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Research on Freeway Traffic Flow Evolution and Cloud Control System Based on Safe Following Distance and Cellular Automata

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Abstract: With the increasing traffic demand, the trade-off between freeway traffic flow and driving safety has become increasingly prominent. Traditional right-driving rules often fail to balance driving safety and road network efficiency under varying traffic densities. This paper aims to deeply explore the impact mechanism of freeway driving rules on the spatio-temporal evolution of traffic flow. First, by introducing the concept of safe following distance, a vehicle anti-collision model under different driving states and overtaking behaviors is constructed to quantify the safety risks in microscopic driving behaviors. Second, a Cellular Automaton (CA) traffic flow simulation model is established to dynamically simulate and reveal the traffic flow evolution patterns and their critical density characteristics under different speed limits and mixed vehicle compositions. The research indicates that under heavy traffic conditions, a single right-driving rule significantly restricts the overall traffic efficiency of the road, while implementing a scientific lane-based speed limit strategy can effectively delay the spread of congestion. To further break the limitations of existing static rules, this paper proposes an intelligent traffic management and control system framework integrating cloud computing and big data. This system utilizes Kalman filtering and Wavelet Neural Network (WNN) for accurate short-term traffic flow prediction, and combines the information interaction between the vehicle private cloud and the platform public cloud to achieve dynamic coordination of individual vehicle behavior and optimal control of global traffic flow. The research results of this paper provide a solid theoretical basis and decision support for future dynamic lane design, speed limit strategy optimization, and the development of intelligent transportation systems on freeways.

Keywords: Freeway, Traffic flow evolution, Safe following distance, Cellular Automata, Intelligent traffic control system, Cloud computing.

1. Introduction

The rapid development of the modern economy has led to a sharp increase in car ownership. As the core backbone of the comprehensive transportation system, the operational efficiency and safety of freeways have always attracted widespread attention from academia and engineering. Globally, most countries and regions adopt the traffic rule of driving on the right for freeways. This static rule effectively ensured traffic order in the early days when traffic volume was low. However, with the continuous increase in traffic load, the single requirement of driving on the right causes vehicles to be highly concentrated in specific lanes. Frequent overtaking and lane-changing behaviors not only increase the potential risk of traffic accidents but also severely limit the overall capacity of the road. Addressing the game between road safety and traffic efficiency, scholars at home and abroad have conducted extensive fundamental research on traffic flow theories [1], [2] and safe distance models [3], [4]. Early research mostly focused on continuum models of macroscopic traffic flow [5], [6], and later microscopic car-following models [7], [8] gradually became the mainstream. Researchers determined the ultimate safe distance between two cars by analyzing physical parameters such as driver reaction time and vehicle braking performance, aiming to eliminate safety hazards at the microscopic level.

In recent years, with the advancement of computer simulation technology, the Cellular Automaton [9], [10] (CA) model has been widely used in the study of spatio-temporal evolution [11], [12] characteristics of traffic flow due to its simple evolutionary rules and its ability to realistically simulate complex traffic jam phenomena [13], [14]. Although existing literature has achieved fruitful results in exploring the impact of lane speed limits and mixed vehicle compositions on traffic flow, most studies are still confined to the objective evaluation of traditional static driving rules, and rarely deeply couple and systematically optimize physical safe following mechanisms, microscopic spatio-temporal evolution laws, and cutting-edge intelligent computing technologies [15], [16]. In view of this, from the perspective of microscopic vehicle following safety, this paper first establishes a safe following distance model that comprehensively considers speed differences and overtaking geometric relationships. Subsequently, using the CA model, the relationship between traffic density and flow evolution under different speed limits and vehicle composition conditions is simulated and analyzed, visually revealing the flow bottleneck of traditional rules under heavy traffic. On this basis, this paper further introduces the concepts of the Internet of Things and cloud computing, innovatively proposes an intelligent traffic control system scheme combining private cloud and public cloud interaction, and utilizes wavelet neural network technology to achieve accurate prediction and dynamic feedback of traffic flow, aiming to provide a brand-new system-level solution that balances safety and efficiency for future intelligent traffic management.

