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Exploring Sustainable Lane-Change Behaviours – Integrated Approach to Modelling Mixed Traffic with Intelligent-Connected Vehicles

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ABSTRACT

This paper proposes two sustainable lane-changing (LC) decision-making models for application in intelligent-connected (I-C) and mixed-traffic environments. The models, with their unique approach, calculate the lane-changing impact area of vehicles, assess interactions with other lane-changing vehicles, and consider factors such as lane-changing conflicts, the number of connected collaborative vehicles and the overall benefits of lane-changing to determine the final lane-changing vehicle. The feasibility of lane changing is also considered when selecting the execution decision. The simulation results show that the proposed model can effectively improve the traffic efficiency. Specifically, in a mixed traffic environment, the model still maintains good lane change performance when the proportion of intelligently connected vehicles exceeds 0.85. The model effectively optimises lane changing conflicts, improves lane changing efficiency and sustainability, and contributes to the development of sustainable transportation in the future. Through micro traffic simulation, when the input flow is $Q3$ and the lane change ratio r is 0.2, the vehicle travel time is reduced by 24.78%, the average delay is reduced by 23.21% and the average speed is increased by 7.77%.

KEYWORDS

sustainable lane-changing decision-making model; mixed-traffic environment; sustainable transportation; intelligent-connected vehicles; lane-changing impact.

1. INTRODUCTION

During the peak hours of urban road traffic, lane-changing behaviours among vehicles become more frequent as the traffic flow increases. Such frequent lane changes increase the risk of traffic accidents and lead to frequent traffic congestion and delays at intersections, which is unfavourable for sustainable development [1, 2]. As a cutting-edge transportation technology, vehicle-infrastructure cooperation (V2X) technology brings new opportunities to research lane changes in urban roads. Through real-time information interaction between vehicles, road infrastructure and other vehicles, it enables more accurate and timelier lane-changing (LC) decisions, significantly enhancing the safety and sustainability of LC behaviours [3, 4]. Conducting in-depth research on LC decision-making models is of crucial importance for enhancing the safety and efficiency of urban transportation [5, 6].

The earliest model to define the LC decision change process as a series of rules was the Gipps model proposed by Gipps [7] in 1986. This model integrates multiple LC influencing factors, aiming to simulate the LC behaviour of drivers when encountering obstacles ahead, providing a basic framework for subsequent research. Based on the logic of the Gipps model, many scholars have conducted further research on LC models. Nagel et al. [8] conducted an in-depth analysis of LC rules for vehicles in highway scenarios. Based on the cellular automaton (CA) model, they designed an LC rule suitable for asymmetric LC models by combining vehicle speed and spacing. The simplified design limitations of asymmetric LC models often make it difficult to adapt to complex mixed traffic flow environments. Halati et al. [9] proposed the CORSIM model, the first to study urban road and highway environments separately. However, because the CORSIM model integrates multiple models, its structure and parameters are relatively complex, resulting in poor generality of the model, especially in some specific traffic scenarios, which may require additional calibration and adjustment. Yang et al. [10] classified LC behaviours into mandatory and discretionary and proposed the MITSIM model using different LC scenarios. Peter [11] proposed the ARTEMiS model considered the situation where the vehicle behind the target lane actively decelerates, incorporating cooperative LC into the model.

With the development and popularisation of I-C vehicle technology, recent research has established many vehicle LC models based on I-C environments, which has greatly promoted the development of sustainable LC [12]. Karimi et al. [13] predicted the motion trajectories of surrounding vehicles based on game theory and the Monte Carlo tree search (MCTS) method, deriving LC decisions for vehicles based on the prediction results. However, in a complex traffic environment, the computational complexity of such an approach will increase significantly as the number of vehicles increases and the complexity of the interaction increases. Alagumuthukrishnan et al. [14] integrated connectivity functions and sensory information obtained from vehicles near the connected autonomous vehicles (CAVs) to provide safe and collaborative LC behaviour, enhancing traffic safety for driving behaviours. This approach is highly dependent on connectivity and communication between vehicles and is often difficult to support in real-world environments. Cai et al. [15] proposed the MCLG model based on a multi-head attention module. The decision-making module that considers interactive information demonstrates higher predictability and accuracy, providing robust support for LC decisions. This model is suitable for normal LC scenarios and may not be well-suited for more complex mandatory LC [10]. Peng et al. [16, 17] analysed LC decision-making problems based on game theory, considering social behaviours, and proposed a method for LC decision-making and motion planning for I-C vehicles that comprehensively considers the social behaviours of surrounding traffic participants. This method can provide safe and feasible LC decisions for I-C vehicles. Yi et al. [18] proposed mandatory LC control in the spatial domain, creating virtual CAV tracking lanes by assigning serial numbers based on the spatial positions of CAVs, systematically achieving car-following and LC efficiency.

Since the I-C environment represents an ideal future traffic scenario, the traffic scenario from the traditional traffic scenario to the I-C environment traffic scenario will inevitably go through the mixed traffic transition stage of the I-C environment. Therefore, this paper hopes to investigate whether LC decision-making in the transition phase of the I-C environment meets the needs of transportation sustainability by studying LC decision-making in the mixed transportation environment [19, 20]. Zhang et al. [21] introduced a discrete, macroscopic and second-order traffic flow model. They conducted extensive numerical simulations based on highway sections with variable speed control, achieving an accurate estimation of mixed-traffic conditions. Fu et al. [22] proposed a conflict model based on mixed-traffic environments that can identify conflicts caused by multiple LC vehicles, decoupling the conflict problem into multiple two-vehicle LC games, thus enhancing the efficiency of various CAVs. Shang et al. [23] considered the LC behaviour and randomness of I-C vehicles, establishing a mixed-integer programming model to optimise the trajectories of vehicle lane changes.

Synthesising the above research, current studies on I-C environments are to some extent overly idealistic, failing to fully account for the complexity of deploying intelligent roadside facilities in practical applications and the potential impact of various factors on vehicle data collection. From the perspective of model application, there is a lack of research on the interaction between multiple vehicles during coordinated LC processes and how to optimise vehicles with conflicting LC needs. From the angle of transportation sustainability, existing studies have not adequately analysed the issue of LC benefits, making it unclear whether the selected LC decisions positively contribute to sustainable transportation.

Based on the current research status, this paper thoroughly examines various factors such as LC influences and conflicts in I-C and mixed traffic environments, while comprehensively considering the overall benefits of lane changing to enhance the sustainability of the lane-changing process. Two lane-changing decision-making control models are proposed. Finally, the effectiveness of the models is verified through microscopic traffic simulation, providing a theoretical model for future lane-changing decisions in mixed traffic environments.

The specific contributions of this paper are threefold: (1) develop sustainable LC decision-making models for the I-C and mixed-traffic environments, (2) develop an optimisation method for LC conflicts that applies to the decision-making models, and (3) develop a method for evaluating the total LC benefits, considering the incentives, benefits and pressure.

The organisation of the rest of this paper is as follows. The second section elaborates on the two proposed models in detail. The third section describes the design of simulation experiments and the analysis of results. The final section summarises the research findings and prospects the future work.

2. PROPOSED MODELS

2.1 Model 1: Intelligent-connected vehicle environment

In the context of I-C vehicles, a sustainable LC decision-making model requires considering the operational status of all vehicles within the communication range (*Figure 2*). I-C vehicles are equipped with vehicle-to-everything (V2X) communication capabilities, enabling real-time sharing of information such as location, speed and lane-changing intentions, and supporting collaborative decision-making with surrounding vehicles and infrastructure. The subject vehicle (SV), which intends to perform a lane change, serves as the primary focus of this study. The lane the subject vehicle aims to enter is called the target lane. The surrounding vehicles of the subject vehicle are defined as follows: LV is the leading vehicle in the current lane of the subject vehicle, FV is the leading vehicle in the current lane of the subject vehicle, TLV is the target lane's leading vehicle and TFV is the target lane's following vehicle. The lane-changing decision-making flow of the model is shown in *Figure 1*.

