Merging Strategy for Autonomous Vehicles on Highways Based on Acceptance Gaps and Model Predictive Control

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Abstract. With the development of autonomous driving technology, highway ramp merging has become a critical challenge. The ramp merging area is a complex node in the highway system, where improper merging can lead to traffic congestion and accidents. Therefore, studying merging strategies for autonomous vehicles at highway entrances is of great significance for improving traffic safety and flow, as well as promoting the overall development of intelligent transportation systems. This paper proposes a merging strategy based on acceptance gaps and a Model Predictive Controller (MPC). A safety acceptance gap model and an experience acceptance gap model were constructed based on the Gipps model and historical data, respectively. By balancing merging efficiency and safety, a dynamic acceptance gap model with linear fusion was proposed. During the merging process, an MPC was used, which constructed the corresponding cost function and constraints based on the characteristics of highway ramp merging. Using the concept of dynamic programming, the MPC designed a merging trajectory controller. Finally, the effectiveness and feasibility of the merging strategy were verified through simulation experiments.

Keywords: Ramp merging, Acceptance Gap, Gipps, MPC.

1. Introduction

The rapid development of autonomous driving technology heralds' profound impacts on society and the economy. Autonomous vehicles are expected to significantly reduce traffic accidents, which are often caused by human errors. However, achieving comprehensive autonomous driving still faces numerous challenges, one of which is the merging problem at highway entrances. Merging refers to the process where vehicles enter the highway from entrance ramps, a particularly complex task in the field of autonomous driving. Merging requires vehicles not only to accurately perceive the surrounding environment but also to make timely and accurate decisions amidst rapidly changing traffic flow. This process involves various technological challenges, such as the accuracy of environmental perception, interaction with human drivers, and adaptation to dynamic traffic conditions [1].

In the application research of Cooperative Vehicle-Infrastructure Systems (CVIS), Zhang et al. and their team [2] utilize this system to obtain real-time vehicle information to assist merging vehicles safely integrate into the main road. Their approach focuses on searching for or adjusting the spacing between vehicles on the main road to provide adequate space for merging vehicles, thereby guiding them to smoothly merge into the main traffic flow. On the other hand, Guo and Ma [3] developed an innovative integrated algorithm that combines speed coordination, Cooperative Adaptive Cruise Control (CACC), and cooperative merging techniques. This algorithm is primarily used to manage traffic in shared lanes within mixed traffic flows, such as High-Occupancy Vehicle (HOV) lanes, aiming to enhance road efficiency and safety. Nishi et al. [4] proposed a multi-strategy decision-making and passive action-evaluation (pAC) RL merging method suitable for high-density traffic flow. This method achieves safe merging by selecting merging candidate points and utilizing learned state values from high-flow traffic conditions. Tianyu et al. [5] proposed a lane-change decision and control method based on hierarchical reinforcement learning. They treat lane-change decision-making and execution control as two interconnected processes and utilize Deep Q-Networks and polynomial trajectories to achieve precise lane changes. Lu Ziyang [6] considered the influence of different driving styles of main road vehicles and traffic flow density on the decision-making behavior of autonomous vehicles during the merging process. They established a decision-making model using reinforcement learning algorithms based on Deep Q-Networks and Deep Deterministic Policy Gradients.

Most of the above-mentioned studies focus on the selection of merging points for vehicles during the merging process, without delving into the analysis and research of the dynamic merging process. Therefore, this paper focuses on the research of gap selection and dynamic merging process of autonomous vehicles during highway entrance merging. Gap selection is carried out through the established gap acceptance model, followed by the control of the dynamic merging process of autonomous vehicles using model predictive controllers.

2. Model and Method

The merging process of autonomous vehicles on highway ramps can be roughly divided into:

State Adjustment Phase:After the ramp vehicle enters the acceleration lane, it needs to adjust its speed according to the vehicles in front and behind on the target lane, as well as the vehicles ahead in the acceleration lane, in preparation for merging into the target lane.

Gap Selection Phase:While the ramp vehicle is driving in the acceleration lane, it continuously adjusts its driving state and identifies corresponding merging gaps, as shown in Fig. 1. The ramp vehicle needs to dynamically determine whether the current gap meets the acceptance gap criteria. If it does, the merging process is executed; if not, the vehicle further adjusts its driving state.