2. Problem Description and Methodology

2.1. Problem Description

The traffic flow and safety conditions of freeways are closely related to freeway driving rules. The core problem of this paper is to deeply analyze the trade-off relationship between road safety and traffic flow. In actual freeway operations, strictly following the "driving on the right" rule often fails to achieve an ideal balance between safety and traffic efficiency when the traffic volume is small or large. To comprehensively evaluate the performance of this driving rule under different traffic densities, we need to not only examine the mutual constraints between traffic flow and safety but also consider the roles played by under- or over-posted speed limit regulations on different lanes. Therefore, this paper first introduces the concept of the safe following distance between two moving cars to characterize and quantify safety risks. Subsequently, based on considering the role of different speed limit rules, a Cellular Automaton (CA) model is established to simulate and draw spatio-temporal evolution patterns under different conditions. Finally, addressing the defect that existing rules cannot effectively increase flow under heavy traffic, this paper further introduces cloud computing and big data mining technologies to propose a future-oriented intelligent traffic management and control system scheme. The overall research idea and program flowchart are detailed in Figure 1.

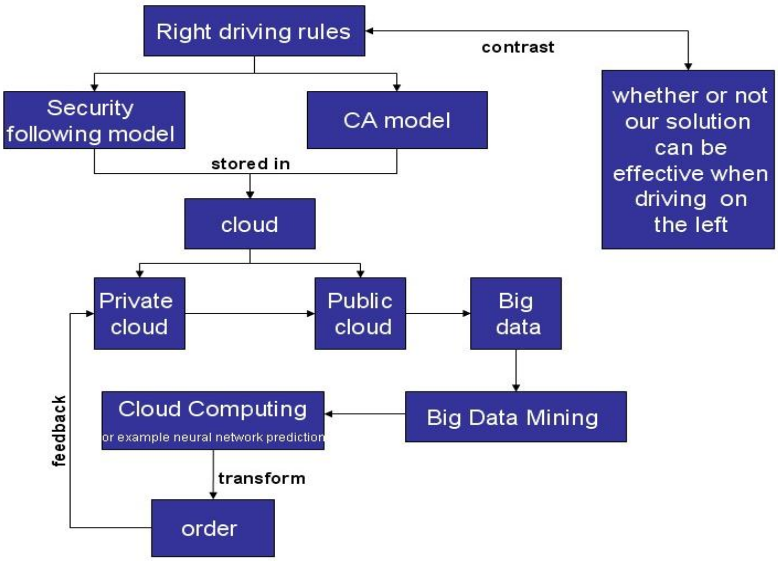

Figure 1. Model framework diagram

2.2. Safe Following Distance Model

To ensure driving safety on freeways, it is necessary to strictly control the longitudinal vehicle spacing between two cars and the lateral distance between vehicles in the rightmost lane and adjacent lanes. Typical driving rules require drivers to drive in the rightmost lane unless they need to overtake, in which case the driver must change to the left lane, complete the overtaking, and then return to the original driving lane. During this process, the vehicle goes through three phases: diverging, overtaking, and returning, as shown in Figure 2. To quantify the safety risks in this process, we constructed a safe following distance model. Assume the vehicle in front is Car 1 and the vehicle behind is Car 2. Their driving speeds are set as v_1 and v_2, and their maximum braking decelerations are a_1 and a_2, respectively. Meanwhile, the deceleration growth time is set as t_1, and the driver and braking system reaction time is t_2.

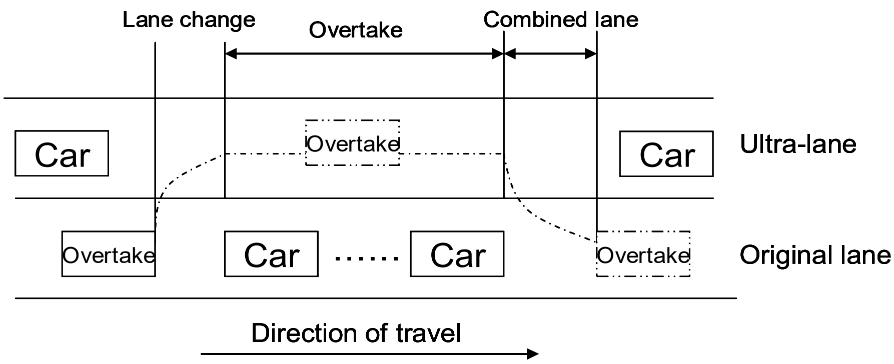

Figure 2. Three phase of overtaking process

We discuss this under three different driving states. First, when the speed of Car 1 is less than the speed of Car 2 (i.e., $v_1 < v_2$), because Car 1 decelerates uniformly with preparation, it does not require reaction time. Therefore, the braking distance of Car 1 is:

