ISSN 1330-3651 (Print), ISSN 1848-6339 (Online)
https://doi.org/10.17559/TV-20220509091105
Original scientific paper

Research on the Safety Characteristics of Mixed Traffic Flow under Different Penetration Scenarios of Autonomous Vehicles

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Abstract: Since it will take time for vehicles to be fully automated, research on mixed traffic flow with different levels of vehicles will be the focus in the future. This paper takes L0, L1, L2, L3, L4, L5 vehicles as the research object, selects the Intelligent Diver Model (IDM), Adaptive Cruise Control (ACC) model, F-STCA model and LC2013 model to construct the vehicle's driving behaviour model, builds SUMO (Simulation of Urban Mobility) and Python co-simulation platform to conduct models simulation verification and safety analysis. The results show that: (1) The improved IDM model can realize the error caused by the heterogeneity of driver's personality; the improved ACC model can improve speed and keep a small change range with the interfering vehicle; the improved F-STCA model can expand the vehicle's lane-changing intention and reflect the driver's driving uncertainty. (2) The increase of penetration can increase the number of lane changes in basic sections, but in merging area, they are proportional at low density and inversely proportional at high density; penetration can reduce the occurrence of traffic conflicts and change the distribution of Time-To-Collision (TTC). This paper can predict the evolution law of traffic flow under the new technology, and provide a reference for future traffic planning and management.

Keywords: driving behaviour model; mixed traffic flow; penetration; SUMO

1 INTRODUCTION

According to statistics, the national motor vehicle ownership will reach 395 million in 2021, an increase of about 6.32% compared to 2020 [1]. While motor vehicles bring convenience to people, they also cause a series of negative social impacts. The application of automation technology in the transportation industry just plays an effective role in improving the safety, efficiency and energy consumption of vehicles [2]. Autonomous vehicles are intelligent machines that rely on sensors to obtain information, process information based on intelligent technology, and then replace part or all of human control of the vehicle. The Society of Automotive Engineers (SAE) divides its development process into six stages: L0 (manual driving), L1 (assisted driving), L2 (partial autonomous driving), L3 (conditional autonomous driving), L4 (advanced autonomous driving), L5 (full autonomous driving). "Intelligent Connected Vehicle Technology Roadmap 2.0" predicts that L2 and L3 autonomous will account for 50% in 2025, 70% in 2030, and L4 will account for 20% in 2030. In 2035, L5 will also begin to penetrate the market [7]. Therefore, the mixed traffic flow consisting of L0 (manual vehicles) and L1, L2, L3, L4 and L5 (different levels of autonomous vehicles) will become the normal traffic flow in the future, hereinafter referred to as M-DLAV (Manual-Different Levels of Autonomous Vehicles) mixed traffic flow. Due to the huge unknown impact of autonomous on the traditional transportation system, many scholars have conducted in-depth research on this problem. For example, from 1998 to 2003, Bose compared and analyzed the impact of autonomous penetration on traffic flow and energy consumption [8]. Bailey takes L2~L3 vehicles as the research object, establishes the following rules with the improved Intelligent Diver Model (IDM), and studies the queue length of road network with different penetration rate scenarios of autonomous based on AIMSUN [11]. Xiao described the driving behavior of manual vehicles and autonomous vehicles by quantifying model parameters, using SUMO (Simulation of Urban Mobility) simulation analysis of the impact of autonomous on traffic flow safety and efficiency [12]. It can be found that, for the simulation object, the scope of the level of the infiltrated autonomous vehicles is relatively limited, along with the development of automation technology, different levels of autonomous vehicles will become the whole object of research, for the research environment, the current research environment for analyzing the characteristics of mixed traffic flow is relatively simple, while the actual road environment is complex and changeable. The expressway is an important facility in traffic, and the degree of mutual interference between vehicles on different road sections is different. Therefore, this paper takes the expressway including the basic road section and the merging area as the research environment, establishes the M-DLAV mixed traffic flow model, builds the SUMO and Python co-simulation platform, and conducts the model simulation verification under the fixed penetration rate of autonomous and discusses the traffic flow safety under different penetration rate scenarios, so as to provide a reference for the new generation traffic environment and future traffic planning and management.

2 DEFINITION OF PENETRATION

This paper believes that the development of autonomous needs to go through a process from scratch, from less to more, from low-level to high-level, that is, the process of gradually infiltrating vehicles with increasing automation into the road. The penetration model can be classified from the perspective of time and space. The spatial penetration model refers to the ratio of the number of autonomous vehicles to the total number of vehicles in a certain road section at a certain time, and the time penetration model refers to the ratio of the number of autonomous vehicles to the total number of vehicles in a certain period of time in a certain road section. In this paper, based on the time penetration model, the ratio of all levels of autonomous driving to the total number of vehicles in the simulation period in the road segment is called the penetration rate. In order to simplify the model, assuming that the number of autonomous vehicles of different levels is the same, there is no degradation of vehicle performance. Therefore, regardless of the distribution of the autonomous space during driving, a group of autonomous of all levels during the simulation period in the road segment can be regarded as autonomous vehicle units (AVU) to achieve the purpose of overall modeling and analysis of different levels of autonomous. In order to ensure the validity of the data, the ratio of the total number of vehicles on the road to the number of elements of the autonomous vehicle unit is regarded as the total vehicle unit, and the ratio of the autonomous vehicle unit to the total vehicle unit is called the penetration rate of the autonomous vehicle unit (Autonomous Vehicle Unit Penetration, AVUP), which is equivalent to the sum of the penetration rates of autonomous vehicles at all levels. Fig. 1 is a form of M-DLAV mixed traffic flow vehicle distribution, Fig. 2 is a schematic diagram of AVU.

Figure 1 Schematic diagram of M-DLAV mixed traffic flow

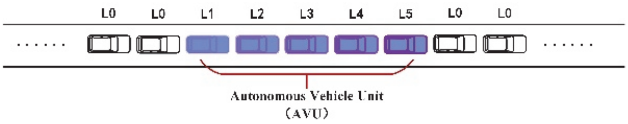


Figure 2 Schematic diagram of AVU

$$N_{\mathrm{AVU}} = \frac{1}{5}\left(N_{\mathrm{L1}} + N_{\mathrm{L2}} + N_{\mathrm{L3}} + N_{\mathrm{L4}} + N_{\mathrm{L5}}\right) \tag{1}$$

$$N_{\mathrm{V}} = \frac{1}{5}\left(N_{\mathrm{L0}} + N_{\mathrm{L1}} + N_{\mathrm{L2}} + N_{\mathrm{L3}} + N_{\mathrm{L4}} + N_{\mathrm{L5}}\right) \tag{2}$$

$$\begin{aligned} \mathrm{AVUP} &= \frac{N_{\mathrm{AVU}}}{N_{\mathrm{V}} + N_{\mathrm{AVU}}} \times 100\% = \\ &= \frac{N_{\mathrm{L1}} + N_{\mathrm{L2}} + N_{\mathrm{L3}} + N_{\mathrm{L4}} + N_{\mathrm{L5}}}{N_{\mathrm{L0}} + N_{\mathrm{L1}} + N_{\mathrm{L2}} + N_{\mathrm{L3}} + N_{\mathrm{L4}} + N_{\mathrm{L5}}} \times 100\% \end{aligned} \tag{3}$$

3 CONSTRUCTION AND ANALYSIS OF VEHICLE DRIVING BEHAVIOR MODEL IN FIXED PENETRATION SCENARIO

3.1 Modeling Ideas and Basic Assumptions of the Model

Fig. 3 is the construction framework of the vehicle driving behavior model. Due to the difference between the driving subjects of the vehicle, the artificially driven vehicle is susceptible to the influence of the external environment, and it presents the characteristics of inaccurate and untimely information transmission, and autonomous vehicle relies on automation technology to improve the speed and accuracy of vehicle information processing and control execution. Based on the differences of vehicle driving subjects, this paper determines the IDM model influenced by the driver's personality and the Adaptive Cruise Control (ACC) model improved by the variable time headway (VTH) strategy represented by the saturation function,chooses F-STCA and LC2013 model to describe the lane changing rules of manual vehicles and autonomous vehicles respectively. Based on the F-STCA model, the range of the driver's lane changing intention is expanded with the advantage of speed, and the model is improved by considering the low probability of emergency braking of the lane changing vehicle after a successful lane change, and defines their own lane changing rules according to the difference of road segment types. Finally, the driving behavior of different levels of autonomous vehicles is characterized by calibrating the relevant parameters of the model. In order to simplify the simulation model, this paper proposes the following three assumptions: 1) There is no difference in the internal parameters of various types of vehicles. 2) Manually driven vehicles only consider free lane change and forced lane change behavior, not overtaking behavior. 3) The road environment is not disturbed by external conditions such as bad weather, and the vehicle runs in an ideal state.