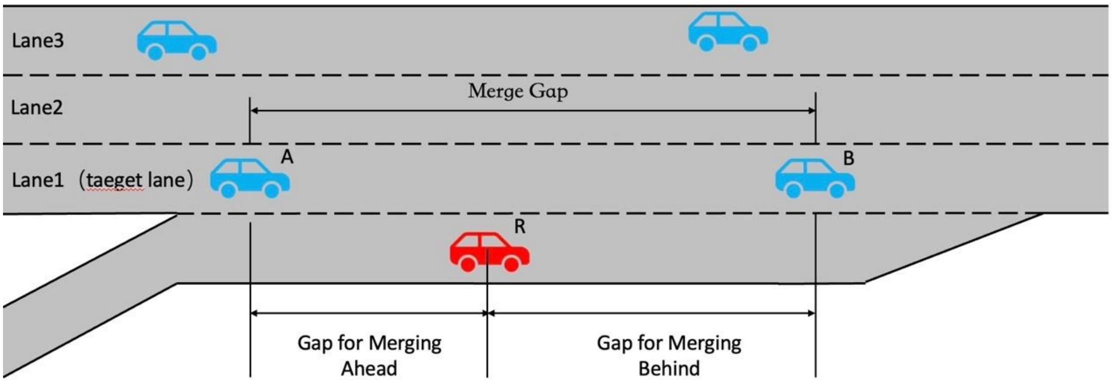


Fig. 1 Vehicle Merging Gaps

Merging Phase:After entering the merging phase, the ramp vehicle performs trajectory control based on the Model Predictive Controller (MPC). By adjusting the steering angle and driving speed, the vehicle gradually changes lanes to the target lane.

Stop and Wait Phase:Due to the limited length of the acceleration lane, if the ramp vehicle has not entered the merging phase when approaching the tapering section, it will actively decelerate and stop before the tapering section, waiting for an appropriate merging gap to appear before merging.

The flowchart of the merging process for autonomous vehicles is shown in Fig. 2.

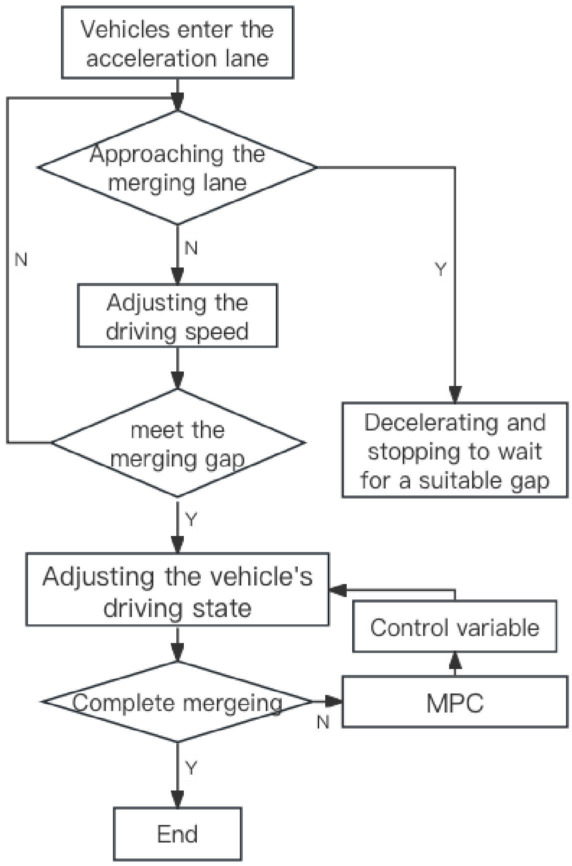


Fig. 2 Flowchart of Ramp Merging Process for Autonomous Vehicles

2.1. Traffic Flow Model

The investigation of merging strategies for autonomous vehicles on highway ramps requires a thorough analysis of the microscopic behaviors of individual vehicles. Consequently, it is imperative to develop corresponding traffic flow models to accurately capture and simulate these behaviors.

2.1.1 Longitudinal Car-Following Model

The Intelligent Driver Model (IDM)[7] converts the position difference, speed difference, and driver behavior parameters during the car-following process into acceleration. By adjusting the acceleration, it controls the distance to the vehicle ahead while attempting to maintain the desired speed. Therefore, this paper adopts the IDM model as the longitudinal car-following model.

$$a = a_{max}[1 - \left(\frac{v}{v_0}\right)^{\delta} - (\frac{s^*}{s})^2] \tag{1}$$

$$s^* = s_0 + \max\{0,\ Tv + \frac{v\Delta v}{2\sqrt{a_{max}b}}\} \tag{2}$$

$$s = d - L \tag{3}$$

Where a represents the vehicle acceleration, a_{max} represents the maximum acceleration of the vehicle, v represents the vehicle speed, v_0 represents the desired speed of the vehicle, δ represents the acceleration exponent, s^* represents the minimum desired gap to the leading vehicle, s represents the actual gap to the leading vehicle, s_0 represents the jam distance, T represents the desired time headway, Δv represents the speed difference between the vehicle and the leading vehicle, b represents the comfortable deceleration, d represents the headway, and L represents the length of the leading vehicle.