$$s_1 = \frac{v_1^2}{2a_1} \tag{1}$$

And Car 2 requires a reaction time t_2 before it starts to decelerate after Car 1 begins to decelerate. Therefore, the total distance traveled by Car 2 is:

$$s_2 = v_2 t_2 + \frac{v_2^2}{2a_2} \tag{2}$$

To ensure that the two cars do not collide after Car 1 stops, the safe following distance d_s between the two cars can be expressed as:

$$d_s = v_2 t_2 + \frac{v_2^2}{2a_2} - \frac{v_1^2}{2a_1} \tag{3}$$

Secondly, when the speed of Car 1 equals the speed of Car 2, the safe following distance model for the two cars remains consistent with the above formula. Finally, when the speed of Car 1 is greater than the speed of Car 2, following is generally safer. But if Car 2's deceleration equals Car 1's speed, Car 2 must take deceleration operations to ensure following safety. At this time, the time required for Car 1 to decelerate to the same speed as Car 2 is:

$$t = \frac{v_1 - v_2}{a_1} \tag{4}$$

During this period, the distance traveled by Car 1 at its original speed is $s_1 = v_1 t$. The distance traveled by Car 2 during this process is:

$$s_2 = v_2 t_2 + v_2 t + \frac{v_2^2}{2a_2} \tag{5}$$

Comprehensive consideration shows that the safe following distance between the two cars now becomes:

$$d_s = v_2 t_2 + v_2 t + \frac{v_2^2}{2a_2} - v_1 t \tag{6}$$

Additionally, in the overtaking scenario, to prevent angular collisions as shown in Figure 3, and combining the overtaking geometric relationship shown in Figure 4, we need to introduce the physical size parameters of the vehicles themselves.

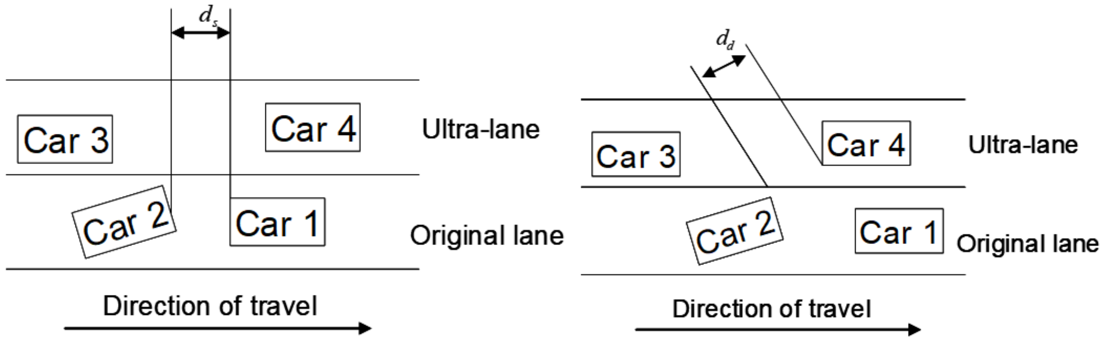

Figure 3. the distance of preventing angle touch

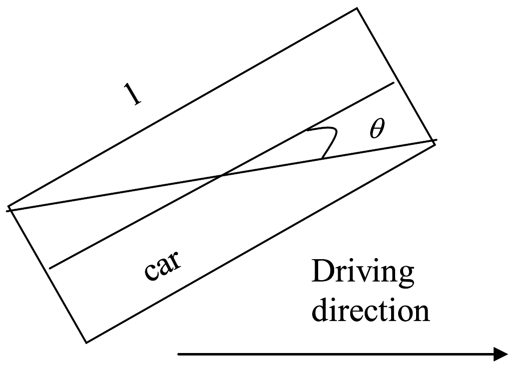

Figure 4. Overtaking Figure

Assume the length of the vehicle is l, and the overtaking angle is θ. When Car 2 executes an overtaking maneuver, if the two cars are in the same lane, considering the projection of the car body length, the safe following distance is corrected to:

$$d_d = d_s + l\cos\theta \tag{7}$$

And when Car 2 executes an overtaking maneuver in a different lane, its safe following distance is adjusted to:

$$d_d = d_s + l\sin\theta \tag{8}$$

Through the parameter substitution and calculation under the different speed limits mentioned above (such as 60km/h and 80km/h).