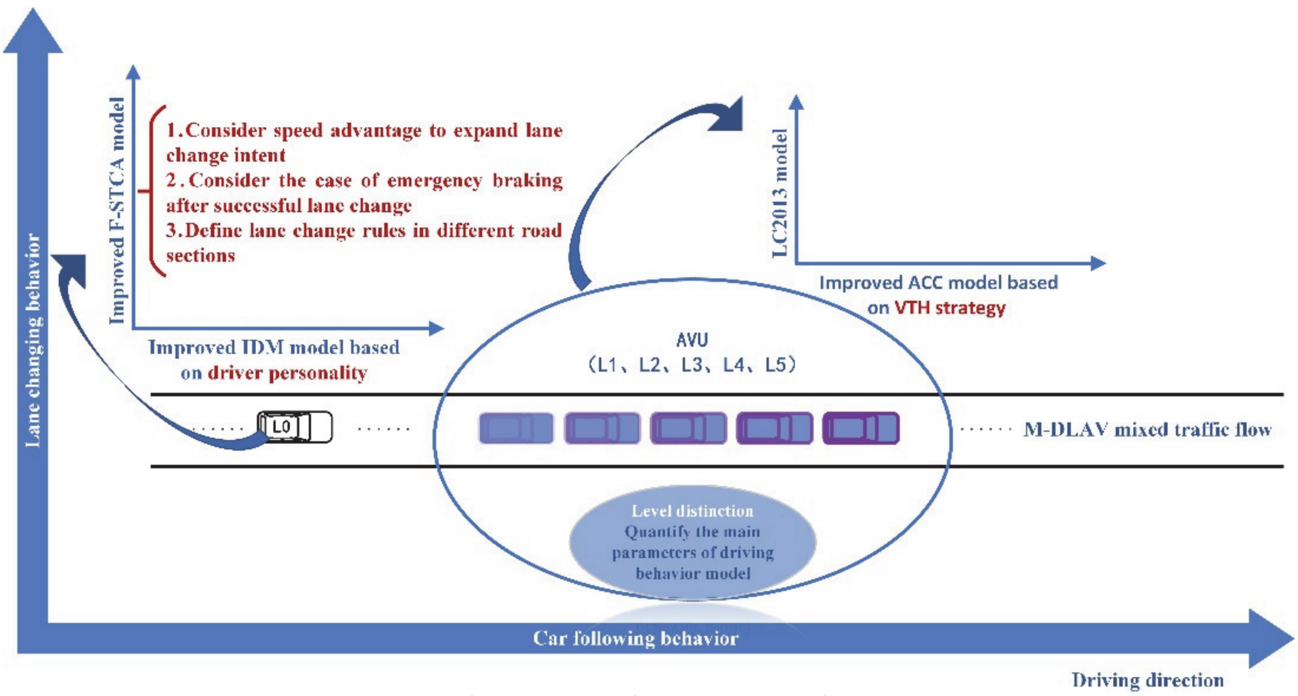


Figure 3 Schematic diagram of driving behavior model framework

3.2 Modeling of Vehicle Following Behavior
3.2.1 IDM Model for Manual Vehicles

The IDM model proposed by Treiber [13] is based on the decision-making basis of the distance and speed of the front and rear vehicles, and outputs a continuous acceleration function [14]. The formula is as follows:

$$a_n(t) = a_0\left(1-\left(\frac{v_n(t)}{v_0}\right)^{\delta}-\left(\frac{s^*\left(v_n(t),\Delta v_n(t)\right)}{s_n(t)}\right)^2\right) \tag{4}$$

$$\begin{cases} s_n(t) = x_{n-1}(t)-x_n(t)-l \\ \Delta v_n(t) = v_n(t)-v_{n-1}(t) \\ s^*\left(v_n(t),\Delta v_n(t)\right) = s_0+\max\left(0, v_nT+\dfrac{v_n(t)\Delta v_n(t)}{2\sqrt{a_0b}}\right) \end{cases} \tag{5}$$

In the formula, $a_n(t)$: acceleration, a_0 : maximum acceleration, $v_n(t)$: vehicle speed, v_0 : free flow velocity, δ: acceleration index, usually take 4, $s^*\left(v_n(t),\Delta v_n(t)\right)$: expected space headway, $s_n(t)$: actual space headway between two vehicles, $x_n(t)$: target vehicle displacement, $x_{n-1}(t)$: front vehicle displacement, l: vehicle length, $\Delta v_n(t)$: speed difference between two vehicles, $v_{n-1}(t)$: front vehicle speed, s_0 : minimum safe space headway, T: minimum safe space headway, b: comfortable deceleration,the values of the model related parameters are shown in Tab. 1.

Table 1 Relevant parameters of IDM model

Parameter	Value
Max acceleration a_0	1 m/s^2
Comfortable deceleration b	1.5 m/s^2
Expect speed v_0	33.33 m/s
Reaction time T	1 s
Min safe space headway s_0	2.5 m

Due to the constraints of speed and distance between the moving vehicles, the driver will manipulate his own motion state the next time on the basis of comprehensively considering the speed difference and distance difference with the preceding vehicle during driving [15]. There are differences in the estimated abilities of drivers with different personalities. Many scholars choose to introduce the driver's psychological or physiological parameters into the acceleration and deceleration motion rules of the traditional cellular automata (CA) model to describe the difference in the driver's driving behavior [16]. In this paper, based on the research ideas of previous literature, the driver personality parameter λ is introduced into the IDM model to represent the driving characteristics of the driver of the manuallydriven vehicle, as shown in the formula:

$$\Delta v_n(t) = v_n(t)-\lambda v_{n-1}(t) \tag{6}$$

$$s_n(t) = \lambda\left(x_{n-1}(t)-x_n(t)-l\right) \tag{7}$$

$\lambda v_{n-1}(t)$ represents the driver's estimate of the speed of the preceding vehicle, $\lambda\left(x_{n-1}(t)-x_n(t)-l\right)$ represents the driver's estimate of the distance to the vehicle in front. If λ is too small, it is easy to cause the rear vehicle to misjudge the speed and position of the preceding vehicle, therefore take $\lambda \in [0.5, 0.9]$, The larger λ is, the more risky the driver is.

3.2.2 ACC Model for Autonomous Vehicles

The ACC model proposed by Shladover et al. includes four strategies: speed control, distance control, distance approach control and collision avoidance control [19]. The speed control strategy means that when there is no vehicle in front of the target vehicle or the distance from the vehicle in front is greater than 120 meters, the preset vehicle speed is used as the control target, and the preset speed and real-time speed error are used as control variables, so that the vehicle can run stably at the preset speed. The formula is as follows:

$$a_n(t+1) = k_1\times\left(v_d-v_n(t)\right) \tag{8}$$

In the formula, $a_n(t+1)$: acceleration at the next simulation time, v_d : desired speed, $v_n(t)$: current speed, k_1 : control gain that determines the jerk deviation rate,therefore take 0.4 s^{-1}.