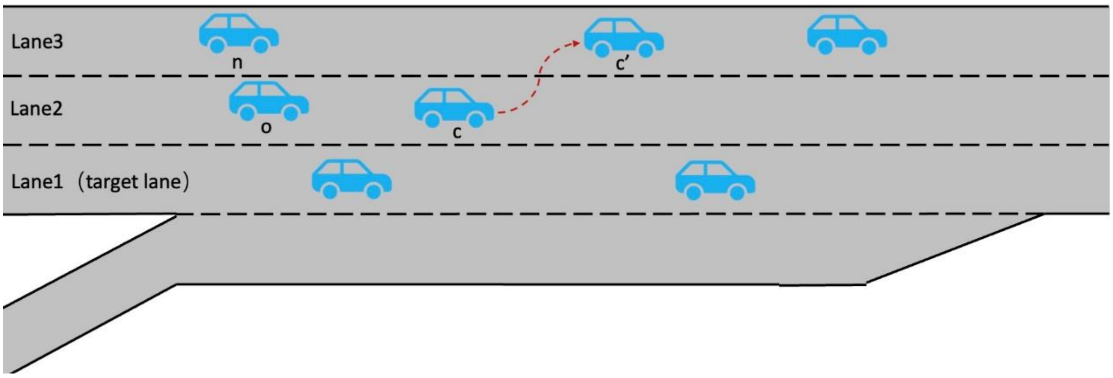
2.1.2 Lateral Lane-Changing Model

For the free lane-changing model of main road vehicles, the focus is on the changes in the driving state of the vehicle when influenced by surrounding vehicles. Therefore, the Minimizing Overall Breaking Induced by Lane Change (MOBIL) model [8] is chosen from the incentive models. The MOBIL model analyzes and determines whether a vehicle should change lanes by comparing the acceleration changes before and after the lane change.

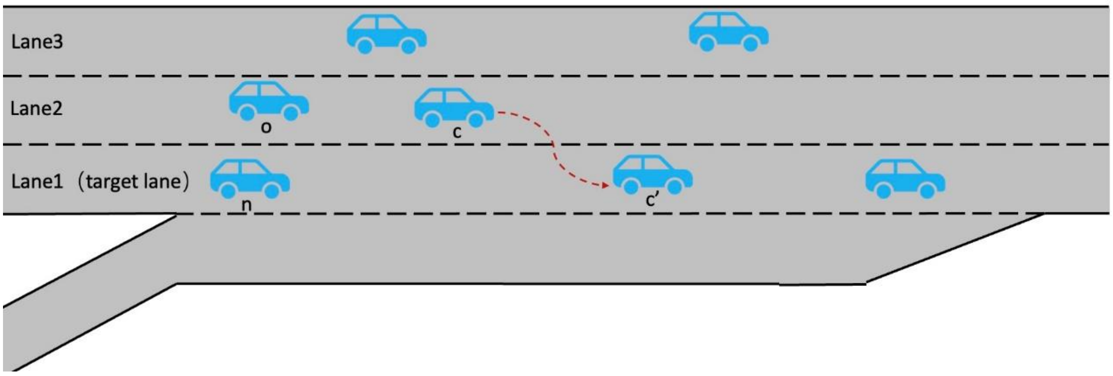
Assume the road situation on the main road lane is as shown in Fig. 3. Here, vehicle c is the vehicle currently under lane change analysis, vehicle c' represents the state of vehicle c after the lane change, vehicle o is the following vehicle before the lane change, and vehicle n is the following vehicle after the lane change. The MOBIL model can be represented as follows:

$$\hat{a}_c - a_c + p[(\hat{a}_n - a_n) + (\hat{a}_o - a_o)] > \Delta a \tag{4}$$

Where $a_c, \hat{a}_c$ represent the acceleration of vehicle c before and after the lane change, respectively, $a_o, \hat{a}_o$ represent the acceleration of the original following vehicle o before and after vehicle c changes lanes, respectively, $a_n, \hat{a}_n$ represent the acceleration of the new following vehicle nn before and after vehicle cc changes lanes, respectively, and Δa is the lane change threshold.



(a) Lane Change to the Left



(b) Lane Change to the Right

Fig. 3 Free Lane Changes for Vehicles on the Main Road

The MOBIL model only models the free lane changes of main road vehicles and does not fully consider the interference caused by merging ramp vehicles. When a ramp vehicle is driving on the acceleration lane and has not yet merged, the vehicles on the target lane may decelerate to give way or change lanes to the left to avoid the merging vehicle. Therefore, the extended formula for the main road lane vehicles is as follows:

$$\begin{cases} \hat{a}_c - a_c + p[(\hat{a}_n - a_n) + (\hat{a}_o - a_o)] > \Delta a \quad , \ rand > q \\ \hat{a}_c - a_{cr} + p[(\hat{a}_n - a_n) + (\hat{a}_o - a_o)] > \Delta a \ , \ rand \le q \end{cases} \tag{5}$$

Where a_{cr} represents the acceleration of vehicle c before the lane change (with the ramp vehicle as the leading vehicle), $rand$ represents a random number, and q represents the yielding probability threshold.

2.2. Acceptance Gap Model

2.2.1 Safety Acceptance Gap Model

The Gipps model is a longitudinal car-following model constructed around the concept of a safe distance. Its core idea is that at any given time, if the vehicle in front brakes suddenly, the following vehicle has enough longitudinal safe distance to stop without colliding with the front vehicle. This paper adopts the Gipps model as the basic model to construct the safe gap model for vehicle merging.