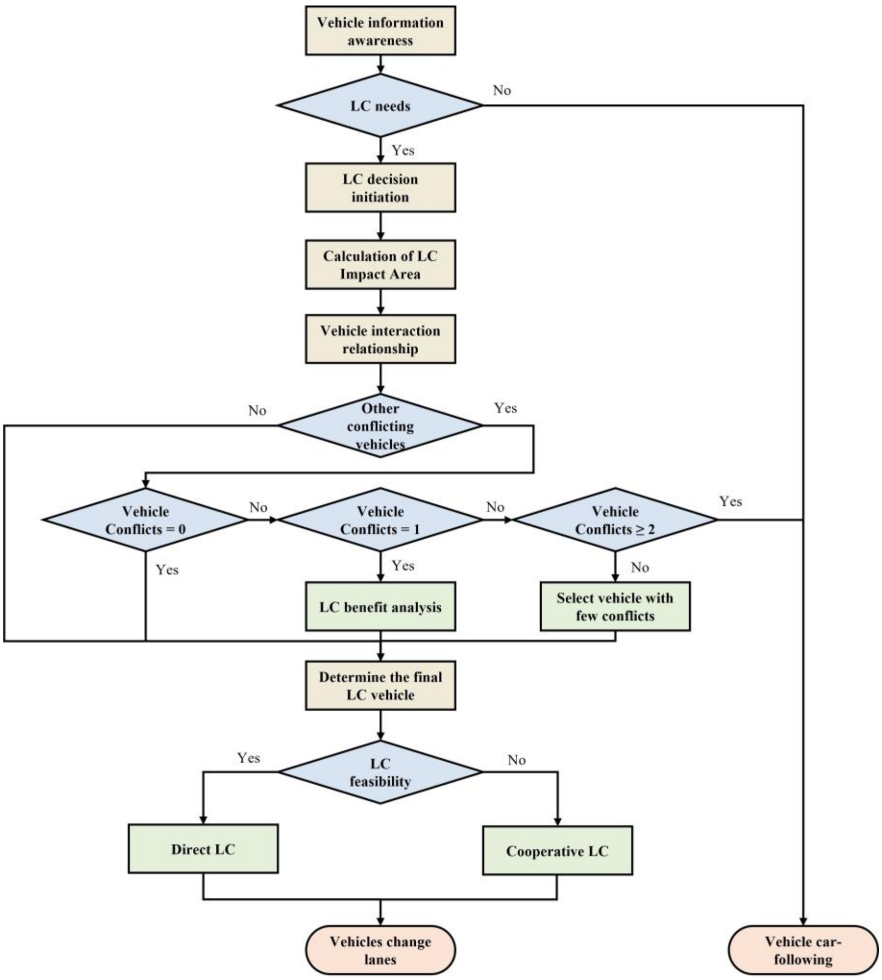


Figure 1 – Model 1: Lane-changing decision-making flowchart

Calculation of LC impact area

When a driver wants to change lanes and has already determined the target lane, the driver's line of sight and attention will be focused on the leading vehicle in the current lane and the vehicles in front of and behind it in the target lane [24]. The objective is to maintain a safe distance during the LC process to prevent collisions with surrounding vehicles.

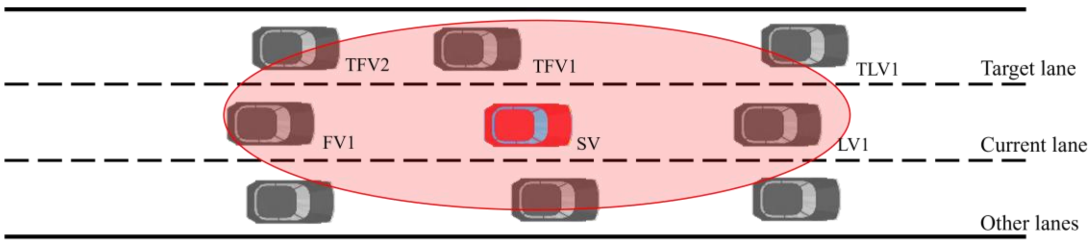


Figure 2 – Driver's field of view during lane changes

During an LC manoeuvre, dynamic interactions occur between the vehicle and its surrounding vehicles. The interactive area between vehicles is not fixed but dynamically adjusts based on changing conditions. In this paper, this constantly changing interactive area is referred to as the LC impact area. According to the literature review, the size of the LC impact area is determined by factors such as vehicle speed, vehicle spacing and safe distance [25].

Given the significant differences in traffic flow at signal-controlled intersections during different times, as well as the obvious synergy and interactivity in the I-C environment, this paper selects the IDM model [26] to describe the car-following behaviour of LC vehicles. The model can effectively adapt to various traffic conditions ranging from free flow to complete congestion, with parameters flexibly adjustable to match the collaborative characteristics of vehicles in intelligent connected environments. It outperforms models such as cellular automata in describing lane-changing dynamic interaction scenarios [8]. By considering the driver's field of vision during the LC preparation process and combining it with the actual LC area during driving, the LC impact area in this paper focuses only on the range between the LC target vehicle and the leading vehicle in the current lane, and the area enclosed by the LC impact distance and the lane. The study focuses on the distances between the target vehicle and the leading vehicle in the current lane and the leading vehicle in the target lane.

1) When the longitudinal distance between the target vehicle and the leading vehicle in the current lane is greater than the longitudinal distance between the target vehicle and the leading vehicle in the target lane, the expected distance between the target vehicle and the leading vehicle in the current lane during the LC process is equivalent to the impact distance of the target vehicle during the LC process, as shown in *Equation 1*:

$$D_{SV,LV}^{ex} = D_{infl} = D_0 + v_{SV}T + \frac{v_{SV}\Delta v_{LV-SV}}{2\sqrt{a_{\max}b}} \tag{1}$$

where $D_{SV,LV}^{ex}$ is the expected distance between the target vehicle and the leading vehicle, D_{infl} is the LC impact distance of the target vehicle, T is the safe time interval, typically taken as 1.5 s, v_{SV} is the current speed of the target vehicle, Δv_{LV-SV} is the speed difference between the target vehicle and the leading vehicle, $a_{\max}$ is the maximum acceleration of the target vehicle, and b is the comfortable deceleration of the target vehicle.

2) When the longitudinal distance between the target vehicle and the leading vehicle in the current lane is less than the longitudinal distance between the target vehicle and the leading vehicle in the target lane, the expected distance between the target vehicle and the leading vehicle in the current lane during the LC process is as follows:

$$D_{SV,TLV}^{ex} = D_0 + v_{SV}T + \frac{v_{SV}\Delta v_{TLV-SV}}{2\sqrt{a_{\max}b}} \tag{2}$$

where $D_{SV,TLV}^{ex}$ is the expected distance between the target vehicle and the leading vehicle in the target lane, and Δv_{TLV-SV} is the speed difference between the LC and the leading vehicles in the target lane.

The impact distance of the target vehicle during the LC process is represented by *Equation 3*, as shown below:

$$D_{infl}=\sqrt{\left(D_0+v_{SV}T+\frac{v_{SV}\Delta v_{TLV-SV}}{2\sqrt{a_{\max}b}}\right)^2-D_w{}^2} \tag{3}$$

where D_w is the lateral required safe distance, taken as the lane width of 3.5 m.