The distance control strategy means that when the distance deviation and speed deviation are less than 0.2 m and 0.1 m/s at the same time [20], the acceleration of the vehicle at the next time will be adjusted according to the distance deviation and speed deviation from the preceding vehicle. The formula is as follows:

$$a_n(t+1) = k_2\times e_n(t)+k_3\times\left(v_{n-1}(t)-v_n(t)\right),\ k_2, k_3 >0 \tag{9}$$

$$e_n(t) = x_{n-1}(t)-x_n(t)-d_h \tag{10}$$

In the formula, $e_n(t)$: distance deviation between the target vehicle and the preceding vehicle, $x_{n-1}(t)$: front vehicle displacement, $x_n(t)$: target vehicle displacement, d_h : desired distance, $v_{n-1}(t)$: speed of the vehicle ahead, $v_n(t)$: target vehicle speed, k_2, k_3: control gain factor for pitch deviation and speed deviation, k_2 = 0.23 s^{-2}, k_3 = 0.07 s^{-1}.

The distance approach control strategy refers to the case when the distance between the target vehicle and the preceding vehicle is less than 100 m, the algorithm logic is realized by modifying the parameters of the distance control strategy, that is, making k_2 and k_3 equal to 0.04 s^{-2} and 0.8 s^{-1} respectively. When the distance is between 100 m and 120 m, convert to the previous control strategy. The collision avoidance strategy is that when the distance between the target vehicle and the preceding vehicle is less than 100m, the distance deviation is negative, and the speed deviation is less than 0.1 m/s, let k_2 and k_3 be 0.8 s^{-2} and 0.23 s^{-1} respectively to avoid vehicle collisions.

Distance control determines the efficiency and safety of road traffic. Typical variable distance control strategies include CTH (Constant Time Headway) strategy and VTH strategy. The CTH strategy refers to obtaining the desired vehicle distance through a constant headway, and the VTH strategy means that the headway changes according to the speed of two adjacent vehicles. The formula is as follows:

$$t_h = t_0 - k_v v_r \tag{9}$$

In the formula,t_h: variable time headway,t_0: basic time headway,k_v: time headway parameters, v_r: the relative speed of the two vehicles,v_{n-1}: speed of the vehicle ahead,v_n: target vehicle speed. If the speed of the preceding vehicle is much lower than the target vehicle speed, t_h will become very large,reducing the utilization rate of the road; if it is much greater than the target vehicle speed, t_h will become very small, making it difficult to ensure safety. According to the saturation function proposed by Yanakiev et al. to keep the time headway in a reasonable range [21], the maximum value $t_{\max}$ is set as the fixed time headway value of each level of autonomous, and the minimum value is the fixed time headway value of the highest level of autonomous. According to the relevant literature, the fixed time headway value of each level of autonomous is taken as 0.95, 0.9, 0.8, 0.7 and 0.6 [23] in order from low to high. The desired vehicle distance is calculated as follows:

$$t_h = \operatorname{sat}(t_0 - k_v v_r) = \begin{cases} t_{\max} & \text{if } \ t_0 - k_v v_r \geq t_{\max} \\ t_0 - k_v v_r & \text{if } \ 0.6 < t_0 - k_v v_r < t_{\max} \\ 0.6 & \text{if } \ \text{otherwise} \end{cases} \tag{10}$$

The main influencing parameters of the car-following model are reaction time, space headway, minimum safe distance, driver imperfection coefficient and vehicle acceleration and deceleration performance. Among them, the driver defect value decreases with the improvement of automatic driving technology, since the vehicle starts from the L4 level, the driving subject changes from the driver to the automatic driving system, so it can be considered that since the L4 level, the vehicle drives with 0 defects, and it is generally believed that the minimum headway and distance of autonomous are significantly smaller than those of manual vehicles. The minimum headway of manual vehicles is generally 0.9 s to 2 s, and that of autonomous can reach 0.3 to 0.6 s [22]. Therefore, combined with relevant literature research [23], this paper sets the minimum time headway of L5 level autonomous as 0.6 s, the minimum time headway of manual vehicles is 1 s, and the L1~L4 level vehicles are set in the range of 0.6~1 s. The specific parameter values settings are shown in Tab. 2.

Table 2 Relevant parameters of ACC model

Parameter	Describe	Value					
		default	L1	L2	L3	L4	L5
Sigma	Driver defect value	0.5	0.4	0.3	0.2	0	0
Tau	Min fixed time headway / s	1.0	0.95	0.9	0.8	0.7	0.6
MinGap	Min space headway / m	2.5	2.5	2	1.5	1.2	1
Accel	Max acceleration / $m{\cdot}s^2$	2.6	2.6	2.6	2.6	2.6	2.6
Decel	Comfortable deceleration / $m{\cdot}s^2$	4.5	4.5	4.5	4.5	4.5	4.5
MaxSpeed	Max speed m/s	55.55	33.33	33.33	33.33	33.33	33.33

3.3 Modeling Vehicle Lane Changing Behaviour
3.3.1 F-STCA Model of Manual Vehicles

(1) F-STCA model description

The Symmetric Two-1ane Cellular Automata (STCA) model rules proposed by Chowdhury et al. are shown in Tab. 3 [24]:

Table 3 STCA model rules

Lane changing motivation	$d_n(t) < \min(v_n(t) + a_n, v_{n,\max})$, $d_{n,\text{other}}(t) > d_n(t)$
Safe lane change conditions	$d_{n,\text{back}}(t) > d_{\text{safe}}$, $d_{\text{safe}} = v_{\max}$

In the formula, $d_n(t)$: the distance between the target vehicle and the vehicle in front of the lane, $v_n(t)$: target vehicle speed, a_n : maximum acceleration, $v_{n,\max}$: maximum speed, d_{safe} : safe distance, $d_{n,\text{other}}(t)$: the distance between the target vehicle and the vehicle in front of the target lane, $d_{n,\text{back}}(t)$: the distance between the target vehicle and the vehicle behind the target lane, but there will be cases where the lane-changing conditions are met but not lane-changing, so the lane-changing probability is introduced.

In order to be more in line with the actual situation, Wang Yongming et al. introduced the risk of changing lanes in the judgment of the safety conditions of the following vehicles, and proposed the F-STCA model [25], which represents the conflict between the vehicles changing lanes and the rear vehicles changing into the lanes, and took $d_\delta \geq 1$ as the buffer distance without collision. Fig. 4 shows the lane changing scene of F-STCA.

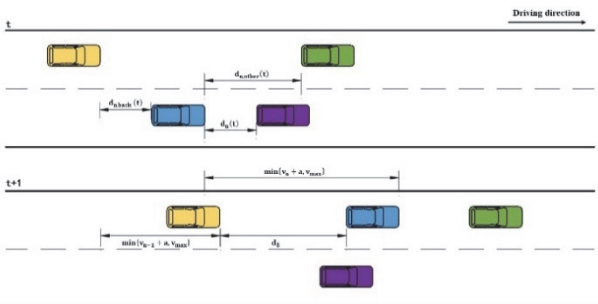


Figure 4 F-STCA lane changing model

$$d_{n,\text{back}} + \min\{v_n + a, v_{max}\} = \min\{v_{n-1} + a, v_{\max}\} + d_\delta \tag{11}$$

Let $d_{\delta} \geq 1$,

$$d_{n,\mathrm{back}} \geq 1+\min\left\{v_{n-1}+a, v_{\max}\right\}-\min\left\{v_n+a, v_{\max}\right\} \quad (12)$$

To improve safety, assuming that the vehicle behind the target lane is moving at the maximum speed $v_{\max}$, then:

$$d_{n,\mathrm{back}} \geq 1+v_{\max}-\min\left\{v_n+a, v_{\max}\right\} \quad (13)$$

(2) Improved F-STCA model

Since the intention of changing lanes in this model only relies on the advantage of driving space, it does not consider the advantage of speed, the judgment rules are limited, and it does not consider the situation that the vehicle changing lanes will take emergency braking after a successful lane change. Therefore, on the basis of this model, this paper expands the range of vehicle lane-changing intentions with the advantage of speed, and improves the model by considering the situation that vehicles in lane changing will take emergency braking after a successful lane change,and use the random braking probability P_{brake} to describe the low probability of the event happening. In order to simplify the model, the random slowing effect value introduced in the STCA model to describe the driver's driving behavior is easily affected by the physical environment or mentality is used.