Assume the road situation is as shown in Fig.1. When the vehicle A in the target lane performs an emergency braking maneuver, the ramp vehicle R and the following vehicles B in the target lane sequentially engage in emergency braking. Once all vehicles have come to a complete stop, the longitudinal displacements are as follows:

$$X_A = \frac{v_A^2}{2a_A} \tag{6}$$

$$X_R = \frac{(v_R+v_R')\tau}{2} + \frac{(v_R+v_R')^2}{2a_R} \tag{7}$$

$$X_B = (v_B + v_B')\tau + \frac{(v_B+v_B')^2}{2a_B} \tag{8}$$

$$v_R' = v_R + a_r\tau \tag{9}$$

$$v_B' = v_B + 2a_b\tau \tag{10}$$

Where X_A, X_R, X_B represent the longitudinal displacements of the vehicle in front on the target lane, the merging vehicle from the ramp, and the vehicle behind on the target lane, respectively, when they start braking suddenly. v_A, v_R, v_B represent the speeds when they start braking suddenly. a_A, a_R, a_B represent the maximum decelerations, and τ represents the reaction time.

Therefore, to avoid collisions, the minimum safety acceptance gap in front and the minimum safety acceptance gap behind are given as follow:

$$G_{amin} = \max\,(X_R - X_A, 0) \tag{11}$$

$$G_{bmin} = \max\,(X_B - X_R, 0) \tag{12}$$

2.2.2 Experience Acceptance Gap Model

In the actual merging process on highway ramps, it is rare for vehicles on the target lane to perform sudden braking. Therefore, the safety acceptance gap model is relatively conservative. Based on actual driving data and prior experience, the headway of traditional vehicles should not be less than 0.9 seconds. The recommended value in relevant U.S. regulations is 2 seconds. For autonomous vehicles, due to their faster reaction times, the headway can be reduced to 0.5 seconds [9].

Therefore, the minimum experience acceptance gap is as follows:

$$E_{amin} = v_R t_{ae} \tag{13}$$

$$E_{bmin} = v_B t_{be} \tag{14}$$

Where E_{amin}, E_{bmin} represent the minimum forward experience acceptance gap and the minimum rear experience acceptance gap, respectively. t_{ae}, t_{be} represent the headway of autonomous vehicles and traditional vehicles, respectively.

2.2.3 Dynamic Acceptance Gap Model

The safety acceptance gap is relatively conservative, which can lead to decreased merging efficiency. On the other hand, the experience acceptance gap, established based on historical data, offers poor safety in unexpected situations. To balance merging efficiency and safety, a dynamic acceptance gap is proposed. As the distance traveled by the autonomous vehicle in the acceleration lane increases, the need for merging becomes more urgent. Therefore, a linear fusion approach is adopted for the safety acceptance gap and the experience acceptance gap, as shown below:

$$C_A = pG_{amin} + (1-p)E_{amin} \tag{15}$$

$$C_B = pG_{bmin} + (1-p)E_{bmin} \tag{16}$$

$$p = \frac{L_{acc}-D_s-S_R}{L_{acc}-D_s} \tag{17}$$

Where p represents the weight of the safety gap, L_{acc} represents the length of the deceleration lane, and S_R represents the distance traveled by the merging vehicle R in the acceleration lane.

2.3. Merging Process Based on Model Predictive Control

2.3.1 Dynamic Model of Autonomous Vehicles

Autonomous vehicles constitute highly intricate systems. This paper specifically investigates the merging process of these vehicles, and thus, a two-degree-of-freedom dynamic model is utilized.

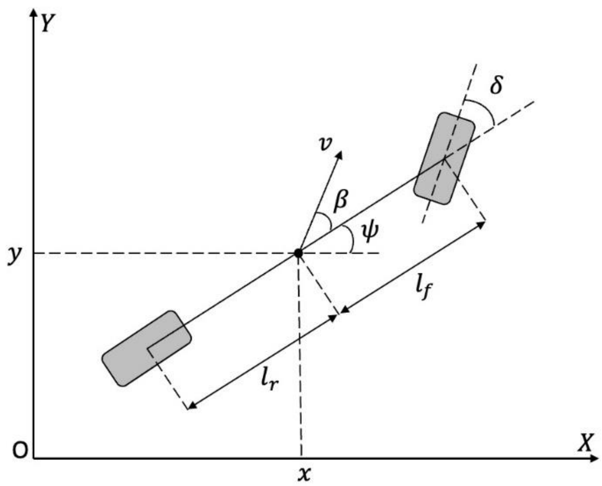


Fig. 4 Two-Degree-of-Freedom Vehicle Dynamic Model

During the highway ramp merging process, the front wheel steering angle of autonomous vehicles is relatively small. Therefore, the auxiliary steering angle of the rear wheels can be neglected. Consequently, the simplified two-degree-of-freedom vehicle dynamic model [10] is as follows:

$$\dot{X} = vcos(\psi+\beta) \tag{18}$$

$$\dot{Y} = vsin(\psi+\beta) \tag{19}$$

$$\dot{v} = a \tag{20}$$

$$\dot{\psi} = \frac{v}{l_r} sin(\beta) \tag{21}$$

$$\beta = \arctan\left(\tan(\delta)\frac{l_r}{l_r+l_f}\right) \tag{22}$$

Where X represents the longitudinal displacement of the vehicle, Y represents the lateral displacement of the vehicle, v represents the vehicle speed, β represents the vehicle sideslip angle, ψ represents the heading angle at the vehicle's center of mass, a represents the vehicle acceleration, δ represents the front wheel steering angle, l_f represents the front wheelbase, and l_r represents the rear wheelbase.