In the formula for the expected LC distance, a minimum separation between two vehicles needs to be maintained. Suppose the speed difference between the preceding vehicle and the LC vehicle exceeds the difference between the expected speed and the LC vehicle's speed. In this case, the calculated impact distance for LC will be significantly larger than the required distance, thereby causing interference in the decision-making process for the vehicle's lane change. As shown in *Figure 3* below:

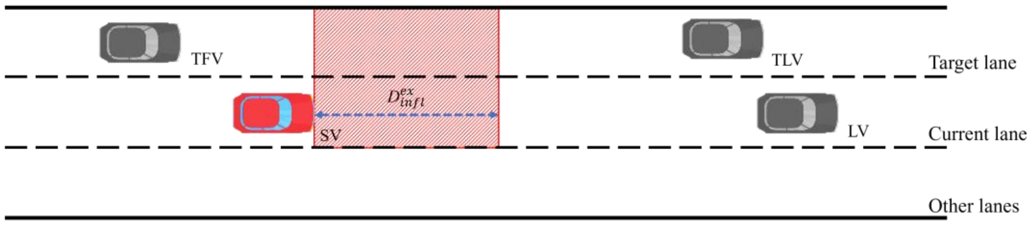


Figure 3 – Distance affected by lane changing at the expected speed

Therefore, when the speed of the leading vehicle in the target lane is greater than the expected LC speed, the following formula applies:

$$D^{ex}_{infl}=D_0+v_{SV}T+\frac{v_{SV}\Delta v_{exp}}{2\sqrt{a_{\max}b}} \tag{4}$$

where D^{ex}_{infl} is the impact distance of the target vehicle during LC at the expected speed and Δv_{exp} is the difference between the speed of the LC vehicle and the expected LC speed.

The final LC impact area is a rectangular region with the length defined by the LC impact distance and the width determined by the sum of the widths of the current lane and the target lane.

Analysis of LC benefits

LC benefit analysis is a sustainable process that focuses not only on the immediate benefits of a single lane change, but also on the long-term impact of lane change on traffic sustainability. It considers a variety of factors, including the speed of travel after LC, safety during LC and the impact on surrounding traffic flow. This analysis selects vehicles with optimal LC benefits to determine the final LC decision, thereby improving road traffic capacity.

1) Incentive benefit

The incentive benefit is used to evaluate the positive gains obtained by the target vehicle when executing an LC behaviour, determining whether this behaviour can bring a faster driving speed or a more spacious driving environment to the target vehicle. As a widely recognised LC model, the MOBIL model [27] utilises the changes in the acceleration of surrounding vehicles to measure the incentive benefit, which reflects the consideration of the driving states of other vehicles. The formula for calculating the incentive benefit in the MOBIL LC model is as follows:

$$u_{SV}=\tilde{a}_{SV}-a_{SV}+p\left(\tilde{a}_{FV}-a_{FV}+\tilde{a}_{TFV}-a_{TFV}\right) \tag{5}$$

where u_{SV} is the LC benefit of the target vehicle, $\tilde{a}_{SV}$ is the acceleration of the target vehicle after LC, a_{SV} is the current acceleration of the target vehicle before LC, $\tilde{a}_{FV}$ is the acceleration of the following vehicle in the current lane after the target vehicle's LC, a_{FV} is the current acceleration of the following vehicle in the current lane before the target vehicle's LC, $\tilde{a}_{TFV}$ is the acceleration of the following vehicle in the target lane after the target vehicle's LC, a_{TFV} is the current acceleration of the following vehicle in the target lane before the target vehicle's LC and p is the LC courtesy coefficient.

To ensure the safety of LC and avoid drivers being unable to complete LC before reaching the latest LC point due to excessive altruistic behaviour, a reasonable egoistic value needs to be set for the LC courtesy coefficient.

2) LC pressure

LC pressure refers to the urgency of a vehicle to execute a lane change. Firstly, during the process of searching for an LC opportunity, vehicles with LC demands will face increasing LC pressure. This is because as their distance from the latest LC point gradually shortens, the urgency of lane changing increases accordingly. Similarly, as this LC pressure rises, the vehicle's willingness to change lanes will also increase correspondingly. Assuming that the length of the LC area is L and the maximum value of the LC pressure when the vehicle is at a distance from the latest LC point is 1, the following formula can be obtained:

$$P_{lp}=\left(1-\frac{\Delta L}{L}\right)p \tag{6}$$

where P_{lp} is the LC pressure of the target vehicle based on its distance from the latest LC point, and ΔL is the distance between the target vehicle and the latest LC point denotes the length of the LC area.

Furthermore, as the traffic density in the road network continues to increase, there is a significant difference between the driving environment of the current lane and the driver's expected speed. If the headway between the adjacent lanes meets the minimum safe distance requirement for LC, the driver may choose to execute a lane-change operation to achieve a higher driving speed. However, this can impact the stability and efficiency of the overall traffic flow, increasing potential conflict points and causing LC delays. Therefore, it is necessary to provide LC guidance as early as possible. Assuming the maximum value of LC pressure due to traffic density is 1, in the case of mandatory LC, it is given as:

$$P_k=p\frac{K}{K_j} \tag{7}$$

where P_k is the LC pressure of the target vehicle due to traffic density, K is the traffic density, K_j is the congestion density.

By integrating the pressure of the LC vehicle approaching the latest LC point with the pressure stemming from the increasing traffic density, the total LC pressure is obtained by:

$$P_{tol}=\varphi_1 P_{lp}+\varphi_2 P_k \tag{8}$$

where P_{tol} is the LC pressure of the target vehicle and φ_1、φ_2 are the weighting coefficients. In the environment of I-C vehicles, where vehicles can receive information from surrounding vehicles, φ_1、φ_2 are generally set to 0.5.

3) Total LC benefit

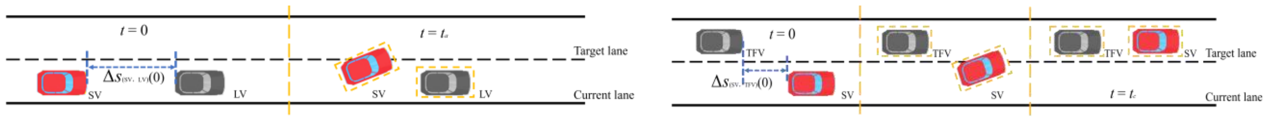
The differences between various influencing indicators will determine the LC sequence of vehicles. Based on the MOBIL LC model, this study introduces the LC pressure index to form a total benefit evaluation framework. By comprehensively considering both incentive benefits and LC pressure, the conflicts between LC vehicles can be reasonably optimised to ensure that vehicles can orderly complete lane changes during the process. The total LC benefit can be derived as:

$$\begin{gathered}U_{tol}=\lambda_1 u_{sv}+\lambda_2 P_{tol}=\lambda_1\left[\tilde{a}_{SV}-a_{SV}+p\left(\tilde{a}_{FV}-a_{FV}+\tilde{a}_{TFV}-a_{TFV}\right)\right]+\lambda_2\left(\varphi_1 P_{lp}+\varphi_2 P_k\right)\\ \lambda_1+\lambda_2=1,\ \ \lambda_1、\lambda_2\in\left[0,1\right]\end{gathered} \tag{9}$$

where U_{tol} is the total LC benefit and λ_1、λ_2 are the weighting coefficients, the values of which are determined by the state of the LC vehicle. When facing different traffic environments, under the condition of ensuring lane-changing safety, the LC process is dynamically adjusted to achieve sustainable benefits. For LC vehicles with low traffic density and a long distance from the stop line, the LC incentive benefit holds a greater weight, resulting in a larger λ_1 and a smaller λ_2.