According to the previous literature, take $P_{\mathrm{brake}} = 0.25$ and the rules are shown in Tab. 4:

Table 4 Improved F-STCA model rules

Lane changing motivation	$\begin{cases} d_n(t) < \min\left(v_n(t)+a_n, v_{n,\max}\right) \\ v_{n,\mathrm{other}} > \theta \times v_{n-1} \end{cases}$, $d_{n,\mathrm{other}}(t) > d_n(t)$
Safe lane change conditions	$d_{n,\mathrm{back}} \geq 1+v_{\max}-\dfrac{v_n^2}{2b_n}$, $P_{\mathrm{brake}}=0.25$ $d_{n,\mathrm{back}} \geq 1+v_{\max}-\min\left\{v_n+a, v_{\max}\right\}$

In the formula, θ is a constant coefficient to prevent vehicles from changing lanes frequently, and its value is 1.5 [26]. b_n: the emergency braking deceleration of the target vehicle.

(3) Definition of lane changing rules for vehicles on different road sections

The lane changing behavior mechanism of vehicles on different road sections is slightly different. For example, vehicles in basic road sections generally only use speed and space advantages to stimulate the generation of free lane-changing motives, while bottleneck sections also generate forced lane-changing motives. Therefore, this paper sets different lane-changing rules for the basic road section and the merging area considering the difference of road segment types. The decision-making diagram is shown in Fig. 5.

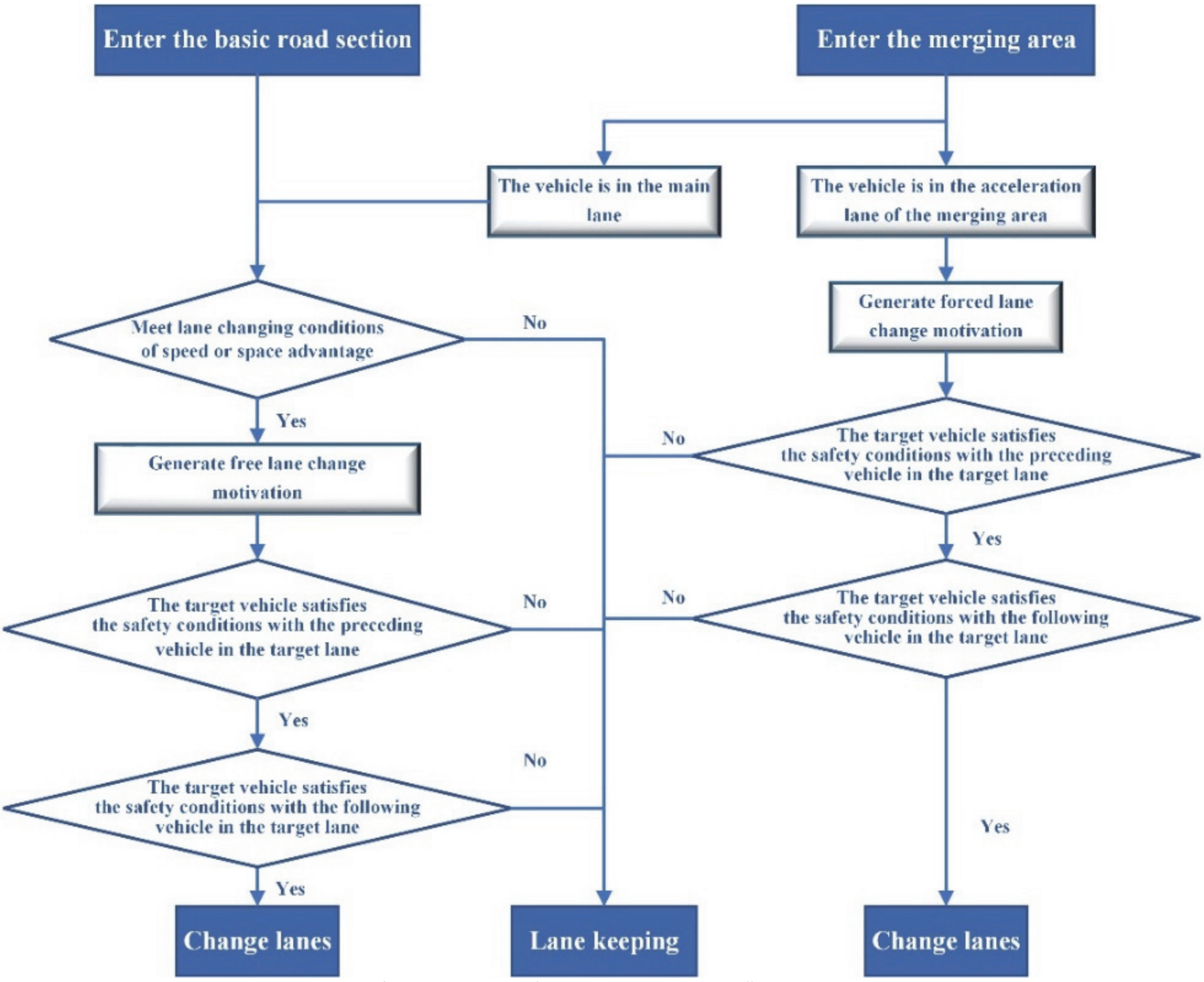


Figure 5 Schematic diagram of lane changing decision in different road sections

Relevant studies have shown that there is a critical point in the occurrence of forced lane changes. Before the critical point, drivers will continue to look for opportunities to change lanes. The closer to the critical point, the lower the safety requirements. There is a logistic trend between the urgency of changing lanes and the position from the critical lane-changing point [27]. Therefore, in this model, the Richards curve is used to describe the driver's mentality of forcibly changing lanes when the vehicle is driving in the merging area. The original equation is as follows:

$$W = A\left(1 - B \times \mathrm{e}^{-k \times t}\right)^{\frac{1}{1-m}} \tag{16}$$

In the formula, A: maximum value, B: initial state parameter, K: parameter determined by the speed of the curve change, m: parameter determined by the curve trend. When m is 2, the logistic curve can be obtained [30], so the urgent value of lane change is calculated as follows:

$$W = 1 - \left(1 + 350 \times \mathrm{e}^{-0.3 \times \mathrm{gap}}\right)^{-1} \tag{14}$$

The smaller the gap from the critical lane change point, the larger the eager value W. Among them, the value of B is 350 m from the connection point between the junction area and the main road to the end of the acceleration lane in the research scene of this paper. The lane changing rules of vehicles in different road sections are defined as shown in Tab. 5.

Table 5 Lane changing rules of vehicles in different road sections

Road section type		Lane changing motivation	Safe lane change conditions
Basic road section		$\begin{cases} d_n(t) < \min\left(v_n(t) + a_n, v_{n,\max}\right) \\ v_{n,\mathrm{other}} > \theta \times v_{n-1} \end{cases}$	$d_{n,\mathrm{back}} \geq 1 + v_{\max} - \frac{v_n^{\,2}}{2b_n}$, $P_{\mathrm{brake}} = 0.25$
		$d_{n,\mathrm{other}}(t) > d_n(t)$	$d_{n,\mathrm{back}} \geq 1 + v_{\max} - \min\{v_n + a, v_{\max}\}$
Merging area	Main lane	Basic road section lane changing rules	
	Acceleration lane	$d_{n,\mathrm{other}}(t) > d_n(t)$	$d_{n,\mathrm{back}} \geq 1 + (1-W)\left(v_{\max} - \frac{v_n^{\,2}}{2b_n}\right)$, $P_{\mathrm{brake}} = 0.25$ $d_{n,\mathrm{back}} \geq 1 + (1-W)\left(v_{\max} - \min\{v_n + a, v_{\max}\}\right)$

3.3.2 LC2013 Model of Autonomous Vehicles

The LC2013 lane change model established by Erdmann is based on the vehicle path and the environmental conditions of the current and previous simulation time to calculate the lane change decision at the next simulation time. The model has a variety of lane changing requirements, including strategic, cooperative, tactical and mandatory [31], and their meanings are shown in Tab. 6:

Autonomous tends to drive at higher speeds and is able to plan early and make changes when the current environment does not meet the desired driving state or driving path requirements [31]. Therefore, the higher the level of autonomous driving, the lower the willingness to return to the right lane after overtaking and the higher the tactical willingness to change lanes to the left, and the higher the willingness to make strategic lane changes. By modifying the four lane-changing motivation-related parameters in the model, the lane-changing behavior of autonomous vehicles of different levels can be directly reflected, as shown in Tab. 7.