2.3.2 Model Predictive Controller

The basic principle of Model Predictive Control (MPC) is to predict the system's state sequence within a fixed time window based on the system dynamics model, solve the objective function to obtain the optimal control sequence, and then use the first solution of the optimal control sequence as the control input to update the system state, with rolling optimization. Therefore, during the merging process of autonomous vehicles, MPC can predict the vehicle's motion state within a certain time window, optimize and solve for the optimal control sequence, and perform rolling optimization to achieve dynamic merging of the vehicle.

The objective function of the system is as follows:

$$J = \sum_{t=0}^{N-1} L(x_t, u_t) + F(x_t) \tag{23}$$

Where J represents the cost function, x_t represents the system state at time t, u_t represents the control input at time t, L represents the intermediate cost, F represents the terminal cost, and N represents the length of the prediction time window.

In this paper, trajectory planning is used to control the merging of autonomous vehicles. Therefore, it is necessary to set target states so that the vehicle state is continuously optimized towards the target state. To ensure the safety of the merging process, the reciprocal of the distance between the merging vehicle and surrounding vehicles is included in the state variables as a safeguard. Thus, the target state variables are as follows:

$$\hat{x} = [X, Y, \delta, v, b_1, b_2, b_3, b_4]^T \tag{24}$$

Where $\hat{x}$ represents the target state, X, Y represent the lateral and longitudinal displacements at the completion of merging, δ represents the front wheel steering angle at the completion of merging, v represents the target speed, and b_1, b_2, b_3, b_4 represent the reciprocals of the distances between the merging vehicle and the vehicles in front, behind, and on the acceleration lane of the target lane, respectively.

The objective function can be rewritten as follows:

$$L = \sum_{t=1}^{N-1} [(x_t - x_{goal})Q(x_t - x_{goal}) + u_t R u_t)] \tag{25}$$

$$F = (x_N - x_{goal})Q'(x_N - x_{goal}) \tag{26}$$

To solve the above optimization problem, differential dynamic programming (DDP) or the Iterative Linear Quadratic Regulator (ILQR) scheme can be used. However, due to the high computational load of DDP and the strong real-time requirements during the vehicle merging process, the ILQR method is employed for solving the problem.

3. Experimental Analysis

Actual highways typically have multiple lanes, allowing vehicles to change lanes while driving. Therefore, to accurately reflect the driving behavior in ramp merging areas while reducing the computational burden of system simulation, this paper uses a single-direction, two-lane highway with a parallel merging entrance ramp as the simulation scenario.

The detailed parameter settings for the road section are shown in Table 1.

Table 1 Parameters of the Main Highway and Ramp

Parameter Name	Value	Unit
Number of Lane	2	/
Number of Ramp	1	/
Width of Lane	3.75	m
Speed of Lane Two	[100,120]	Km/h
Speed of Lane One	[60,100]	Km/h
Speed of Ramp	[40,80]	Km/h

The parameter settings of the vehicle model are shown in Table 2.

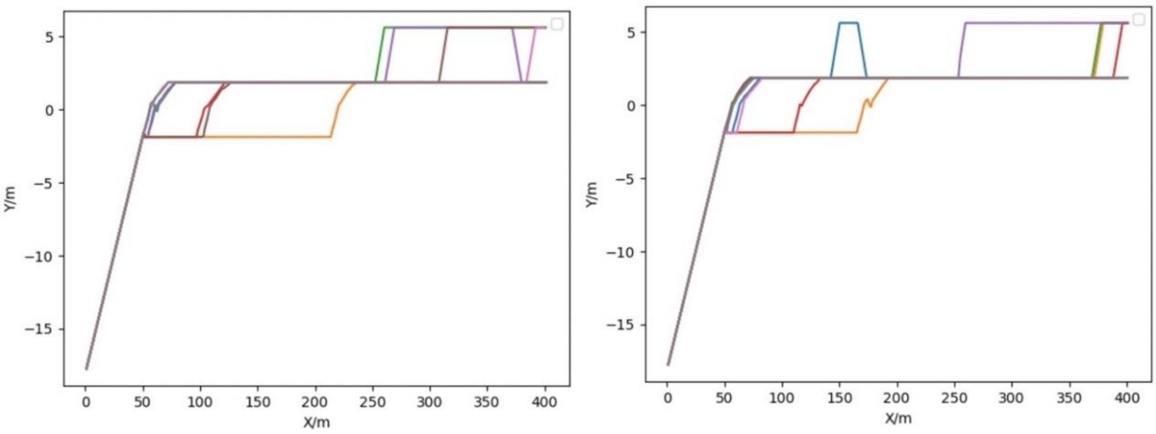
Table 2 Vehicle Model Parameters

Parameter Name	Value	Unit
Length	3.8	m
Width	1.6	m
Front Axle Distance	1.2	m
Rear Axle Distance	1.2	m
Front Wheel Steering Angle	[-30,30]	degree
Maximum Acceleration	5	m/s^2
Maximum Deceleration	8	m/s^2
Observation Range	150	m

The traffic flow on the two lanes of the main road is set to 1000 veh/h and 1500 veh/h, respectively. And the traffic flow on the ramp is set to 400 veh/h.