LC Feasibility analysis

The feasibility analysis of vehicle LC primarily focuses on safety during the LC process, considering the vehicle's own speed and direction, and the position and driving direction of surrounding vehicles. Therefore, the first step is to conduct a safety analysis of the preceding vehicle of the LC vehicle, calculating the minimum safe distance as a constraint for the LC safety conditions, as shown in *Figure 4(a)*. The second step involves a safety analysis of the distance between the LC vehicle and the following vehicle in the target lane, which is used to determine the LC method, as shown in *Figure 4(b)*.



(a) (b)

Figure 4 – Position relationship diagram during lane change between target, preceding and front vehicles: a) Target and preceding vehicles; b) Target vehicle and front vehicle in target lane

During the LC process of the target vehicle, to prevent a collision with the preceding vehicle in the current lane, it is necessary to ensure that the distance between the target vehicle and the preceding vehicle in the current lane is greater than 0 before the target vehicle crosses the lane line and enters the target lane, which is given as:

$$\Delta s_{(SV,LV)}(0)+\int_0^t\int_0^\tau\left(a_{LV}-a_{SV}\right)dtd\tau+\left(v_{LV}(0)-v_{SV}(0)\right)t>0,\quad t\in[0,t_a] \tag{10}$$

where $\Delta s_{(SV,LV)}(0)$ is the relative distance between the target vehicle and the preceding vehicle at the initial moment of lane change, a_{LV} is the longitudinal acceleration of the preceding vehicle, a_{SV} is the longitudinal acceleration of the target vehicle, $v_{LV}(0)$ is the longitudinal speed of the preceding vehicle at the initial moment, $v_{SV}(0)$ is the longitudinal speed of the target vehicle at the initial moment, t_a is the duration of lane change, and t_a is the integral variable.

However, in actual driving scenarios, if the distance between the two vehicles is too small, it not only degrades the driving experience but may also interfere with the LC behaviour of the vehicles. Therefore, a certain safe distance will be maintained, which is given as:

$$D_{safe}(t)=D_0+v_{SV}T_r \tag{11}$$

where $D_{safe}(t)$ is the safe distance between the two vehicles at time, D_0 is the braking distance, typically ranging from 2 to 5 m, and T_r is the reaction delay of the I-C vehicle (0.2 to 0.3 s).

Therefore, *Equation 10* is modified accordingly and is given by:

$$\Delta s_{(SV,LV)}(0)+\int_0^t\int_0^\tau\left(a_{LV}-a_{SV}\right)dtd\tau+\left[v_{LV}(0)-v_{SV}(0)\right]t>D_{safe}(t),\quad t\in[0,t_a] \tag{12}$$

The longitudinal speed of SV at time t is given by:

$$v_{SV}(t)=v_{SV}(0)+\int_0^t a_{SV}dt,\quad t\in[0,t_a] \tag{13}$$

By combining and substituting *Equation 13* into *Equation 12* with the assistance of *Equation 11*, the minimum safe distance for lane changing between the SV and LV in the current lane can be obtained as:

$$D_{\min}(SV, LV) = \max \begin{Bmatrix} \int_0^t \int_0^\tau (a_{SV} - a_{LV}) dt d\tau + [v_{SV}(0) - v_{LV}(0)]t \\ + \left[v_{SV}(0) + \int_0^t a_{SV} dt \right] T_r + D_0 \end{Bmatrix}, \quad t \in [0, t_a] \tag{14}$$

After satisfying the constraint of the minimum safe distance for lane changing between the SV and the preceding vehicle during the LC process, it is necessary to further analyse the safety of the distance between TFV and SV to determine the LC strategy. To prevent a collision between the SV and the following vehicle during lane changing, it is necessary to ensure that the distance between the SV and TFV exceeds the safe distance before the SV crosses the lane line and enters the target lane, as shown in *Equation 15*

$$\Delta s_{(SV,TFV)}(0) + \int_0^t \int_0^\tau (a_{SV} - a_{TFV}) dt d\tau + (v_{SV}(0) - v_{TFV}(0))t > D_{safe}(t), \quad t \in [0, t_c] \tag{15}$$

where $\Delta s_{(SV,TFV)}(0)$ is the relative distance between the SV and TFV at the initial moment of LC, a_{TFV} is the longitudinal acceleration of the TFV, $v_{TFV}(0)$ is the longitudinal speed of the TFV at the initial moment, and t_c is the longitudinal speed of the preceding vehicle at the initial moment.

The longitudinal speed of TFV at time t is given as:

$$v_{TFV}(t) = v_{TFV}(0) + \int_0^t a_{TFV} dt, \quad t \in [0, t_c] \tag{16}$$

By combining and substituting *Equation 16* into *Equation 15* with the assistance of *Equation 11*, the minimum safe distance for lane changing between the SV and TFV can be obtained.

$$D_{\min}(SV, TFV) = \max \begin{Bmatrix} \int_0^t \int_0^\tau (a_{TFV} - a_{SV}) dt d\tau + [v_{TFV}(0) - v_{SV}(0)]t \\ + \left[v_{TFV}(0) + \int_0^t a_{TFV} dt \right] T_r + D_0 \end{Bmatrix}, \quad t \in [0, t_c] \tag{17}$$

When the distance between the TFV and SV is no less than the minimum safe distance for lane changing, a direct LC strategy is adopted during the LC process. The SV does not need to consider any potential impact from the following vehicle and can directly change lanes. However, when the distance between the TFV and SV is less than the minimum safe distance for lane changing, a coordinated strategy is implemented during the LC process: SV can actively accelerate to avoid a collision with the preceding vehicle in the target lane while improving LC efficiency. This means that the longitudinal speed of SV at time t needs to be greater than the distance between SV and TFV that satisfies the minimum safe distance for lane changing, which is given as:

$$v_{SV}(t) > v_{SV}(0) + \int_0^t a_{SV} dt, \quad t \in [0, t_c] \tag{18}$$

The TFV actively decelerates to increase the gap, or the longitudinal speed of the TFV at time t needs to be less than the distance between the TFV and SV that satisfies the minimum safe distance for lane changing. This is the longitudinal speed of the TFV at time t when the distance between the TFV and SV meets the minimum safe distance for lane changing, and is given as:

$$v_{TFV}(t) < v_{TFV}(0) + \int_0^t a_{TFV} dt, \quad t \in [0, t_c] \tag{19}$$

2.2 Model 2: Mixed-traffic environment

In a mixed-traffic environment, traffic flow primarily comprises I-C and human-driven vehicles. For the convenience of discussion, the following definitions will be used in this section: CV refers to I-C vehicles, and HV refers to human-driven vehicles. The lane-changing decision-making flow of the model is shown in *Figure 5*.