Table 6 Lane changing types of LC2013 model

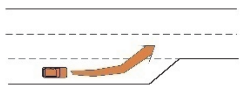
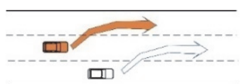
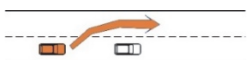
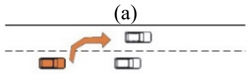
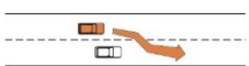
Lane change type	Meaning	Representative diagram	Emoticons (Yellow vehicle: target vehicle)
Strategic lane changing behavior	There is no connection between the driving lane and the driving path		It indicates that the target vehicle is approaching the end of the driving lane. If the target vehicle wants to reach the end of the driving path, it must execute the strategic lane change behavior.
Cooperative lane changing behavior	Being notified of obstructing a nearby vehicle while driving		It Indicates that the target vehicle finds itself obstructing the implementation of lane change of vehicles on the right lane, and needs to adjust its own state to provide enough lane changing space for the right vehicle.
Tactical lane changing behavior	For the pursuit of high speed or more comfortable space	 (a)  (b)	Both (a) and (b) indicate that the speed of the target vehicle is greater than that of the preceding vehicle, but (a) indicates that there is no vehicle in the adjacent lane, while (b) indicates that there is a vehicle, and it is assumed that the speed of the preceding vehicle in the adjacent lane is greater than that of the target vehicle.
Forced lane changing behavior	Return to the original lane after overtaking by traffic regulations		The white vehicle is about to be overtaken, indicating that the target vehicle is about to overtake and return to the original lane.

Table 7 Relevant parameters of LC2013 model

Parameter	Describe	Value					
		Defaults	L1	L2	L3	L4	L5
lcStrategic	Strategic lane change willingness, the higher the value, the earlier the lane change	1	1	1.2	1.6	3	4
lcCooperative	Cooperative lane change willingness, the higher the value, the stronger the willingness	1	1	1	1	1	1
lcSpeedGain	Tactical lane change willingness, the higher the value, the more frequent the lane change	1	1	1.2	1.6	5	5
lcKeepRight	Willingness to follow traffic laws, the higher the value, the sooner you change lanes to the right	1	2	2	1.8	1.2	1

4 BUILDING A HYBRID TRAFFIC FLOW SIMULATION PLATFORM INTEGRATING SUMO AND PYTHON

SUMO is a micro open source multi-modal traffic simulation software developed by the German Aerospace Center in 2001 [33]. Due to its good development, high running speed, wide application, multi-source road import such as VISSIM and OSM and complete modules, it has become one of the most widely used traffic simulation systems. The implementation of SUMO simulation requires at least three files: road (*.net.xml), path (*.rou.xml) and configuration (*.sumocfg). If you want to achieve specific simulation effects, such as adding speed limit signs or outputting required simulation data, you need to create additional files (*.add.xml). A road file is a description of the road a vehicle travels on,the path file is a description of the vehicle, vehicle type, driving track and rules and other related information,configuration files are files that configure roads, paths, and detectors, and add simulation parameters such as simulation step size. Additional files are non-essential files for the simulation to run.

As an object-oriented interpretive programming language, Python has simple and easy-to-read code, wide application, rich function libraries, and easy to implement various models and algorithms. Most of the source code of SUMO is developed in Python, and a special interface TraCI is reserved for Python. Real-time control of the simulation process can be realized. Therefore, this paper adopts Python as the programming environment. The simulation process is shown in Fig. 6:

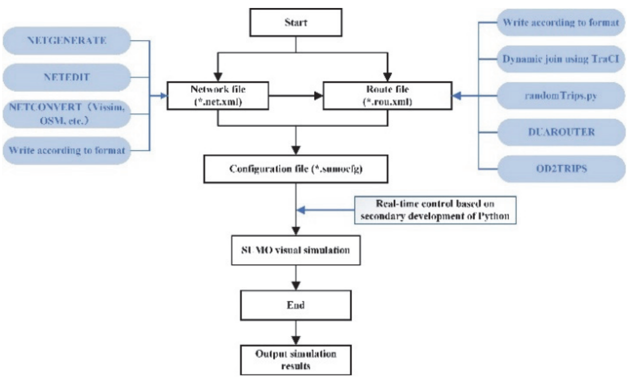


Figure 6 Simulation flow chart of SUMO

The simulation platform of this paper is for the safety research of M-DLAV mixed traffic flow, so it needs to realize the functions of scene visualization, algorithm control, related data recording and simulation result evaluation. The system framework is shown in Fig. 7.

The system framework is divided into three modules: input, simulation and output. The underlying structure of the input module is SUMO, which can input basic traffic information and initial vehicle status, etc.,the underlying architecture of the simulation module is Python, which implements algorithm control according to the input module information and generates relevant data,the output module is to output the data obtained by the simulation module in a specific format, and the input module and the simulation module are connected through TraCI.

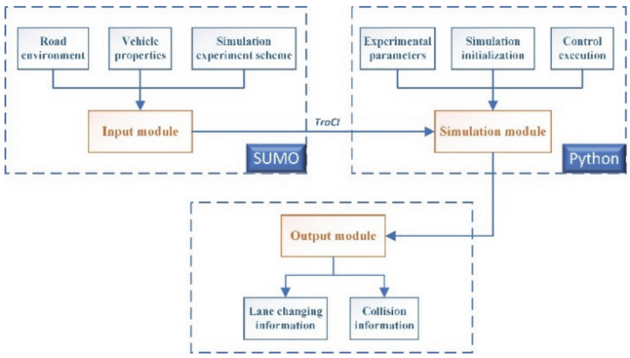


Figure 7 Schematic diagram of the simulation platform system framework

5 SIMULATION REALIZATION AND ANALYSIS OF THE IMPROVED MODEL UNDER THE FIXED PENETRATION SCENARIO

5.1 Simulation Realization and Analysis of an Improved Car-Following and Lane-Changing Model

5.1.1 Improved IDM Car Following Model

By comparing the AVUP = 0 scene, the average road speed and loss time are obtained by different models to analyze the effectiveness of the model. The scheme is designed as follows: acceleration a = 1 m/s^2, deceleration b = 1.5 m/s^2, emergency deceleration is 9 m/s^2, vehicle length is 5 m, the maximum travel speed is 33.33 m/s, a 10 km one-way single-lane section is constructed and the design speed of the road section is 33.33 m/s. E1 and E2 detectors with length of 2 km and 7 km are added at 5 m, 1 km and 3 km away from the starting position of the section respectively. The number of vehicles is 100, the simulation time is 1200 s, the simulation step is 0.1 s, and the collection frequency is 60 steps to obtain vehicle data in the last 7 km road section, as shown in Fig. 8 and Fig. 9. Among them, the driver's personality parameter is randomly selected from 0.5 to 0.9.

Fig. 8 and Fig. 9 are the trend graphs of the average speed of the road and the time of road loss, which mainly analyze the influence of the driver's personality on the traffic efficiency. It can be seen from the figure that after considering the influence of the driver's personality, the average road speed decreases and the road loss time increases as a whole. This is because this paper believes that the driver's personality directly affects the driver's estimation of the motion state of the preceding vehicle during driving. Conservative drivers always think that the driving speed of the preceding vehicle is low, they need to maintain a lower speed or a greater distance to ensure safety, so the average speed of the road decreases, and the time lost to not meeting the desired speed increases.