3.1. Merging Trajectory Simulation Analysis

The trajectories of the ramp vehicles are shown in the Fig. 5.



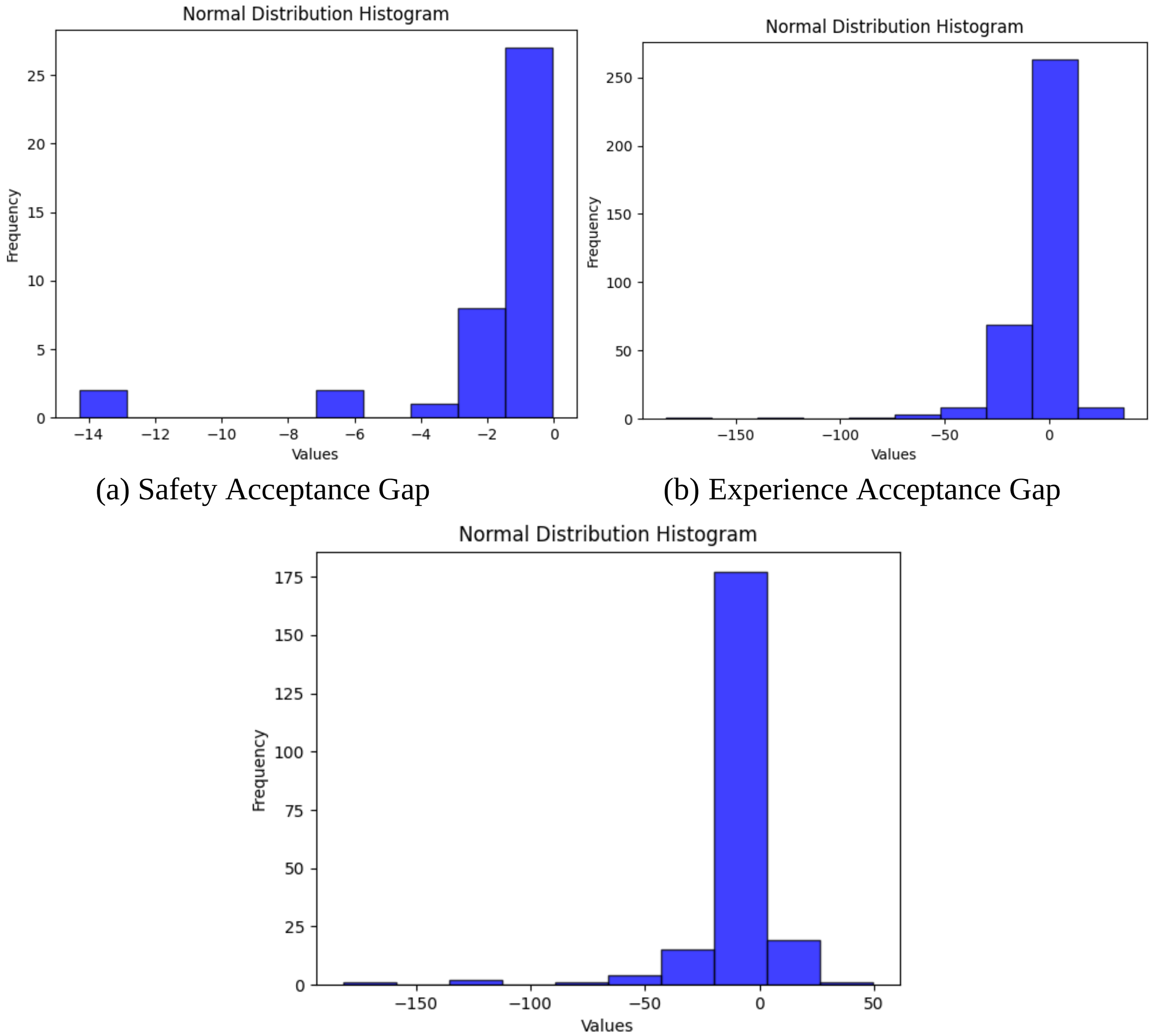
(a) 1000 veh/h (b)1500 veh/h

Fig. 5 Vehicle Merging Trajectory

The figure illustrates the lateral trajectory of vehicles during merging and lane-changing processes. It is evident from the plot that the lateral movements exhibit a smooth profile, suggesting a high level of performance by the model.

3.2. Analysis of Time to Collision (TTC)

The models corresponding to three acceptance gaps are shown in Fig. 6.



(a) Safety Acceptance Gap (b) Experience Acceptance Gap

(c) Dynamic Acceptance Gap

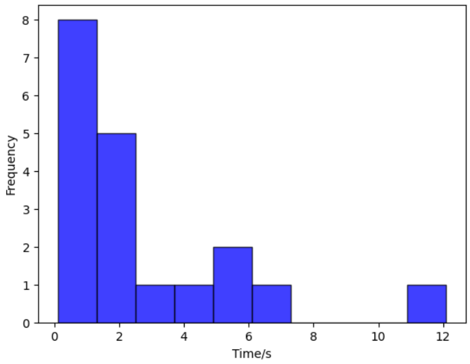
Fig. 6 Collision Time Under Different Acceptance Gaps

When TTC is less than 0, it indicates that the speed of the following vehicle is lower than that of the leading vehicle, thus no collision will occur. When TTC is greater than 0, the longer the collision time, the higher the safety level.