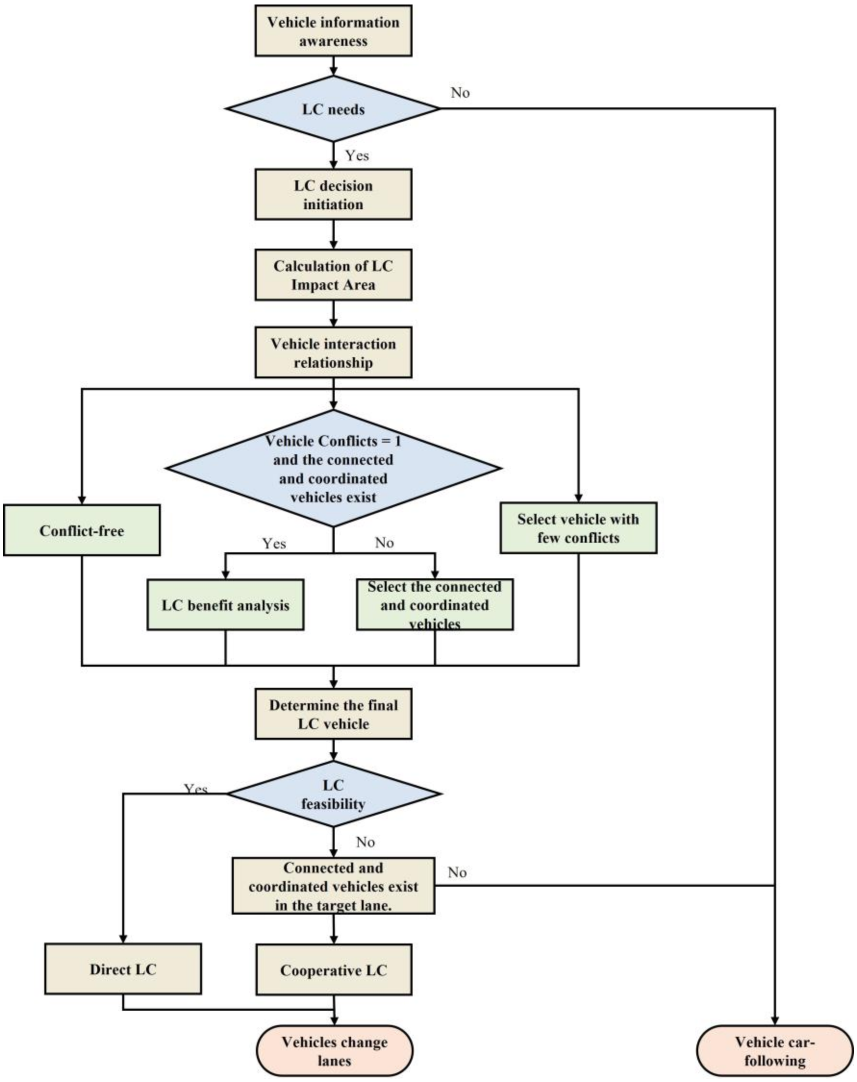


Figure 5 – Model 2: Lane-changing decision-making flowchart

Calculation of LC impact area

In the mixed environment of I-C vehicles, calculating the LC impact area for the target vehicle needs to consider the presence of human-driven vehicles. With the aid of intelligent roadside sensing equipment deployed along the roadsides and high-precision positioning devices, the precise driving positions and speed data of human-driven vehicles and I-C vehicles can be monitored and obtained in real time, which will reduce the occurrence of traffic accidents and congestion. Therefore, the IDM model [26] can also be effectively applied in the car-following situation of human-driven vehicles.

When the longitudinal distance between the target vehicle and the preceding vehicle in the current lane is greater than the longitudinal distance between the target vehicle and the preceding vehicle in the target lane, the desired distance between the target vehicle and the preceding vehicle in the current lane during the LC process is equal to the impact distance of the target vehicle during the LC process, which is given as:

$$D_{SV,LV}^{ex} = D_{infl} = D_0 + v_{SV}T + \frac{v_{SV}\Delta v_{LV-SV}}{2\sqrt{a_{\max}b}} \tag{20}$$

When the longitudinal distance between the preceding vehicle in the target lane and the preceding vehicle in the current lane is less than the longitudinal distance between the target vehicle and the preceding vehicle in the target lane, the expected distance between the target vehicle and the preceding vehicle in the current lane during the LC process is given as:

$$D_{SV,TLV}^{ex} = D_0 + v_{SV}T + \frac{v_{SV}\Delta v_{TLV-SV}}{2\sqrt{a_{\max}b}} \tag{21}$$

The impact distance of the target vehicle during the LC process is given as:

$$D_{infl}=\sqrt{\left(D_0+v_{SV}T+\frac{v_{SV}\Delta v_{TLV-SV}}{2\sqrt{a_{\max}b}}\right)^2-D_w{}^2} \tag{22}$$

When the speed difference between the preceding vehicle and the LC vehicle exceeds the speed difference between the desired speed and the LC vehicle, and the speed of the preceding vehicle in the target lane is greater than the desired LC speed, the LC impact distance is given as:

$$D_{infl}^{ex}=D_0+v_{SV}T+\frac{v_{SV}\Delta v_{exp}}{2\sqrt{a_{\max}b}} \tag{23}$$

The calculation process of the LC impact area in this subsection is the same as that in Subsection 2.1 Calculation of LC impact area.

Analysis of LC benefits

After the target vehicle generates an LC demand and determines the LC impact area, it is necessary to consider whether surrounding vehicles within the LC impact area also have LC demands and further analyse the vehicles that may have LC conflicts. The detailed analysis is presented next.

When there are LC conflicts between I-C vehicles within the LC impact area of the target vehicle, the number of LC conflicts within each vehicle's LC impact area will be counted as follows. (1) If the number of LC conflicts in each vehicle's LC impact area is greater than or equal to 2, none of them will execute LC. (2) If one vehicle has an LC conflict count of 1, while the other vehicle's LC conflict count is greater than or equal to 2 within their respective LC impact areas, the vehicle with a conflict count of 1 will be the final LC vehicle, while the other vehicle will continue to follow without executing LC. (3) If both vehicles have an LC conflict count of 1 within their respective LC impact areas, the total LC benefits will need to be calculated separately to determine the final LC vehicle.

In the case where both vehicles have an LC conflict count of 1, in a mixed-traffic environment, before considering the analysis of LC benefits, it is necessary to compare whether there are connected and coordinated vehicles within each vehicle's LC impact area. (1) If one of the LC conflict vehicles has connected and coordinated vehicles within its LC impact area, while the other does not, the vehicle with connected and coordinated vehicles will be the final LC vehicle to execute LC. (2) If both LC conflict vehicles have or do not have connected and coordinated vehicles within their respective LC impact areas, further calculation of the total LC benefits will be required to determine the final LC vehicle. The specific analysis of LC benefits can be found in Subsection 2.1 Analysis of LC benefits. However, in a mixed traffic environment, the values of φ_1、φ_2 need to consider the driving behaviours of human-driven vehicles. When a vehicle approaches the latest LC point (a P_{lp}-dominated traffic scenario), the driver will allow a smaller car-following distance to shorten the LC time window and tend to initiate LC behaviour in advance. When traffic density approaches the jam density (a P_k-dominated scenario), drivers will focus more on their own acceleration benefits while reducing consideration for following vehicles, which increases the risk of LC conflicts.

$$\begin{cases} U_{tol}=\lambda_1 u_{sv}+\lambda_2 P_{tol} \\ u_{SV}=\tilde{a}_{SV}-a_{SV}+p\left(\tilde{a}_{FV}-a_{FV}+\tilde{a}_{TFV}-a_{TFV}\right) \\ P_{tol}=\varphi_1 P_{lp}+\varphi_2 P_k \end{cases} \tag{24}$$

LC feasibility analysis

During the LC execution decision-making phase, to ensure the accuracy of the vehicle's decision-making and the safety of the LC process, it is crucial to maintain the necessary minimum spacing with the preceding and following vehicles. This is achieved by employing a minimum safe distance model [28] for calculation. Similarly, a safety analysis is first conducted for the preceding vehicle of the LC vehicle to determine the minimum safe distance, which serves as a constraint for the LC safety conditions. Additionally, the LC impact area is searched to identify if there are any connected and coordinated vehicles, leading to the implementation of the corresponding LC strategy.

