway increases. At 800 and 1,000 demand, the number of stops at both levels of demand is zero because congestion rarely exists on the freeway, and both controls produce gain effects to a lesser extent, and as the level of demand increases, the gain effect becomes more pronounced. However, at the 1,200 and 1,400 demand levels, the higher vehicle inputs caused the frequency of congestion to increase on the freeway, and both controls produced a more significant gain effect.

From the analysis of the two control cases, the overall effect of case 2 is better than case 1 for different demand splits and demand levels. At low levels of demand, both cases show insignificant optimisation effects, and as the level of vehicle demand increases, the gain of case 2 over case 1 is significantly higher.

From the analysis of the demand split of vehicles, the road access pressure at the 1,400 demand level is the largest. At this time, it can be seen that the road access efficiency of case 1 and case 2 has the most significant gain effect. From 80-20 to 50-50 demand split scenarios, it can be found that the number of vehicles on the ramp rises gradually, at which point both scenarios have more significant gain effects as the demand level increases; and the larger the demand level, the more efficiency gains are seen in case 2 than case 1.

In addition, vehicle trajectories on all lanes are extracted and visualised. In this study, the positions of vehicles in all lanes are transformed into global coordinates, which allows us to obtain the global positions of all vehicles in that scenario for each simulation second of the vehicle. *Figure 12* shows the vehicle trajectories for a simulation time of 300-500 seconds at 1,200 demand levels with an 80-20 demand split. The thick grey dashed line represents the merge point location. The blue line represents the outer lane vehicles and the red line represents the on-ramp vehicles.