2.3. Cellular Automaton Traffic Flow Simulation Model

To further explore the relationship between time and space under different traffic conditions and speed limits, this paper established a Cellular Automaton (CA) model to simulate the characteristics of continuous traffic flow on a two-lane freeway. In the model setting, each lane is divided into L consecutive cells. Each cell can be empty or occupied by a vehicle with speed v, where the value range of v is $0,1,2,\dots,v_{max}$, and v_{max} represents the maximum allowed driving speed of the vehicle. We use $x(i,t)$ to denote the position of the i-th vehicle at time t, and use $v(i,t)$ to denote its speed at that time. At time t, the number of spatial cells between the i-th vehicle and the vehicle in front of it is defined as:

$$gap(i,t) = x(i-1,t) - x(i,t) - L \tag{9}$$

Where L also represents the number of cells occupied by the vehicle itself.

During the CA model simulation process, all vehicles located in the cells will undergo synchronous state updates in each time step following the four core evolution rules shown in Figure 5:

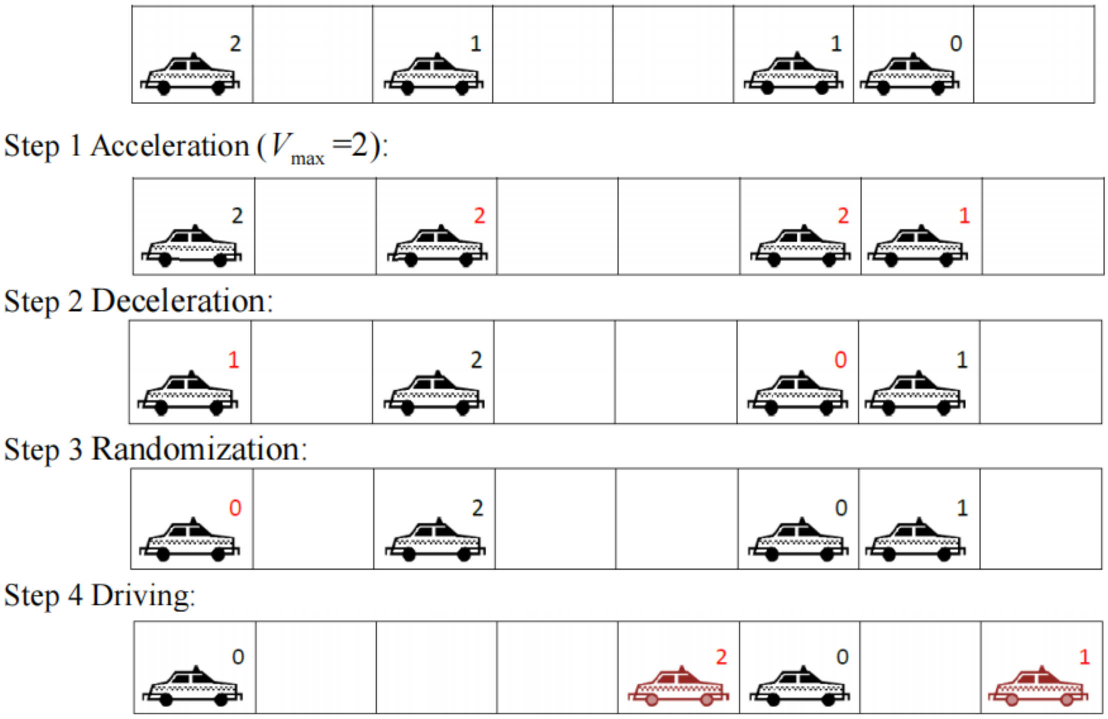

Figure 5. Movement process diagram

First, the acceleration phase. This phase reflects the characteristic that drivers desire to reach the maximum driving speed in reality. When a vehicle enters the speed limit area, its speed is updated to:

$$v(i,t+1) = \min(v(i,t)+1, v_{max}) \tag{10}$$

Second, the deceleration phase. To avoid colliding with the vehicle in front, the driver must take deceleration measures. At this time, the speed is updated to:

$$v(i,t+1) = \min(v(i,t), gap(i,t)) \tag{11}$$

Third, the random randomization phase. Considering vehicle deceleration caused by various uncertain factors, the model introduces a random randomization probability p. With probability p, the vehicle speed decreases, that is:

$$v(i,t+1) = \max(v(i,t)-1,0) \tag{12}$$

Fourth, the position update phase. The vehicle moves forward according to the adjusted final speed, and its position update formula is:

$$x(i,t+1) = x(i,t) + v(i,t+1) \tag{13}$$

By simulating a two-lane highway with a length of 3000 meters and consisting of 2000 cells (with a simulation step size of 1s), we can plot the spatio-temporal evolution patterns under different speed limits, and then analyze the diffusion and dissipation mechanisms of traffic flow when the road encounters bottlenecks or congestion.