When analysing the safety of the spacing between the target vehicle and the preceding vehicle, regardless of whether the preceding vehicle is a manually driven or an I-C vehicle, in an I-C environment, data such as the position and speed of the preceding vehicle can constantly be obtained and transmitted to the target vehicle. This ensures that the SV maintains a comprehensive grasp of the LV dynamic information throughout the LC process. Therefore, the minimum safe distance for LC between SV and LV can be calculated according to Subsection 2.1 LC Feasibility analysis.

$$D_{\min}(SV,\ LV) = \max\begin{Bmatrix} \int_0^t\int_0^\tau (a_{SV} - a_{LV})dtd\tau + [v_{SV}(0) - v_{LV}(0)]t \\ +\left[v_{SV}(0) + \int_0^t a_{SV}dt\right]T_r + D_0 \end{Bmatrix},\ t\in[0,t_a] \tag{25}$$

where the longitudinal speed of SV at time t is given by:

$$v_{SV}(t)=v_{SV}(0) + \int_0^t a_{SV}dt,\ \ t\in[0,t_a] \tag{26}$$

The minimum safe distance for LC between SV and TLV is given by:

$$D_{\min}(SV, TLV) = \max\begin{Bmatrix} \int_0^t\int_0^\tau (a_{SV} - a_{TLV})dtd\tau + [v_{SV}(0) - v_{TLV}(0)]t \\ +\left[v_{SV}(0) + \int_0^t a_{SV}dt\right]T_r + D_0 \end{Bmatrix},\ t\in[0,t_b] \tag{27}$$

The longitudinal speed of SV at time t is given by:

$$v_{SV}(t)=v_{SV}(0) + \int_0^t a_{SV}dt,\ \ t\in[0,t_b] \tag{28}$$

After satisfying the constraint of the minimum safe distance for LC between the target vehicle and the preceding vehicle, a safety analysis will be conducted on the spacing with the vehicle in the target lane behind, to determine the LC strategy accordingly. The minimum safe distance for LC between SV and TFV can be calculated from Subsection 2.1 LC Feasibility analysis.

$$D_{\min}(SV, TFV) = \max\begin{Bmatrix} \int_0^t\int_0^\tau (a_{TFV} - a_{SV})dtd\tau + [v_{TFV}(0) - v_{SV}(0)]t \\ +\left[v_{TFV}(0) + \int_0^t a_{TFV}dt\right]T_r + D_0 \end{Bmatrix}, t\in[0,t_c] \tag{29}$$

where the longitudinal speed of TFV at time t is given by:

$$v_{TFV}(t) = v_{TFV}(0) + \int_0^t a_{TFV}dt,\ \ t\in[0,t_c] \tag{30}$$

Regarding the LC strategy, the condition for the target vehicle to adopt a direct LC strategy is that the spacing between the target vehicle and the vehicle in the target lane behind is not less than the minimum safe distance for LC. That is,

$$\Delta s_{(SV,TFV)}(t) \geq D_{\min}(SV, TFV)\ ,\quad t\in[0,t_c] \tag{31}$$

where $\Delta s_{(SV,TFV)}(t)$ is the relative distance between the target vehicle and the vehicle in the target lane behind at time *t*.

When the spacing between the vehicle in the target lane behind and the target vehicle is less than the minimum safe distance for LC, a collaborative strategy is initiated during the LC process. In this case, possible measures include the target vehicle actively accelerating or the vehicle in the target lane behind actively decelerating. Therefore, the longitudinal speed of SV at time t needs to be greater than the longitudinal speed of SV at time t when the spacing between the target vehicle and the vehicle in the target lane behind satisfies the minimum safe distance for lane changing, as shown in Equation 32.

$$v_{SV}(t) > v_{SV}(0) + \int_0^t a_{SV}dt,\ \ t\in[0,t_c] \tag{32}$$

Alternatively, the longitudinal speed of TFV at time *t* needs to be less than the longitudinal speed of TFV at time *t* when the spacing between the vehicle in the target lane behind and the target vehicle satisfies the minimum safe distance for LC, as shown in *Equation 33*.

$$v_{TFV}(t) < v_{TFV}(0) + \int_0^t a_{TFV} dt, \quad t \in [0, t_c] \tag{33}$$

The condition for the target vehicle to adopt a direct LC strategy is that the spacing between the target vehicle and the vehicle in the target lane behind is not less than the minimum safe distance for LC, as shown in Equation 34.

$$\Delta s_{(SV,TFV)}(t) \geq D_{\min}(SV, TFV), \quad t \in [0, t_c] \tag{34}$$

When the gap between the vehicle in the target lane behind and the target vehicle is less than the minimum safe distance for LC, it is necessary to determine whether there are connected and collaborative vehicles in the LC impact area of the target vehicle. If there is a connected and collaborative vehicle in front of the target lane, and the target vehicle has no preceding vehicle in its current lane, or the distance to the preceding vehicle meets the condition for the target vehicle to perform a catch-up lane change, then the catch-up LC distance is less than the distance between the target vehicle and the latest LC point. This connected and collaborative vehicle is labelled as TCV, and a collaborative LC strategy is initiated. The target vehicle will accelerate to catch up, while the connected and collaborative vehicle decelerates. The positions of the two vehicles at time t_d are illustrated in *Figure 6* below.

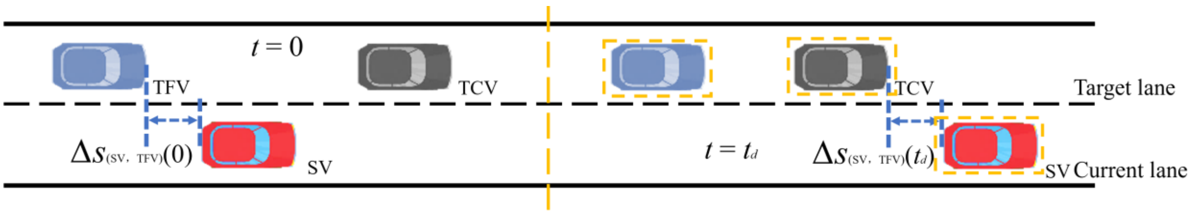


Figure 6 – Position relationship diagram during lane change for the target vehicle and the connected cooperative vehicle (a)

The longitudinal speed of SV at time t is given as:

$$v_{SV}(t) = v_{SV}(0) + \int_0^t a_{SV} dt, \quad t \in [0, t_d] \tag{35}$$

The longitudinal speed of TCV at time t is given by:

$$v_{TCV}(t) = v_{TCV}(0) - \int_0^t a_{TCV} dt, \quad t \in [0, t_d] \tag{36}$$

where $v_{TCV}(t)$ is the longitudinal speed of the connected and collaborative vehicle (TCV) at time t, $v_{TCV}(0)$ is the initial longitudinal speed of the TCV, a_{TCV} is the longitudinal acceleration of the TCV, and t_d is the duration of the LC process. The LC operation is further executed, as shown in *Figure 7*.

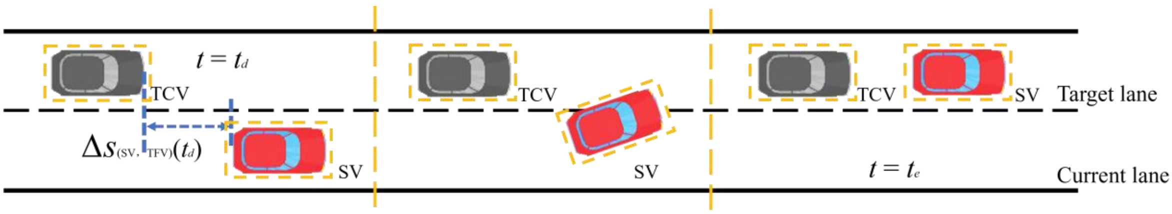


Figure 7 – Position relationship diagram during lane changes for the target vehicle and the connected cooperative vehicle (b)

At this moment, the minimum safe distance for LC between SV and TFV is given as:

$$D_{\min}(SV, TCV) = \max \left\{ \begin{array}{l} \int_0^t \int_0^\tau (a_{TCV} - a_{SV}) dt d\tau + [v_{TCV}(t_d) - v_{SV}(t_d)]t \\ + \left[v_{TCV}(t_d) + \int_0^t a_{TCV} dt \right] T_r + D_0 \end{array} \right\}, \quad t \in [t_d, t_e] \tag{37}$$

where t_e is the duration of the LC process.