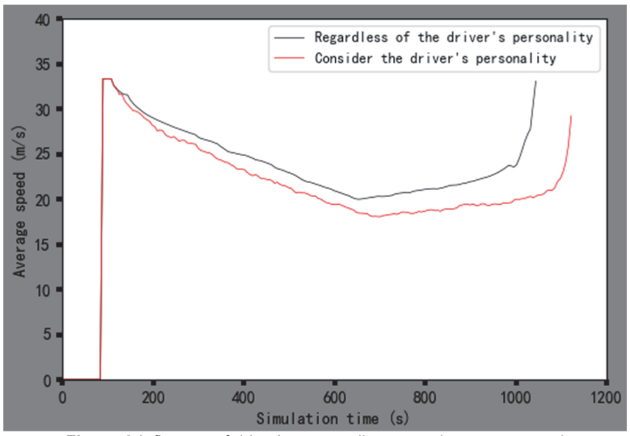


Figure 8 Influence of driver's personality on road average speed

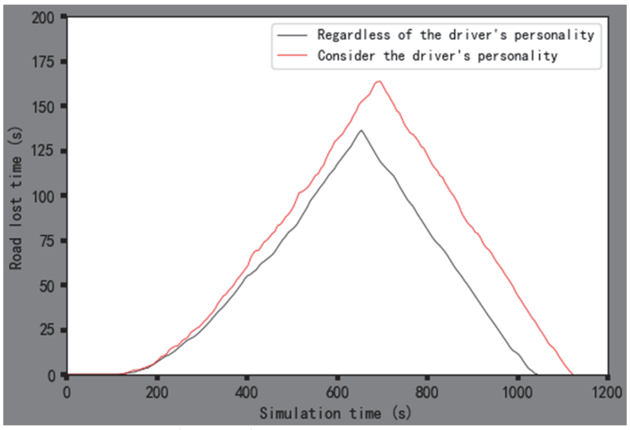


Figure 9 Influence of driver's personality on road loss time

5.1.2 Improved ACC Car Following Model

Simulation of steady-state vehicle-following disturbance is the most effective method to compare the variation of vehicle speed with different time-spacing strategies. In this paper, by presetting the motion state of the interference vehicle or the changing state of the road scene during the simulation process,obtain the state evolution process of the entire fleet and individual vehicles under different strategies,investigate the response ability and tracking ability of vehicles to environmental changes under different time-distance strategies from the whole and part. The scheme design is as follows: acceleration a = 1 m/s^2, deceleration b = 1.5 m/s^2, emergency deceleration is 9 m/s^2, vehicle length is 5 m, and the maximum travel speed is 33.33 m/s.

(1) Overall analysis scheme design: the length of single road section is 3 km,and the design speed of the road section is 33.33 m/s, add E1 detectors at 5 m, 500 m and 1 km from the starting position of the road section, add E2 detectors with lengths of 500 m and 2 km, the number of vehicles is 500, AVUP = 1, simulation time is 500 s, simulation step size is 0.1 s, set the speed limit interference signal of the road section: during the period of 100 s to 500 s, with a span of 50 s, the speed limit changes from 33.33 m/s to 10 m/s, and then from 10 m/s to 33.33 m/s until the end of the simulation, taking 10 steps as the collection frequency, get the average speed of the road in the last 2 km under different strategies, as shown in Fig. 10.

(2) Local analysis scheme design: taking L1-level autonomous as an example,building a 21 km long one-way single-lane section with a design speed of 33.33 m/s, the E1 and E2 detectors with lengths of 500 m and 2 km are added at 5 m, 500 m and 1 km from the starting position of the road segment respectively. The number of vehicles is 3, the simulation time is 500 s, and the simulation step is 0.1 s.The lead vehicle is used as the jamming vehicle and sets the speed fluctuation jamming signal. During the simulation period, the speed of the control interference vehicle changed from 33.33 m/s to 10 m/s, and then from 10 m/s to 33.33 m/s until the end of the simulation,taking 10 steps as the collection frequency, the change of single speed in the last 20 km under different strategies is obtained, as shown in Fig. 11.

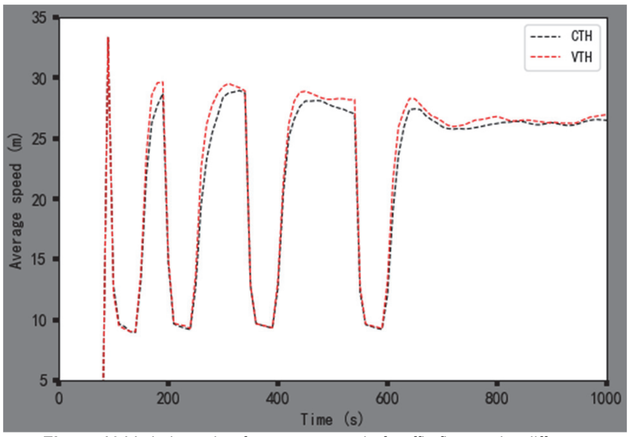


Figure 10 Variation rule of average speed of traffic flow under different strategies

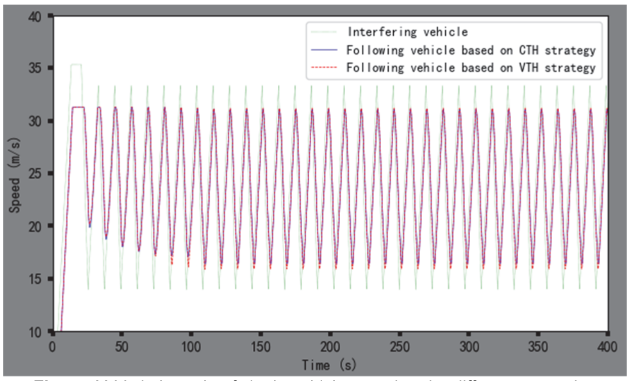


Figure 11 Variation rule of single vehicle speed under different strategies

Fig. 10 and Fig. 11 show the changes of the average speed of the traffic flow and the individual vehicle speed under different time headway strategies. First of all, the average speed of the traffic flow fluctuates in the range of 10 m/s to 33.33 m/s under the influence of the road speed limit interference signal and the speed of the following vehicle under the influence of the interference vehicle. This is because the emergency deceleration of the vehicle under different time headway strategies is the same, which is 9, so the vehicle will brake urgently in a very short time and reach the speed limit standard. Secondly, it can be seen from Fig. 10 that during the acceleration process of the vehicle, because the VTH strategy makes the time headway obtained by the driver less than or equal to the fixed time headway value, the expected vehicle distance is reduced, resulting in a larger vehicle distance error, and the vehicle can obtain higher acceleration even to the desired speed. It can be seen from Fig. 11 that in each speed change cycle, the distance between the vehicle and the preceding vehicle based on the VTH strategy remains small, indicating that the degree of influence by the preceding vehicle is weak. Corresponding to real life, drivers at the same road section position expect different distances, and they think that the distance error with the preceding vehicle will be different. Among them, the driver who expects a small distance between the vehicles will think that there is a large distance error with the vehicle in front, and then take a large acceleration to drive, and try to maintain a small distance from the vehicle in front.

5.2 Simulation Realization and Analysis of Improved F-STCA Lane Changing Model

A one-way two-lane road section with a length of 8 km is established, the design speed of the road section is 33.33 m/s and 27.78 m/s, the traffic flow is 1000 veh/h, AVUP = 0, the simulation time is 3600 s, the simulation step is 0.1 s, the collection frequency is 60 simulation steps, and the data within the last 6km is obtained.