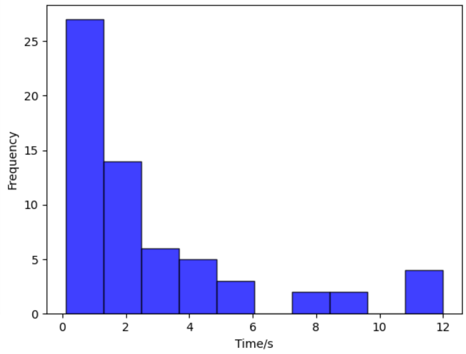
From Fig. 6(a), it can be observed that the TTC values for the safety acceptance gap are all negative, indicating no collision risk between the leading and following vehicles. Comparing Fig. 6 (b) and Fig. 6 (c), it can be seen that under both acceptance gaps, collision times are concentrated between [-50, 50]. In terms of TTC values greater than 0, the distribution based on the dynamic acceptance gap is relatively larger compared to the distribution based on the experience acceptance gap. This indicates that the dynamic acceptance gap model combines the effectiveness of both the safety acceptance gap model and the experience acceptance gap model.

3.3. Analysis of Merging Time

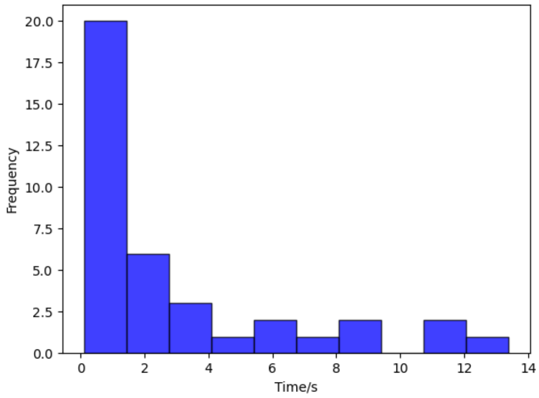
The distribution of ramp merging times for the ramp flow is shown in Fig. 7.



(a) Safety Acceptance Gap



(b) Experience Acceptance Gap



(c) Dynamic Acceptance Gap

Fig. 7 Merging Time Under Different Acceptance Gaps

According to Fig. 7(a), it can be observed that the merging time for the safety acceptance gap is mainly distributed between 0-12 seconds, but with a relatively low frequency, indicating a comparatively lower efficiency in vehicle merging. From Fig. 7 (b), it is evident that under the experience acceptance gap model, the distribution of merging times is more concentrated between 0-2 seconds, with a higher frequency, indicating higher efficiency in vehicle merging. From Fig. 7 (c), it can be observed that compared to the experience acceptance gap model, there are fewer merging times distributed between 0-2 seconds, resulting in an overall increase in merging time. Although the merging efficiency slightly decreases, compared to the safety acceptance gap model, there is a significant improvement in merging efficiency.

3.4. Analysis of Number of Vehicles Waiting in Queue

The number of vehicles waiting in the transition zone for merging is depicted in Fig. 8.

