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A Lane Change Model Considering the Stability of Cooperative Adaptive Cruise Control Platoon Fleet

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Abstract: In this article, lane change models for mixed traffic flow under cooperative adaptive cruise control (CACC) platoon formation are established. The analysis begins by examining the impact of lane changes on traffic flow stability. The influences of various factors such as lane change locations, timing, and the current traffic state on stability are discussed. In this analysis, it is assumed that the lane change location and the entry position in the adjacent lane have already been selected, without considering the specific intention behind the lane change. The speeds of the involved vehicles are adjusted based on an existing lane change model, and various conditions are analyzed for traffic flow disturbances, including duration, shock amplitude, and driving delays. Numerical calculations are provided to illustrate these effects. Additionally, traffic flow stability is factored into the lane change decision-making process. By incorporating disturbances to the fleet into the lane change income model, both a lane change intention model and a lane change execution model are constructed. These models are then compared with a model that does not account for stability, leading to the corresponding conclusions.

Keywords: Cooperative adaptive cruise control platoon; Lane change models; Stability; Traffic flow

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1. Introduction

The term "intelligent network-connected vehicle" refers to the integration of vehicle networking with intelligent vehicles. These vehicles are equipped with advanced onboard sensors, controllers, actuators, and other devices while incorporating modern communication and network technology. This integration facilitates intelligent information exchange and sharing between vehicles and various entities (including people, vehicles, roads, cloud platforms, etc.), aiming to achieve safe, comfortable, energy-saving, and efficient driving for a new generation of vehicles [1]. As these intelligent connected vehicles enter the road network, they will inevitably experience a transitional phase of mixed driving with non-connected vehicles. This transition will affect user information acquisition methods, road network familiarity, micro-driving behaviors, and macro path selection behaviors.

According to research on collaborative driving of fleets, the operation modes of connected vehicles include convoy driving, autonomous driving of individually connected vehicles, and mixed driving with non-connected vehicles. Depending on the operational mode, travel behavior and traffic flow will follow different patterns, presenting new challenges for traffic management and control under these evolving conditions.

Significant progress has been made in modeling and simulating the lane change behavior of vehicle-connected mixed traffic flow. A lane change test was conducted on 66 subjects under high-density traffic conditions to analyze drivers' lane change behavior. Factors influencing lane changes were extracted using lane change test data, followed by an in-depth analysis of the decision-making mechanism. Some scholars, after analyzing the micro-behaviors of manually driven vehicles, have discussed the impact of lane changes on overall traffic flow. Simulation tests under multiple scenarios have been conducted to study the effects of lane changes on traffic efficiency, safety, and fuel consumption, through a detailed analysis of microscopic dynamic tracking and lane change models. Quoc and Seiichi conducted a real-world lane-change test, establishing a lane-change model simulating manual driving by analyzing human drivers' lane-change behavior [2].

In parallel with lane change influence analysis, scholars have also developed theoretical models for vehicle operation during lane changes. The vehicle lane change model based on clearance acceptance thresholds has paved the way for further lane change research and development. Peter categorized lane change behavior into free lane change, forced lane change, and cooperative lane change, based on the interaction between vehicles during the lane change process [3]. Lane change trajectories were analyzed using vehicle system dynamics, dividing the lane change behavior into three stages: preparing for lane change, executing the lane change, and continuous lane change. A decision-making model for vehicle adaptive cruise systems and lane change systems was developed using game theory, considering the virtual collision area of the vehicle as the game payoff, which ensures high safety. Habel and Schreckenberg studied vehicle lane change behavior based on the layered Logit model, quantitatively analyzed and evaluated the benefit function of lane selection, and provided a theoretical foundation for understanding the behavioral interactions between vehicles [4]. Ahmed *et al.* used a three-step method to describe lane change behavior [5]. First, vehicles with lane change motivation make a lane change decision, then search for potential lanes to merge into, and finally wait for the opportunity to execute the lane change. Liu and Shi developed a traffic flow model based on cellular automata, using a driving simulation system to filter and analyze the decision factors affecting lane changes. They used a BP neural network to make lane change decisions for vehicles, which effectively simulated drivers' vehicle turning behavior [6].