2.4. Intelligent Traffic Control System Method Combined with Cloud Computing

When exploring future traffic rule formulation and lane design, relying solely on static rules is often insufficient to cope with complex real-time traffic conditions. Therefore, this paper introduces an intelligent traffic management and control system containing dynamic traffic flow data and static road environment data, and innovatively integrates big data and cloud computing technologies. The intelligent transportation system closely combines people, vehicles, and roads, comprehensively utilizing information technology, data communication transmission technology, intelligent control technology, and sensor technology.

In the proposed intelligent control system architecture, each running vehicle acts as an independent node with its own "private cloud." The private cloud is responsible for collecting and storing real-time information about the vehicle itself and its surrounding environment, such as its coordinate position, vehicle priority, current vehicle speed, maximum braking deceleration, braking reaction time, vehicle length, and number of passengers. Subsequently, these decentralized private cloud information will be uploaded via the network and aggregated into the "public cloud" platform of that road section.

The public cloud not only receives individual data from all vehicles but also integrates external data such as real-time weather conditions, map network information, and freeway speed limit rules. Within the public cloud platform, various complex data mining and intelligent processing algorithms are deployed. By comprehensively calculating vehicle priority, safety distance model output, and road network status, the public cloud intelligent processing system can generate specific guiding instructions for each vehicle, such as whether overtaking is allowed, the steering angle size for overtaking, whether to yield to other vehicles, and the current most appropriate vehicle distance. It then feeds these instructions back to each vehicle's private cloud, thereby guiding the vehicle to automatically execute response activities such as acceleration, deceleration, or lane changing.

To achieve more precise traffic flow regulation, the public cloud system also embeds a short-term traffic flow prediction module. This module is built based on Kalman filtering theory and Wavelet Neural Network (WNN), and its schematic diagram is shown in Figure 6.

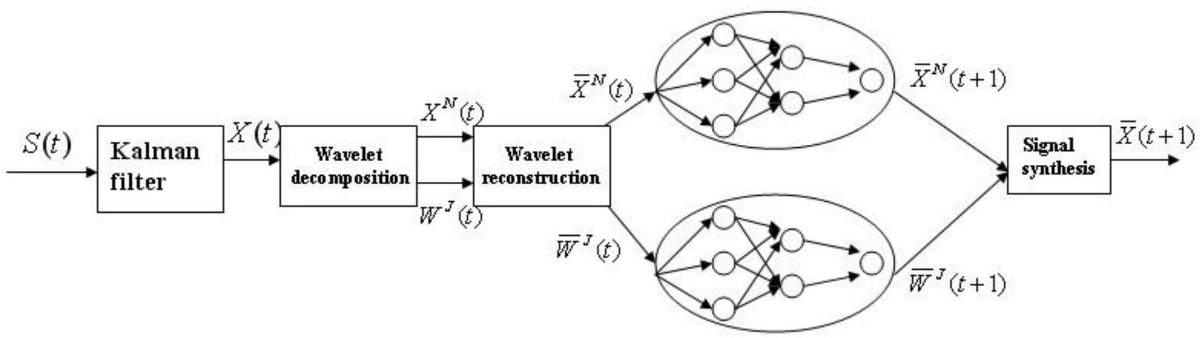

Figure 6. Wavelet and Kalman filter schematics

The specific algorithm process is as follows: First, a Kalman filter is used to filter the original data samples to eliminate noise interference and obtain filtered samples. Subsequently, the wavelet network parameters are initialized, including the scaling factor and translation factor of the wavelet function, network connection weights, and learning rate. Then, the filtered samples are divided into a training set and a testing set, and input into the network for forward calculation to obtain predicted values and calculate the expected output error. Finally, the expected error is used to inversely correct and perfect the wavelet function parameters and network weights, iterating continuously until the algorithm converges and ends. Through this intelligent prediction model, the public cloud can predict the traffic flow for a period of time in the future in advance, and synchronously feed the prediction results back to other vehicles, thereby assisting vehicles in effectively avoiding peak congestion and choosing the safest and most efficient driving plan.