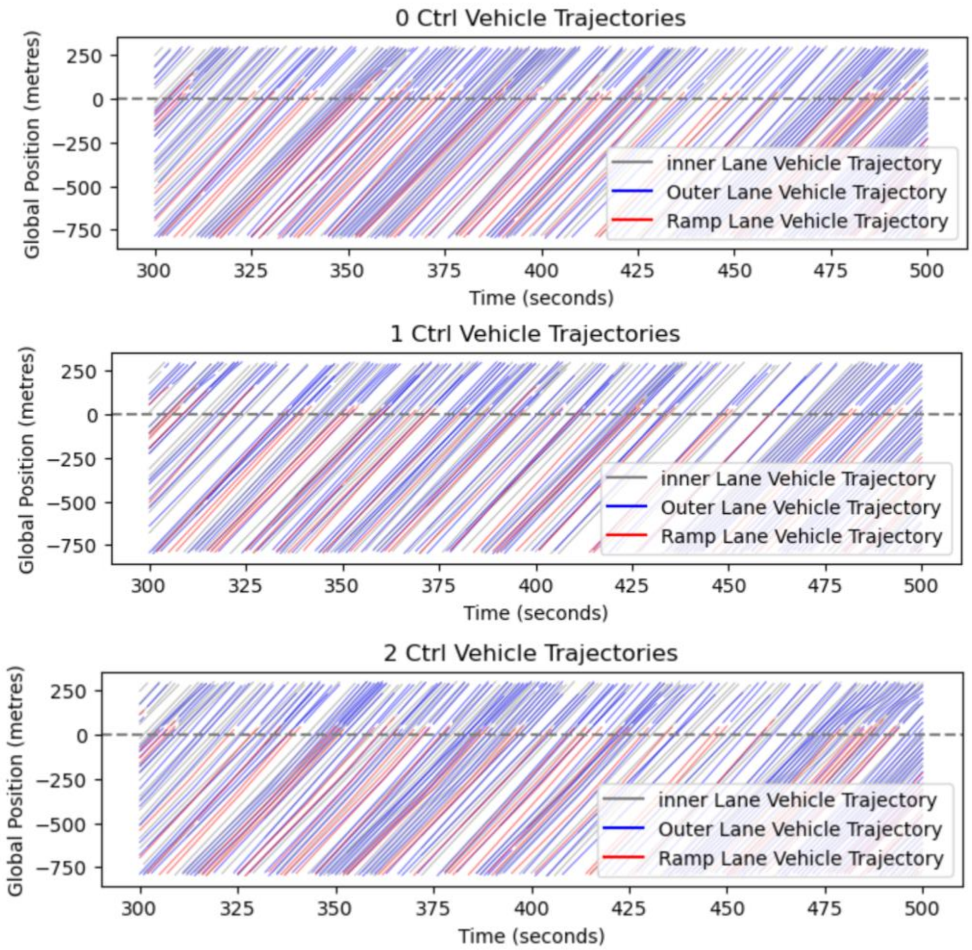

Figure 12 – Vehicle trajectory data visualisation and analysis

Comparing the vehicle trajectory data of case 0 and case 1, it can be found that the number of vehicles in the outer lane of the lane change optimisation area (-700 ~ -500) decreases significantly with the increase of the simulation time. The lane change control algorithm makes the CAV change lanes from the outer lane to the inner lane in advance according to the factors of the ramp flow rate and the balance of the downstream lanes, so that the number of inner-lane vehicles increases while the number of vehicles in the outer lanes decreases, and the merging area is reserved with more space for the merging zone, which improves the efficiency of vehicle merging in the merging zone and results in smoother downstream traffic distribution. Comparing the vehicle trajectory data for case 0 and case 2, the number of vehicles optimised within the trajectory optimisation area for case 0 increases, thereby increasing delay time and driving risk. In contrast, the vehicles in case 2 increased the overall traffic speed due to the better speed and acceleration regulation obtained in the trajectory optimisation area.

4.3 Discussion

Although the freeway merging area optimisation framework and lane-changing optimisation strategy proposed in this study show good results in simulation experiments, there are still some potential limitations that deserve further discussion. First, the study assumes that lane-changing behaviours are instantaneous, which does not match the complexity of lane-changing behaviours in reality, where the lane-changing process in practice may involve longer decision-making and execution times. Second, the study ignores the communication delays between the roadside communication and the computing centre, as well as the vehicle, which may have an impact on the real-time control of CAVs in real-world applications. In addition, the effects of external factors such as weather and road conditions on vehicle behaviour were not adequately considered in this study. Finally, although the VISSIM simulation model is widely used in traffic studies, it is still unable to fully simulate all the details of the real traffic environment, which may limit the accuracy of the model in predicting real traffic situations.

In addition to the limitations mentioned above, this study also raises a number of issues that deserve further investigation. First, the current research results are mainly focused on two-lane freeway merging areas, and future research could explore the applicability of extending this optimisation framework and control strategy to multi-lane environments. Second, considering the impact of driver behaviour in mixed traffic flows on the overall traffic system, it will be important to study in depth the driver behaviour in the autopilot environment. Finally, an analysis of the economic and social benefits of the freeway merging zone optimisation framework will help to fully assess its long-term implications for traffic management and urban planning. These discussions provide a wealth of ideas for future research directions that are expected to further promote the development of freeway merging zone optimisation and autonomous driving technology.

5. CONCLUSION

This study presents a framework for optimising two-lane freeway merging areas and lane-changing control strategies in a connected and autonomous driving environment. The framework divides the merging zone into a cooperative lane-changing area and a trajectory optimisation area, allowing real-time control of continuous traffic flow. In the cooperative lane-change area, on the one hand, the optimal number of lane-changing vehicles is determined considering the balance of the traffic distribution between the inner and outer lanes downstream of the merging area. On the other hand, the sequence and combination of cooperative lane-changing vehicles are determined based on the analysis of the CAV cooperative lane-changing approach. In the trajectory optimisation area, a linear time-discrete model is built to maximise the speeds of all CAVs in the current lane-changing cycle by optimising the speed and acceleration data of each vehicle in real time, and to be able to pass through the merging point safely and collision-free along the optimised trajectory. In order to evaluate the effectiveness of the proposed strategies, this study uses VISSIM to construct the research traffic scenarios and perform simulation validation, employing the platforms of VISSIM COM and Python to implement the control logic of the CAVs. The strategies were evaluated in terms of average speed, average delay time and throughput using the developed simulation platform and compared with the case without control, respectively. The simulation results express the good performance of the freeway merging area optimisation framework proposed in this study. In future work, it is necessary to consider adding communication delays to the lane changing and merging behaviour of vehicles in freeway merging areas, which is necessary to study the behaviour and macro-control of vehicles travelling on freeways.

AUTHORS CONTRIBUTION STATEMENT

Xuling Liu: research framework development, model formulation and validation, simulation experiments and development, and paper writing and revision. Xiaoning Zhang: research framework development, research supervision, paper revision.

ACKNOWLEDGEMENTS

This study has been substantially supported by the research grant from the National Natural Science Foundation of China (No. 72021002).

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