Although research on lane change behavior in vehicle-connected mixed traffic flow has made significant progress, several problems still require further exploration, such as cooperative lane changes between intelligent and conventional vehicles, the benefit function of lane change decisions, optimization strategies for lane change behavior, and the stability of traffic flow affected by lane changes. Addressing these issues will improve vehicle safety and efficiency and promote the application of vehicle-connected hybrid flow in real-world traffic systems.

2. Multi-objective optimization model of fleet formation

In mixed traffic flow, mid-lane changes affect speed fluctuations, traffic delays, and the stability of the fleet. When lane changes cause the fleet to split and reorganize, this can lead to significant disruptions. Factors such as the distance between vehicles, the type of vehicle changing lanes, and the position of the lane-changing vehicle within the fleet greatly impact stability. To enhance efficiency, vehicles evaluate traffic conditions in different lanes and switch to lanes with more space and higher speeds. Based on the location and purpose of lane changes, lane change behavior is categorized into three types: autonomous lane change, anticipated lane change, and forced lane change. This section determines the lane change intention and lane selection of vehicles by analyzing factors such as lane change scenarios and vehicle types.

For vehicle i that needs to exit from the ramp, when its position meets $x_i(t) \geq \beta \times x_i$, it indicates that the vehicle is approaching the exit ramp. If the vehicle is not in the rightmost lane connected to the ramp, it must forcibly change lanes to the rightmost lane as soon as possible to avoid missing the exit. The primary goal of forced lane change behavior is to move towards the ramp exit. Unlike autonomous lane change, the vehicle should only prioritize lane change safety in this scenario, specifically as follows:

(1) When the gap in the right lane satisfies $x_{j,i}(t) \geq g_i(t)$, $x_{i,j-1}(t) \geq g_i(t)$, the vehicle can safely change lanes, and the forced lane change is performed immediately.

$$g_j(t) = T_j(t) * v_j(t) + L , T_j(t) = max\{x_{j,j-1}(t), T_{j,i}(t)\} \quad (1)$$

$$g_i(t) = T_i(t) * v_i(t) + L , T_i(t) = max\{x_{i,i-1}(t), T_{i,j}(t)\text{-}1\} \quad (2)$$

(2) When the gap in the right lane satisfies $x_{j,i}(t) \geq g_j(t)$, and $x_{i,j-1}(t) \geq g_i(t)$, the lane change gap is insufficient. Vehicles i and j must adjust to widen the gap. If vehicle i needs to change lanes twice to reach the rightmost lane, it will adjust its lane change at maximum speed, as shown in **Equation (3)**. If only one lane change is needed, the distance to the exit ramp is considered, and a comfortable speed reduction will be applied to avoid excessive lane change time. This process is governed by **Equations (3)–(7)**. Vehicle j is simultaneously following with vehicles i and $j\text{-}1$ in front.

$$a_i(t) = max\{-d_{max}, v_{min}\text{-}v(t)\} \quad (3)$$

$$v_{j-1}(t) \times t_s\text{-} \left(v_i(t) \times t_s + \frac{1}{2} a \times t_s^2\right) \geq g_j(t)\text{-}x_{i,j-1}(t) \quad (4)$$

$$t_s = \frac{x_s\text{-}x_i(t)}{v_i(t)} \quad (5)$$

$$a = min\{2 \times \frac{\Delta v_{j-1,i}(t) \times t_s\text{-} (g_i(t)\text{-}x_{i,j-1}(t))}{t_s^2}, -b\} \quad (6)$$

$$a_i(t) = max\{-d_{max}, a, v_{min}\text{-}v_i(t)\} \quad (7)$$

(3) When the gap in the right lane satisfies $x_{i,j-1}(t) \geq g_i(t)$, and $x_{j,i}(t) \geq g_j(t)$, the lane change gap is insufficient. If vehicle i needs to make two lane changes to reach the rightmost lane, vehicle j will adjust its lane change at maximum speed reduction, following **Equations (3)–(7)**. If only one lane change is needed, the distance to the exit ramp is considered to determine speed reduction, also following **Equations (3)–(7)**. Vehicle i follows both vehicles $i\text{-}1$ and j.

(4) When the gap in the right lane does not meet lane change safety criteria, i.e., $x_{i,j-1}(t) < g_i(t)$ and $x_{j,i}(t) < g_j(t)$, the lane change gap is insufficient. In this case, both vehicles i and j adjust their speeds with maximum reduction.