3. SIMULATION EXPERIMENTS

To verify the control effect of the model proposed in this paper, VISUAL C++ was used to call VISSIM COM and import the proposed model into simulation experiments. These simulation experiments can visually observe the lane-changing behaviour of the proposed model and directly output indicators such as travel time, delay and speed. Two consecutive signal-controlled intersections within Fuzhou city were selected as the simulation objects to build an LC decision-making simulation scenario in a vehicle-infrastructure cooperative environment. The simulation network map is shown in Figure 8, the basic situation of each intersection is shown in Table 1, and the default simulation parameter settings are listed in Table 2. The inflow at each entrance of the intersection from low flow to high flow throughout the day is shown in Table 3. The simulation experiment of this study lasted for 3,600 seconds, with the first 600 seconds as the warm-up period. Each group of optimisation experiments was repeated 15 times to take the average value, and the random seed was set to 42.

Figure 8 – Simulation road network base map

Table 1 – Basic information of each intersection

Intersection number	Import road direction	Normal segment number of lanes	Channelisation number of lanes	Lane divider solid line length/m	Lane changes are allowed length/m
1	East	65	3	5	60
2	East	53	3	5	50

Table 2 – Simulation parameter setting

Parameter	Explanation	Valid values
V_{max} (km/h)	Maximum speed	65
V_{exp} (km/h)	Expected lane-changing speed	53
T (s)	Safe time interval	1.5
d_{min} (m)	Static safety distance	7
a_{max} (m/s^2)	Maximum acceleration	4
b (m/s^2)	Comfortable deceleration	2
p	LC courtesy coefficient	0.2
K_j (pcu/km)	Jam density	124
W (m)	Lane width	3.5

Note: The jam density is based on the measured data of urban roads in Fuzhou, and pcu is based on standard passenger cars with a coefficient of 1.0.

Table 3 – The inbound flow of each inlet road at the intersection

Intersection number	1			2	
Import road direction	East	South	North	South	North
Low flow $Q1$(veh/h)	825	157	136	97	112
Medium flow $Q2$(veh/h)	1204	188	178	132	146
High flow $Q3$(veh/h)	1486	232	218	157	197

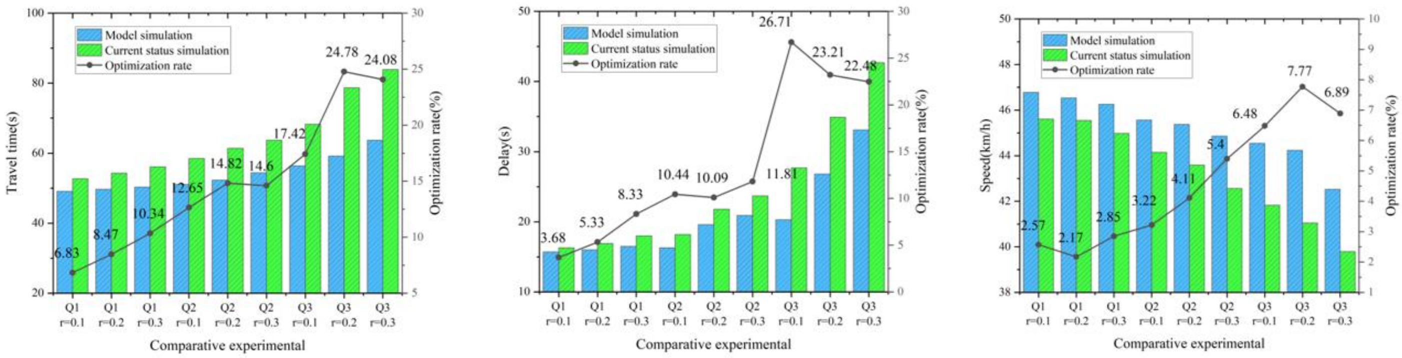
3.1 Comparative experimental analysis

A comparative experiment was designed to validate the control effect of the proposed LC decision-making model in an intelligent-connected vehicle environment. An orthogonal experiment is conducted with the current simulation as the control group, considering two influencing factors: traffic flow and LC ratio. The design of the orthogonal experiment is presented in *Table 4*.

Table 4 – Orthogonal experimental design table

Experimental plan	Traffic flow Q(veh/h)	Lane-changing ratio r
1	$Q1$	0.1
2	$Q1$	0.2
3	$Q1$	0.3
4	$Q2$	0.1
5	$Q2$	0.2
6	$Q2$	0.3
7	$Q3$	0.1
8	$Q3$	0.2
9	$Q3$	0.3

For all the simulation results output from the experiments, data analysis was conducted separately for the experimental group and the control group, focusing on the two influencing factors of traffic flow and LC ratio. The evaluation using indicators such as travel time, delay and speed can fully simulate the traffic movement benefit of vehicles to verify the effectiveness of the proposed model. The experimental results are directly output by the VISSIM simulation, and the comparison results are shown in *Figure 9*.



(a) (b) (c)

Figure 9 – Comparison of model and simulation results: a) Travel time; b) Delay; c) Speed

When a low traffic flow Q1 is input, there is less mutual interference between vehicles, and road resources are relatively sufficient. As the LC ratio r increases, the experimental group that applies the LC decision-making model shows an upward trend in optimisation for all three indicators, but the optimisation effect is insignificant. When the input flow is Q2, road resources remain relatively sufficient, and the mutual influence between vehicles is within a controllable range. However, when a higher traffic flow Q3 is input, the traffic density is greater, and road resources are relatively tight. Frequent LC behaviours not only increase mutual interference between vehicles but may also lead to traffic congestion and accident risks. After applying the model, all three indicators show significant optimisation, demonstrating a good effect. Based on the comprehensive experimental results, when the input flow is Q3, and the LC ratio r is 0.2, implementing the model achieves the best optimisation effect, with a 24.78% reduction in travel time, a 23.21% reduction in average delay, and a 7.77% increase in average speed within 0-3,600 s. The proposed model can significantly reduce travel time and delays for vehicles entering the intersection, improve driving speed, and thus enhance the intersection's traffic efficiency.

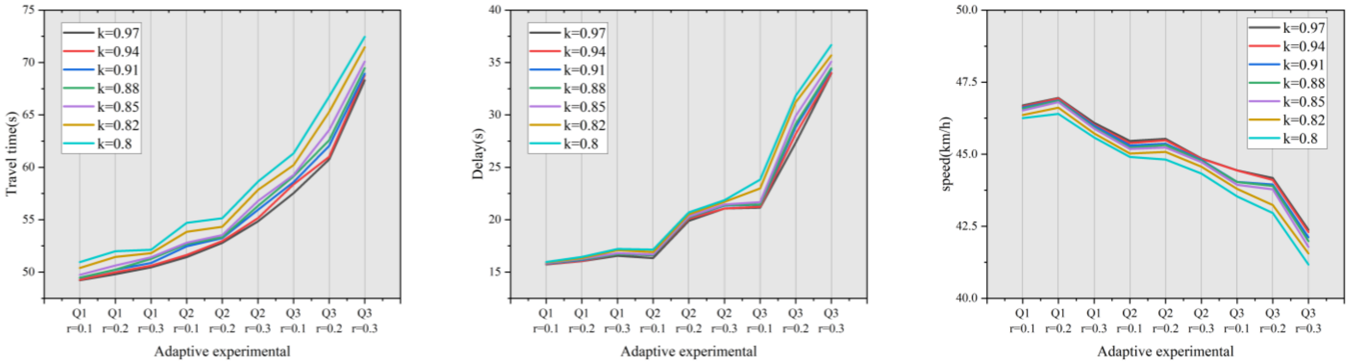
3.2 Adaptive experimental analysis

The control effect of the sustainable LC decision-making model in a mixed-traffic environment is primarily influenced by factors such as traffic flow, LC ratio and the proportion of I-C vehicles. Therefore, an adaptive experiment is designed to explore the adaptability of the proposed model under varying conditions of traffic flow, LC ratio and the proportion of I-C vehicles. Specifically, the proposed model under different proportions of I-C vehicles is investigated by setting the proportion of I-C vehicles to k = 0.97, k = 0.94, k = 0.91, k = 0.88, k = 0.85, k = 0.82 and k = 0.80. A total of 63 sets of model control simulation experiments are designed, and the experimental design is presented in *Table 5*.