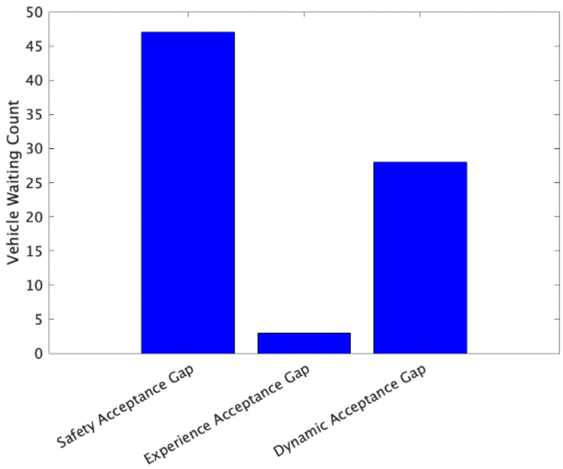
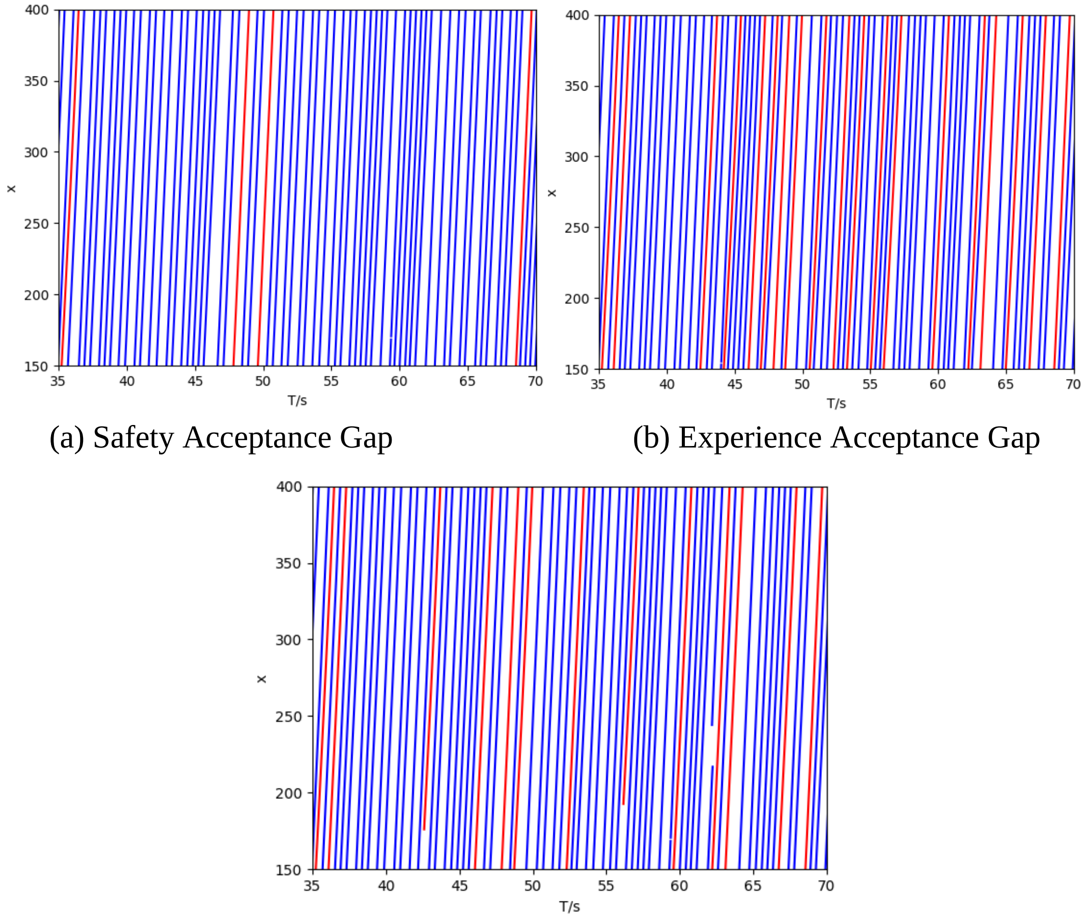


Fig. 8 The number of vehicles waiting in queue

From Fig. 8, it is visually evident that the maximum number of vehicles waiting in queue is observed for the safety acceptance gap, while the minimum number of vehicles waiting in queue is observed for the experience acceptance gap. The number of vehicles waiting in queue for the dynamic acceptance gap falls between these two extremes, indicating a balanced efficiency achieved by adopting the dynamic acceptance gap model between the safety acceptance gap and the experience acceptance gap models.

3.5. Analysis of Spatio-Temporal Trajectories in the Longitudinal Position

The time and longitudinal displacement trajectories between merging vehicles and vehicles in the target lane are illustrated in Fig. 9.



(a) Safety Acceptance Gap (b) Experience Acceptance Gap

(c) Dynamic Acceptance Gap

Fig. 9 Longitudinal Position Spatio-Temporal Trajectory

In Fig. 9 the blue line represents vehicles on the main road, while the red line represents merging vehicles from the ramp. The horizontal axis represents time, and the vertical axis represents the longitudinal displacement of vehicles. From the figure, it can be observed that under the gap models, collisions occur between vehicles. The sparsity of the red lines representing ramp vehicles indicates that under the safety gap model, the merging efficiency of vehicles is the lowest, but the distance between the leading and following vehicles is relatively large, ensuring safety. Under the experience gap model, the merging efficiency of vehicles is the highest, but the distance between vehicles is relatively small, leading to slightly lower safety. Under the dynamic gap model, while ensuring efficiency, the distance between vehicles is moderate, leading to a more balanced performance.

4. Conclusion

This paper focuses on the merging problem of autonomous vehicles at highway entrances. The entire merging process is divided into two parts: merging gap selection and dynamic merging process.

For merging gap selection, acceptance gap models are employed. Specifically, we establish a safety acceptance gap model based on the Gipps model, an experience acceptance gap model based on experience data, and a dynamic acceptance gap model that balances merging efficiency and safety.

In dynamic merging control, a model predictive controller (MPC) is utilized, designed with the principles of dynamic programming. Additionally, to ensure safety, the distance between preceding and following vehicles is introduced as a state variable. Analysis of longitudinal and lateral trajectory data from simulation experiments indicates that under the control of the MPC controller, vehicles can safely and efficiently merge.

For merging gap selection, acceptance gap models are employed. Specifically, we establish a safety acceptance gap model based on the Gipps model, an experience acceptance gap model based on experience data, and a dynamic acceptance gap model that balances merging efficiency and safety. In simulation experiments, analysis of collision events, merging times, and longitudinal spatio-temporal trajectory charts reveals the following conclusions: the safety acceptance gap model demonstrates high safety levels, the experience acceptance gap model exhibits higher merging efficiency, while the dynamic acceptance gap model effectively balances merging efficiency and safety.

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