3. Examples and analysis of results

This example primarily considers the influence of stability on overall traffic flow during lane change decisions. A three-lane test section with a length of 4900 m is set up without designated lanes. The simulation time is 100 seconds, vehicle entry follows a Poisson distribution with a 3-second interval, and the ratio of ordinary vehicles to connected vehicles is 7:3. The initial speed of the entering vehicles is randomly assigned within the range of [10, 25] m/s, and acceleration is randomly assigned within the range of [-3, 3] m/s². The expected lane change distance from the exit ramp is 910 m, and the forced lane change distance is 341 m. The entering lane is randomly selected at the initial moment.

During the 100-second simulation time, a total of 100 vehicles entered, including 70 connected vehicles and 30 ordinary vehicles. The results show that the average speed of lane changes considering stability is 16.92 m/s in the two groups of experiments, while the average speed is only 16.46 m/s in the comparison experiment. By recording the distance between vehicles, it was found that under this algorithm, the average headway distance of connected vehicles was 246.47 m, and that of ordinary vehicles was 265.23 m. In comparison, the average headway distance in random lane changes was 281.91 m for connected vehicles and 298.00 m for ordinary vehicles. The reduced distance between vehicles increased the density of traffic flow, with noticeable changes in the ordinary vehicles.

The simulation results are presented in **Figures 1** and **2**. **Figure 1** shows the average disturbance time of vehicles changing lanes at different following distances between ordinary and connected vehicles, while **Figure 2** presents the average running delay for the two types of vehicles during lane changes when different types of vehicles are behind the target lane. Additionally, **Figures 3** and **4** demonstrate the distribution of ACC and HDV vehicles across the lanes. There is an unbalanced speed phenomenon while maintaining team stability, which increases overall traffic flow stability and improves the average speed.