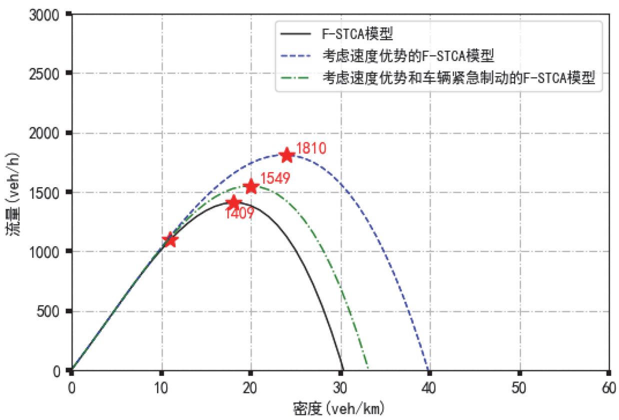


Figure 12 Road capacity analysis under different models

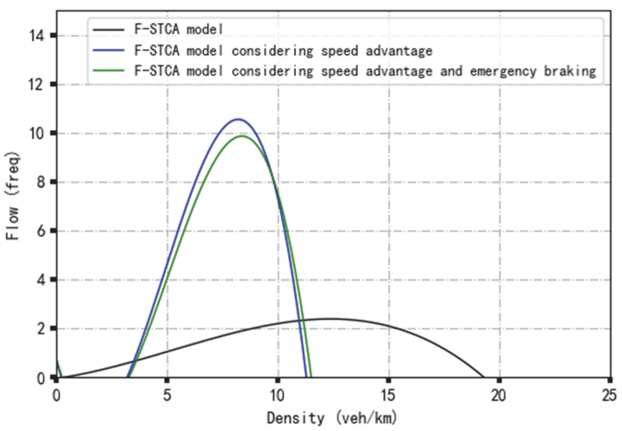


Figure 13 Relationship between the number of lane changes and density under different models

Fig. 12 and Fig. 13 show the variation of road capacity and lane changing times with traffic density under different models. It can be seen from Fig. 12 that when the traffic density is less than about 11 veh/km, expanding the lane-changing intention with the speed advantage has little effect on the driver's driving behavior. Corresponding to real life, when the traffic flow density is small, drivers can generally drive at expected speed without changing lanes; when the traffic density is greater than 11 veh/km, considering the speed advantage, the traffic flow on the road can be significantly increased. Corresponding to Fig. 13, it can be found that the number of vehicle lane changes increases, indicating that drivers frequently change lanes in order to increase the vehicle speed or a more comfortable driving environment, which speeds up the overall speed of traffic flow and improves road flow. Considering the low probability event of emergency braking of lane-changing vehicles, both the peak flow and the number of lane changes are reduced, which also conforms to the reality that not all drivers will continue to fulfill their needs after lane changes, reflecting the uncertainty of drivers in the driving process.

6 SIMULATION AND ANALYSIS OF SAFETY CHARACTERISTICS OF M-DLAV MIXED TRAFFIC FLOW UNDER DIFFERENT PENETRATION SCENARIOS

6.1 Simulation Scene Realization

Fig. 14 and Fig. 15 are the schematic diagram of the simulated road section and the detector settings for the M-DLAV mixed traffic flow safety research in this paper, respectively. The section with a length of 500 m in the middle of section 2 in Fig. 14 is selected as the research environment for the basic road section, and the section 3 as the research environment of the merging area. The simulation start time is 0 s, the end time is 3600 s, and the simulation step size is 0.1 s. E1 and E2 detectors are used, and the relevant data information of the studied road section is counted every 10 steps.

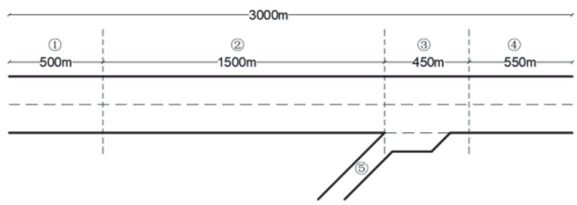


Figure 14 Schematic diagram of road scene

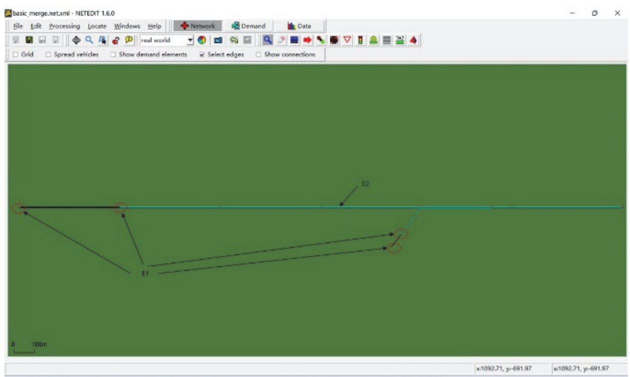


Figure 15 Schematic diagram of detector setting

Based on the idea of holistic modeling, this paper makes the following settings for AVUP: based on 0% and

20% as the step, there are 6 groups of 0%, 20%, 40%, 60%, 80%, and 100% with different ratios, and other conditions remain unchanged. Correspondingly, the penetration rate of each level of autonomous in each AVUP is 0%, 4%, 8%, 12%, 16%, and 20%. The experimental protocol is shown in Tab. 8.

Table 8 Traffic composition

AVUP	Vehicle composition					
	Different levels of autonomous vehicles					Manual vehicles (L0)
	L1	L2	L3	L4	L5	
0%	0%	0%	0%	0%	0%	100%
20%	4%	4%	4%	4%	4%	80%
40%	8%	8%	8%	8%	8%	60%
60%	12%	12%	12%	12%	12%	40%
80%	16%	16%	16%	16%	16%	20%
100%	20%	20%	20%	20%	20%	0%

6.2 Analysis of Simulation Results

6.2.1 Lane Change Frequency

The ratio of the number of lane-changing behaviors to the total number of vehicles on the road segment per unit time is called the lane-changing frequency. Fig. 16 is a diagram of the lane-changing frequency of vehicles in different AVUP scenarios. The abscissa in the figure is the penetration rate of autonomous vehicle units, and the ordinate is the lane-changing frequency of the whole road in the simulation time under different road sections.

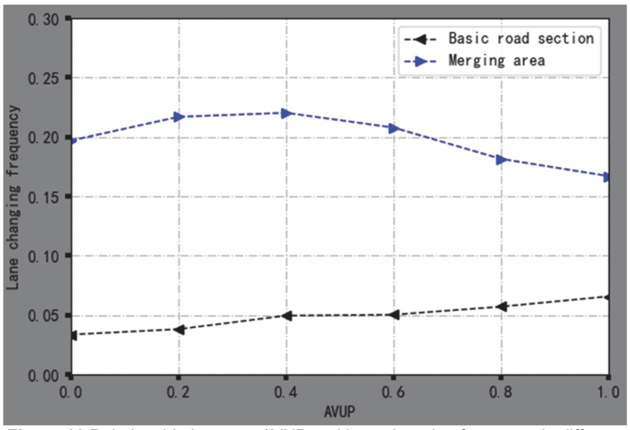


Figure 16 Relationship between AVUP and lane changing frequency in different road sections

It can be seen from the figure that the frequency of vehicle lane changing is affected by AVUP, but different road sections are affected to different degrees. The lane-changing frequency of vehicles on the basic road section is positively correlated with AVUP, and the scene with AVUP of 1 has the highest lane-changing frequency, however, in the merging area, when the AVUP exceeds 0.4, the lane-changing frequency is negatively correlated with the AVUP. The higher the AVUP, the lower the lane-changing frequency. This is mainly because: 1) The threshold of autonomous for lane change safety is lower than that of manual vehicles, and it can choose the optimal behavior in time, change lanes frequently under the premise of traffic safety, and avoid slowing down or stopping to wait. 2) In the basic road section, driving is generally free, and the penetration of autonomous accelerates the overall running speed of the road, but also causes vehicles to change lanes frequently. The frequency of lane changing reflects the frequency of the above process. 3) The driving conditions in the merging area are worse than those of the basic road section, which makes the interaction between vehicles large, which cannot meet the pursuit of higher speed or more comfortable driving space, and the frequent change of lanes is not conducive to the stability of traffic flow, and the driving safety is low.