3. Experiments and Results

3.1. Data Description

To comprehensively verify the effectiveness of the safe following distance model and Cellular Automaton (CA) simulation model proposed in this paper, we strictly initialized and set multiple core parameters during the experimental phase. In the numerical experiment of the safe following distance model, we set the general value of the driver's reaction time and the braking system's coordinated reaction time to $1.2s$. The deceleration growth time is set to $0.1s$, and the maximum braking deceleration for both test vehicles is set to a conventional value of $8m/s^2$. In spatial geometric calculations involving overtaking anti-collision, we set the physical length of a standard vehicle to $6m$ and the deflection angle during vehicle overtaking and lane changing to $20°$. To simulate different traffic operating environments, we selected $60km/h$ and $80km/h$ as the speed limit benchmarks for the original lane and the adjacent lane, respectively, and tested the safe distance data under these speed limit conditions when the front and rear vehicles had different speed combinations (for example, the front vehicle's speed is $50km/h$ or $60km/h$, and the rear vehicle's speed varies from $40km/h$ to $80km/h$).

In the CA traffic flow evolution simulation experiment, we constructed a two-lane freeway physical space with a total length of $3000m$. For discrete calculation, this road section is finely divided into multiple cells, and the physical length of each cell is defined as $1.5m$. Thus, each directional lane consists of 2000 consecutive cells. Regarding space occupation, each standard car occupies the length of 4 cells, and the simulation time step is strictly set to $1s$. To eliminate the interference caused by instability in the initial stage of the simulation system starting up, all microscopic state data were collected and recorded after the system continuously ran for 10^3 evolution steps. On this basis, under the same experimental conditions, we tested the spatial evolution patterns under different speed limit thresholds such as $40km/h$, $60km/h$, $120km/h$, and $150km/h$. Meanwhile, to examine the sensitivity impact of the large truck proportion and different speed limit rules on macroscopic traffic flow, we set the random deceleration probability to 0.2 in subsequent experiments and tested the traffic flow evolution when the maximum speed limit variable took values from 1 to 5, respectively.

3.2. Results Analysis

Through the comprehensive processing and analysis of experimental data, this paper has drawn significant conclusions regarding road safety, spatio-temporal evolution of traffic flow, and traffic density relationships. First, based on the calculation results of the safe following distance model shown in Table 1, we found that within a specific road section, when the speed of the front car is lower than that of the rear car, the required safe following distance between the two cars reaches its minimum.

Table 1. Safe Following Distance under different speed limits

Condition	Vehicle	Speed limit (60km/h)		Speed imit (80km/h)	
$v_1 > v_2$	car 1	50	50	60	60
	car 2	55	60	70	80
	ds(m)	16.77	21.16	24.16	34.86
	dd(m)	16.81	21.20	24.20	34.90
$v_1 = v_2$	car 1	50	60	70	80
	car 2	50	60	70	80
	ds(m)	12.30	14.90	17.06	19.30
	dd(m)	12.34	14.94	17.10	19.34
$v_1 < v_2$	car 1	50	50	70	70
	car 2	40	45	50	60
	ds(m)	8.88	11.61	5.52	13.78
	dd(m)	8.92	11.65	5.56	13.82

This indicates that if absolute road safety (i.e., no collision accidents occur) is guaranteed, requiring all vehicles to strictly abide by the established rule of "driving in the rightmost lane unless overtaking" will cause the vehicle spacing in the same lane to be significantly lengthened. Under heavy traffic conditions, forcing the conditions of the safe following distance to be met to eliminate safety hazards will inevitably slash the actual traffic flow of the road, proving that after the traffic volume reaches a certain scale, a single right-driving rule will inevitably restrict overall traffic efficiency due to safety constraints.

Second, the CA model vividly demonstrated the spatio-temporal evolution patterns of traffic flow under different speed limits. By comparing the spatial evolution graphs of the right lane under different speed limit conditions shown in Figure 7, we found that under the premise of ensuring traffic safety, reasonable speed limits can maximize road capacity. An excessively high speed limit setting cannot effectively shorten the time it takes for vehicles to arrive and pass through congested areas. An excessively low speed limit, while able to suppress the deterioration of traffic congestion, causes vehicles to take too long to pass through the speed limit zone, which may instead trigger congestion in upstream road sections and reduce the road's actual capacity. Experimental simulation results specifically indicate that when the freeway speed limit interval is controlled at $60 \sim 120km/h$, the system can achieve an optimal state; that is, through reasonable speed control, the spread of congestion is effectively delayed, and the time required for traffic jams to dissipate is significantly shortened.