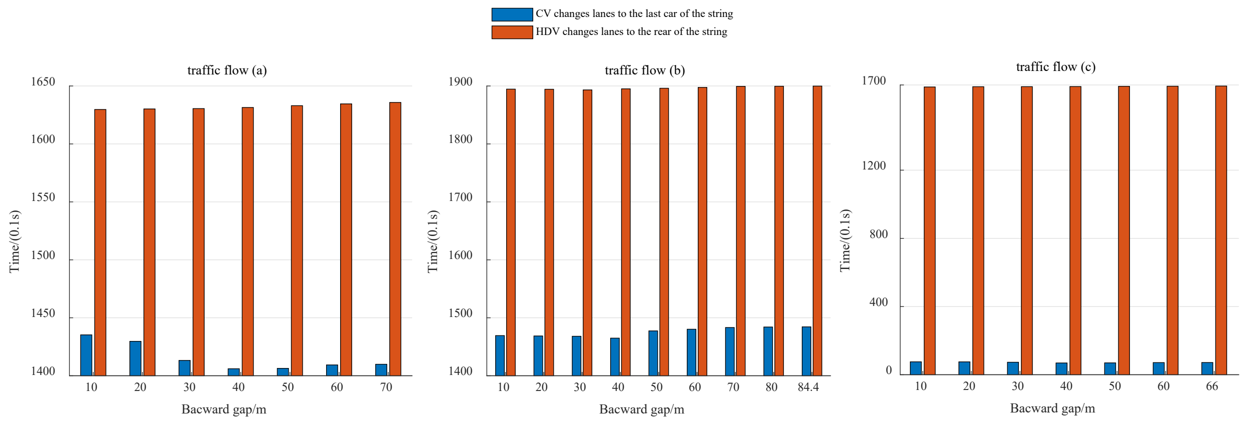

Figure 1. Mean perturbation time comparison

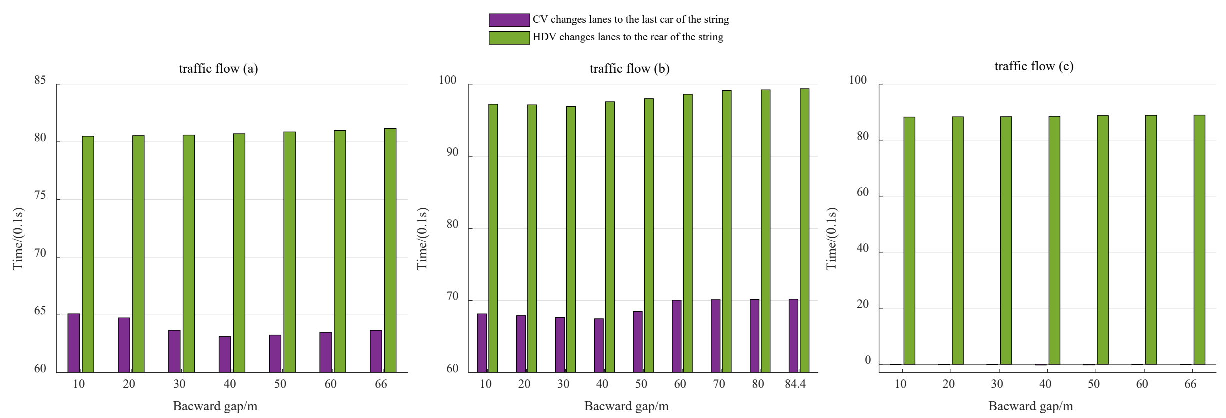

Figure 2. Average travel delay comparison

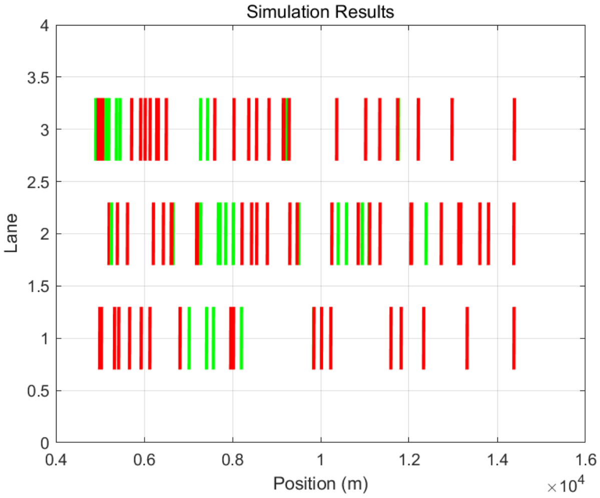

Figure 3. The final position of the lane change regardless of stability

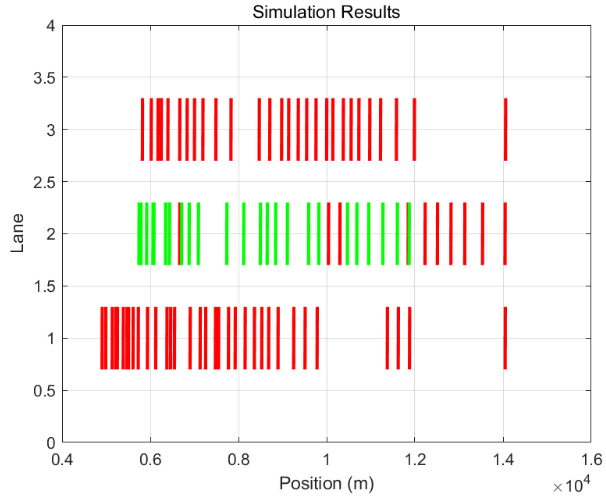

Figure 4. Consider the final position of the stable lane change

As can be seen from **Figures 3** and **4**, when stability is considered, the number of lane changes is reduced, the team formation ratio of networked vehicles is high, and the distance between vehicles is small, which improves traffic efficiency. In contrast, in the comparison experiments, vehicles prioritize high-speed, frequent lane changes, resulting in a lower fleet formation ratio. The distribution of traffic flow becomes relatively chaotic, and networked vehicles cannot fully utilize their small-spacing capabilities, making it difficult to form a stable fleet.

5. Conclusions

Based on the driving characteristics of connected and ordinary vehicles, this paper analyzes the team formation and lane change rules in mixed traffic flow. A following model for both connected and ordinary vehicles is established, along with a speed adjustment model for each vehicle during lane changes. Additionally, Matlab simulations were conducted to examine the operation of mixed traffic flow during lane changes, analyzing the effects of different traffic flow distributions, lane change spacing, lane change points, and the penetration rate of connected vehicles on fleet stability.

On this basis, stability is incorporated into the lane change intention model, and the driving state of the fleet in the target lane is considered when calculating lane change benefits and selecting lane change points.

In a networked environment, road testing equipment can be fully utilized to provide real-time driving information to networked vehicles, offering them more data to select appropriate lane change points, reduce the impact of lane changes, ensure lane change safety, and improve overall traffic efficiency.

Disclosure statement

The authors declare no conflict of interest.

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