6.2.2 Traffic Conflict

Surrogate Safety Measures (SSM) is an indirect safety evaluation software for conflict identification of vehicle trajectories [34]. The directly available ones in SUMO are Time-To-Collision (TTC), Post Encroachment Time (PET) and Deceleration Rate to Avoid Collisions (DRAC), compared as follows:

Table 9 Index comparison of SSM

SSM	Meaning	Characteristic
TTC	The time difference from conflict to collision when there is a certain distance and speed difference between two adjacent vehicles at a certain moment in the process of following and the two vehicles do not take any measures.	(1) The smaller the value, the greater the collision risk. (2) It considers the speed and position. (3) The conflict threshold range is clear and operability is strong. (4) The moving vehicle must maintain a constant speed.
PET	The time difference between the rear bumper of the preceding vehicle leaving the conflict zone and the front bumper of the following vehicle entering the same conflict zone.	(1) The smaller the value, the more likely is a conflict. (2) Only time data is needed, and the operation is simple. (3) Vehicle speed is not considered, and there is a large deviation from the actual situation.
DRAC	The minimum deceleration taken at the next moment by the preceding and following vehicles in conflict to avoid a collision.	(1) The smaller the value, the smaller the probability of emergency braking. (2) The speed, position and braking performance of the vehicle are considered. (3) The occurrence of deceleration may only be subjective, and it is impossible to determine the time and location of the conflict.

By comparison, this paper uses TTC to analyze the safety of traffic flow. It is stipulated in "Road Traffic Conflict Analysis Technology and Application" that when TTC $\leq$ 2 s, vehicles will have serious conflicts, when 2 s < TTC $\leq$ 3 s, there will be general conflicts, and when TTC > 3.0 s, there will be no conflicts [35]; the more conflicts, the lower the safety of the road section. Fig. 17 shows the number of traffic conflicts in different road sections from different AVUP scenarios, and Fig. 18 shows the distribution changes of TTC values in different road sections under different AVUP scenarios.

It can be seen from Fig. 17 that the number of serious conflicts continues to be 0 on the basic road section, and the general conflict gradually decreases until it reaches 0 with the penetration of autonomous, indicating that under the simulated traffic flow density conditions set in this paper, no serious conflict occurs on the basic road section, and the traffic flow is smooth. With the penetration of autonomous in the merging area, the number of serious traffic conflicts and general conflicts decreased； this is because autonomous responds quickly, can detect dangerous information in time and take emergency measures, and the emergency acceleration and deceleration performance of autonomous vehicles is better than that of manual vehicles, so when there are many manual vehicles, it is easy to cause traffic conflicts.

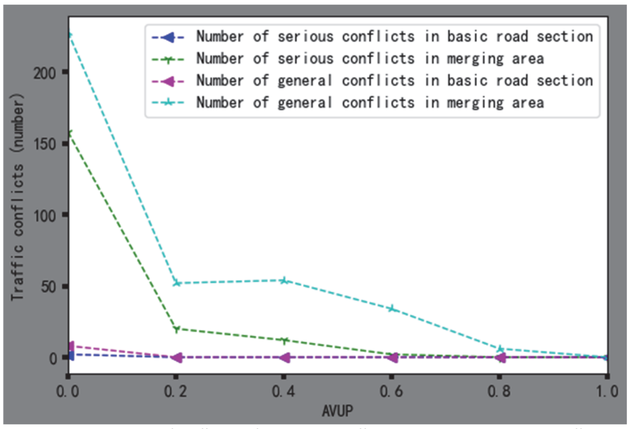
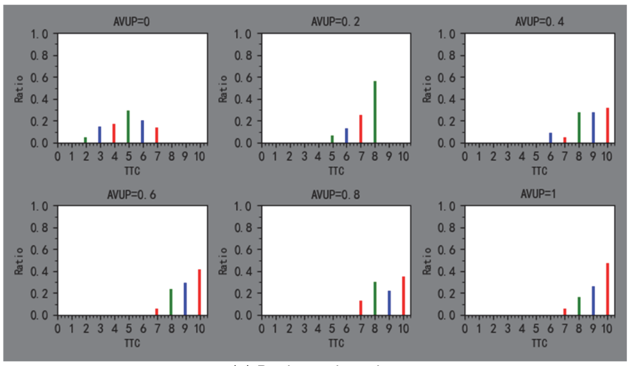
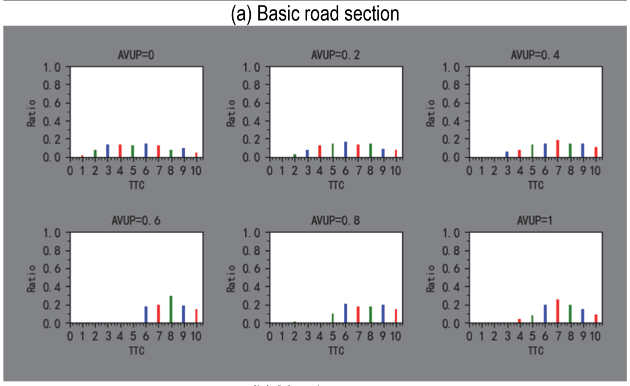


Figure 17 Number of traffic conflicts under different AVUP scenarios in different sections



(a) Basic road section



(b) Merging area

Figure 18 TTC distribution in different road sections

The smaller the proportion of TTC, the more likely the vehicle is to collide. The larger the proportion of TTC, the safer the traffic flow. That is to say, if the proportion of the left side in Fig. 18 is large, it means that the safety of traffic flow is low, and if the proportion of the right side is large, the traffic flow is safer. It can be seen from the figure that in the simulation scenario studied in this paper, under any road section, the distribution ratio of TTC will increase or move from left to right with the infiltration of autonomous vehicles, indicating that the increase of autonomous can gradually increase TTC, reduce potential dangers and improve traffic safety conditions. However, different penetration rate scenarios have different distributions of TTC. In the basic road section, as long as there is infiltration of autonomous vehicles, the TTC will increase, while in the merging area, the infiltration of autonomous has a smaller impact on TTC than the basic road section. This is also because the merging area is more likely to be congested than the basic road section, which increases the possibility of collision between vehicles. It may also be because the autonomous vehicles frequently change lanes in pursuit of high speed, resulting in vehicle driving status imbalance in congested traffic flow.

7 CONCLUSION

This paper firstly determines the autonomous driving penetration model and traffic flow composition, proposes the idea of integrated modeling, and then determines the IDM and ACC models as manual vehicles and different levels of autonomous vehicles car-following models, improved by driver personality and VTH strategy respectively. Meanwhile, The F-STCA model and the LC2013 model are determined as manual vehicles and different levels of automatic vehicles lane change models. Based on the F-STCA model, the limitation of the range of lane change intention generation is broken with the advantage of speed, the situation of emergency braking occurs after successful lane change is considered, and the Richards curve is used to define the lane-changing rules of manual vehicles on different road sections. Finally, SUMO and Python are integrated to build a simulation platform to verify the validity of the model in the scenario of autonomous with fixed penetration rate, and discuss the safety of traffic flow in scenarios with different penetration rate, providing support for future simulation tasks of complex mixed traffic organization.

However, the expressway model in this article is just a simplified model. In reality, there are one-way expressways with three or more lanes. Although one-way two-lane expressways can explain some problems, they are different from multi-lane lanes. This paper only uses the previous literature to distinguish the autonomous level by quantifying the model parameters, the analysis angle is relatively limited, in the future, more practical parameter values can be calibrated through real vehicle tests. In order to simplify the model, this paper proposes to take the autonomous unit as the overall modeling object, but in actual traffic, the proportion of various levels of autonomous on the road is generally different.

Acknowledgments

The authors would also like to acknowledge the support of the participating organization and its personnel who provided various effective assistance, such as data collection and the case study project. Lastly, they sincerely thank the financial support provided by the abovementioned mechanism. This research was funded by Postgraduate Research & Practice Innovation Program of Jiangsu Province (SJCX20_1117, SJCX21_1420, and KYCX21_2999), Construction System Project of Jiangsu Province (2020ZD14 and 2018ZD258), Suzhou Social Science Fund (Y2020LX017 and Y2020LX025), General Project of Jiangsu Natural Fund (BK20151201 and BK20160357), and Philosophy and Social Science Projects of Universities in Jiangsu Province (2018SJA1348).

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