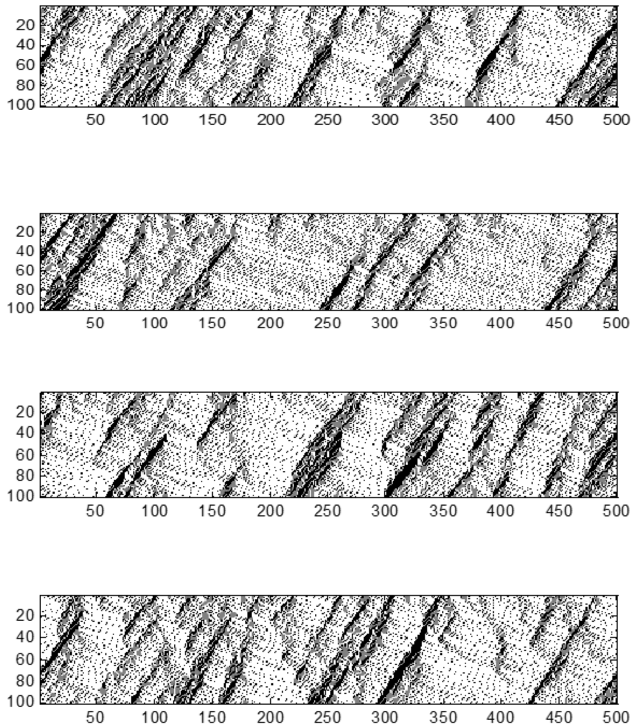

Figure 7. Spatio-temporal evolution graph

To break the flow bottleneck caused by existing rules, this paper analyzed an alternative scheme of increasing the number of feasible lanes and relaxing lane-change return restrictions as shown in Figure 8. The results show that under the condition of ensuring safe following distance, dispersing vehicle driving trajectories can effectively increase the overall traffic flow.

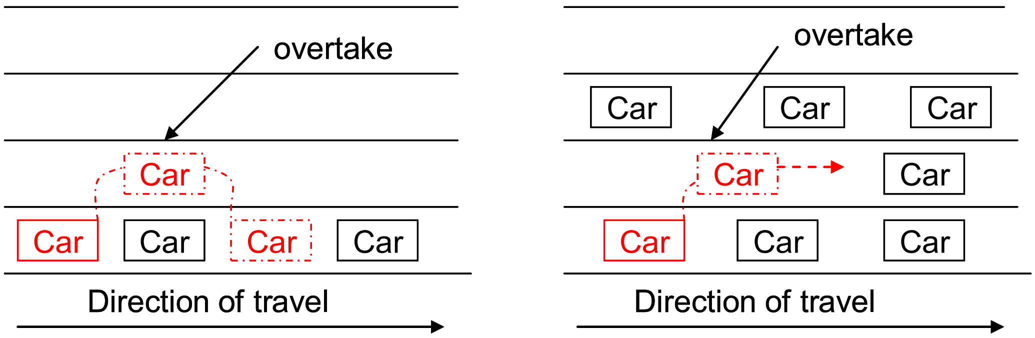

Figure 8. The difference between two-lane and multi-lane diagram

Meanwhile, considering the characteristics of mixed traffic flow on real-world freeways, this paper specifically evaluated the impact of the large truck occupancy rate on road network performance (detailed in Figure 9, Traffic flow changes with the rate of large truck).