Table 5 – Experimental design table

Experimental plan	Proportion of I-C vehicles k	Traffic flow Q(veh/h)	LC ratio r
1	0.97	$Q1$	0.1
2	0.97	$Q1$	0.2
3	0.97	$Q1$	0.3
4	0.97	$Q2$	0.1
5	0.97	$Q2$	0.2
6	0.97	$Q2$	0.3
7	0.97	$Q3$	0.1
8	0.97	$Q3$	0.2
……			
56	0.8	$Q1$	0.2
57	0.8	$Q1$	0.3
58	0.8	$Q2$	0.1
59	0.8	$Q2$	0.2
60	0.8	$Q2$	0.3
61	0.8	$Q3$	0.1
62	0.8	$Q3$	0.2
63	0.8	$Q3$	0.3

For all the simulation results output from the experiment, the evaluation is conducted using indicators such as travel time, delay and speed, to explore the adaptability of the LC decision-making model in a mixed-traffic environment under varying conditions of traffic flow, LC ratio and the proportion of I-C vehicles. The control effect under different proportions of I-C vehicles is also investigated. The experimental results are directly output by the VISSIM simulation, and the analysis graphs for each indicator are shown in *Figure 10*.



(a) *(b)* *(c)*

Figure 10 – Adaptability of model and simulation results: a) Travel time; b) Delay; c) Speed

From an overall trend analysis, the travel time and delay of vehicles gradually increase as the proportion of I-C vehicles decreases, while the speed shows a gradual decline. Under consistent LC ratios, with the increase in traffic flow, the travel time and delay correspondingly show an upward trend, while the speed exhibits a downward trend. When the traffic flow is Q1 and Q2, the increase in the LC ratio has a relatively low impact on each indicator. However, under high-flow conditions (Q3), the LC ratio has a more significant impact on the trends of these indicators.

Furthermore, the sustainable LC decision-making model in a mixed-traffic environment can maintain good LC performance when the proportion of I-C vehicles exceeds 0.85. As the proportion of I-C vehicles decreases, there is a relatively small fluctuation in various indicators. However, when the proportion of I-C vehicles is less than 0.85, it can be found that the optimisation effect of the model is significantly reduced. This is due to the driving habits and characteristics of manually driven vehicles, with increased conflicts during driving, resulting in a decrease in the overall traffic efficiency of the vehicle. Therefore, mixed traffic scenarios with a proportion of I-C vehicles below 0.8 will not be considered in this study.

3.3 LC decision analysis

Based on the above analysis, it is evident that the two proposed models demonstrate better optimisation effects under high traffic flow conditions, improving road traffic operation status and enhancing traffic efficiency. To further validate the role of LC decision-making processes in the models, we take the sustainable LC decision-making model in a mixed traffic environment as the research object. An experimental group with a proportion of intelligent and connected vehicles of k=0.85, traffic flow of Q3 and an LC ratio of r=0.2 is selected. Using the LC process data obtained from this experimental group as an example, a total of seven sets of LC decisions and data samples are collected within the selected time frame under four different LC scenarios. A detailed analysis of the LC decision-making processes under different scenarios is conducted to examine whether the proposed model meets the demand for maximising LC benefits. The LC process data samples are presented in *Table 6*.

Table 6 – A sample of LC process data

Number	Vehicles in the affected area	Vehicle conflicts in the affected area	Connected and cooperative vehicles in the affected area	Total benefits of LC
1	0	0	/	/
2	1	0	/	/
3	1	0	/	/
4	1	1	1	/
5	1	1	0	/
6	1	1	1	1.24
7	1	1	1	2.2

The analysis of the data reveals the following. (1) Vehicle 1 determined that there were no other vehicles changing lanes within its LC influence area. After satisfying the safe LC distance, it directly executed the LC manoeuvre. (2) Vehicle 2 and Vehicle 3, although within each other's LC influence area, did not create an LC conflict. After satisfying the safe LC distance, both vehicles could execute their respective LC manoeuvres. (3) Vehicle 4 and Vehicle 5 were within each other's LC influence area and created an LC conflict. Upon further analysis of the total number of connected and cooperative vehicles within their respective LC influence areas, Vehicle 4 had 1 connected and cooperative vehicle, while Vehicle 5 had 0. The model selected Vehicle 4 to execute the LC manoeuvre, while Vehicle 5 remained in follow-the-leader mode, awaiting the next opportunity for LC. (4) Vehicle 6 and Vehicle 7 were within each other's LC influence area and created an LC conflict. Upon further analysis of the total number of connected and cooperative vehicles within their respective LC influence areas, they had 1 connected and cooperative vehicle. The model then calculated the total benefits of LC, resulting in 1.24 for Vehicle 6 and 2.2 for Vehicle 7. Therefore, Vehicle 7 was selected to execute the LC manoeuvre. At the same time, Vehicle 6 remained in follow-the-leader mode, awaiting the next opportunity for LC.

The proposed model can implement diverse LC decisions based on different LC scenarios and needs. It optimises vehicle conflicts while ensuring safety and making superior LC decisions that enhance the sustainability of the LC process.

4. CONCLUSIONS

This paper introduces two significant types of sustainable LC decision-making control models. It demonstrates their profound effectiveness in mixed-traffic environments of I-C vehicles through meticulous microscopic simulation experiments. The simulation results unveil the following:

1) The sustainable LC decision-making model for intelligent-connected environments showcases exceptional control performance, significantly enhancing evaluation indicators such as travel time, delay and speed. The optimal results are achieved when the input flow rate is Q3, and the LC ratio (r) is 0.2, leading to a remarkable 24.78% reduction in travel time, a substantial 23.21% decrease in average delay, and a notable 7.77% increase in average speed within the 0-3,600 s interval.
2) The sustainable LC decision-making model in a mixed-traffic environment maintains robust LC performance when the proportion of I-C vehicles exceeds 0.85. This model can execute different LC decisions based on various LC scenarios and demands, optimising vehicle conflicts while ensuring safety and making optimal LC decisions, thereby showcasing the practicality of lane changes.
3) It can be inferred that both the proposed models and the current simulation are influenced by factors such as traffic flow, LC ratio and the proportion of I-C vehicles, which align with actual traffic phenomena. This suggests that the models presented in this paper can effectively mirror the sustainable LC decision-making process in mixed-traffic environments, improve the operation efficiency of vehicles in mixed traffic environments and alleviate the pressure of road traffic flow.
4) This study still has certain limitations. The optimisation effect of the model decreases significantly when the proportion of I-C vehicles is lower than 0.85, and the impacts of extreme weather or special traffic events have not been fully considered. Future work will further explore lane-changing strategies for mixed traffic under low proportions of I-C vehicles to improve the model's adaptability and attempt to enhance the model for extension to complex traffic scenarios.

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