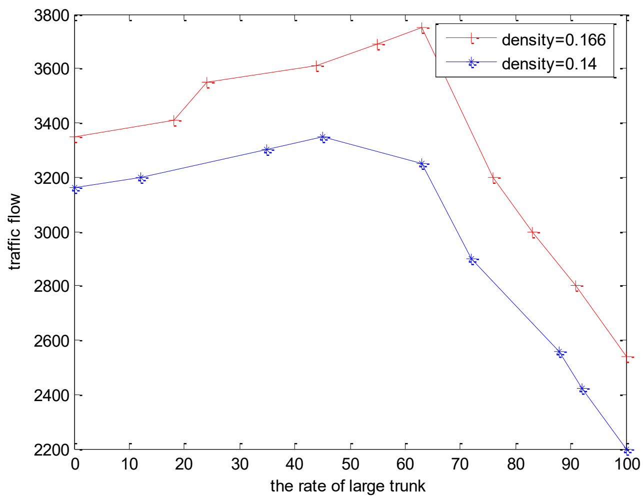

Figure 9. Traffic flow changes with the rate of large truck

As traffic density climbs, total traffic volume increases while average speed decreases; more importantly, as the proportion of large trucks increases, traffic flow exhibits a trend of first increasing and then decreasing. The inherent reason for this phenomenon is that due to their longer body lengths, large trucks require significantly longer safe following distances than small cars. To seek the greatest common divisor between safety and efficiency, this paper proposes that separate lane and separate speed limit management must be implemented for small and large vehicles, and detailed speed limit standards for different lanes as shown in Table 2 were formulated.

Table 2. Different lane speed limit tables

	Road type	Maximum speed	Minimum speed
Two-lane	The most right lane	100km/h	60km/h
	Heretics	120km/h	60km/h
Three-lane	The most right lane	80km/h	60km/h
	The second road	100km/h	60km/h
	Heretics	120km/h	60km/h
Four-lane	The most right lane	80km/h	60km/h
	The second road	100km/h	60km/h
	The third road	120km/h	60km/h
	The fourth road	120km/h	60km/h

Finally, the sensitivity analysis conducted in this paper further revealed the mathematical relationship among the maximum speed limit, density, and flow, with results shown in Figure 10.

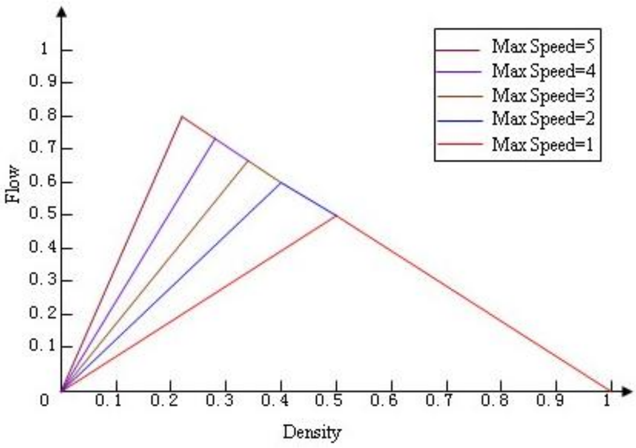

Figure 10. Sensitivity analysis Graph

The figure intuitively reflect that the higher the maximum speed set by the system, the more obvious the kurtosis of the flow-density curve. For different maximum speed settings from 1 to 5, their corresponding critical densities when producing maximum flow are 0.5, 0.33, 0.26, 0.2, and 0.17, respectively. This result provides a solid theoretical basis for dynamically adjusting freeway speed limits to match real-time traffic density.

4. Conclusion

This paper conducted systematic microscopic and macroscopic validation research on the complex coupling relationship among freeway driving rules, traffic safety, and traffic efficiency. By establishing a safe following distance model based on physical kinematics theory, this paper accurately quantified the anti-collision safety thresholds for vehicles under different driving states and complex overtaking and lane-changing processes. The study found that strictly abiding by the static rule of driving on the right inevitably leads to widened vehicle spacing to guarantee absolute safety under heavy traffic environments, thereby irreversibly cutting the actual traffic flow of the road. Spatio-temporal evolution simulation experiments based on the Cellular Automaton model further confirmed this conclusion and revealed the positive role of reasonable speed limit intervals in maximizing road capacity. Experiments explicitly indicated that an increase in the proportion of large trucks in mixed traffic flow significantly changes the critical density of traffic flow, objectively requiring traffic management departments to implement more refined lane-based and speed-based management strategies. To thoroughly overcome the inherent defects of traditional static traffic rules in improving macroscopic flow, this paper forward-lookingly designed an intelligent traffic collaborative control system integrating big data mining and cloud computing technologies. By building a dual-layer communication and computing architecture of individual vehicle private clouds and regional platform public clouds, combined with advanced filtering algorithms and wavelet neural network models, this system can not only achieve efficient prediction of short-term traffic flow states but also provide real-time, dynamic, and optimal driving behavior instructions for individual vehicles within the road network. Overall, this paper not only theoretically reveals the internal mechanisms between traffic flow evolution and road speed limit rules but also provides a practical technical path for the architectural design and dynamic right-of-way intelligent allocation of future intelligent transportation systems at the engineering application level.

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