# ADVANCES IN TRANSPORTATION STUDIES
## *An International Journal*

Guest Editors: L.G. Mo, Z.W. Liu

2023 Special Issue, Vol. 2

**Contents**



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*Advances in Transportation Studies an international Journal* 2023 Special Issue, Vol. 2

ISBN 979-12-218-0834-6 – ISSN 1824-5463 – DOI 10.53136/97912218083461 – pag. 3-12

# Real time assignment method of urban dynamic traffic flow in social governance

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**Abstract**

Real time allocation of urban dynamic traffic flow can effectively improves urban traffic congestion and travel efficiency. Aiming at the problems of poor road network capacity and high traffic congestion index under the current allocation methods, this paper proposes a real-time allocation method of urban dynamic traffic flow in social governance. Firstly, use wireless sensor networks to collect real-time traffic flow data and perform dimensionality reduction processing on the collected data; Then, based on the data dimension reduction results, the urban dynamic traffic flow is predicted using the generated adversarial network; Finally, use the shortest path algorithm to allocate urban dynamic traffic flow in real time, calculate the shortest driving path of vehicles, and achieve optimal allocation of traffic flow. The experimental results show that the traffic congestion index and the road network capacity of the proposed method in this article are effectively improved. The research results provide a new approach to preventing congestion and improving traffic efficiency.

*Keyword - social governance, urban transportation, generative adversarial network, shortest path algorithm*

## 1. Introduction

With the continuous acceleration of urbanization, urban traffic flow continues to increase, and the problem of traffic congestion is becoming increasingly prominent. In order to alleviate traffic congestion and improve the operational efficiency of urban transportation, real-time allocation of urban dynamic traffic flow has become an important research field [16, 12]. Real time allocation of urban dynamic traffic flow refers to the monitoring, analysis, and regulation of urban traffic flow through information technology to achieve optimization and reasonable allocation of traffic flow. The research on real-time allocation of urban dynamic traffic flow is of great significance for urban social governance [10, 1]. It can effectively solve the problem of urban traffic congestion, improve the travel efficiency and quality of life of the people. Therefore, real-time allocation of urban dynamic traffic flow has important practical significance and development prospects.

Long et al. [8] proposes a congestion traffic flow allocation method that takes into account the different rationality of travelers, considers the difference in psychological perception of travel time and queue time, and constructs a Statistical model of path selection under different rationality to achieve traffic flow allocation. The results indicate that this method can be applied to traffic guidance of congested road networks, which is beneficial for promoting the rational utilization of road resources. However, after applying this method, the traffic congestion index is still high. Yue et al. [19] proposed a static traffic flow allocation method of road network considering congestion space queuing and overflow. First, enrich and improve the relevant assumptions of static traffic flow allocation considering congestion space queuing and overflow; Secondly, establish network bottleneck identification algorithms and spatial queuing backtracking algorithms; Finally, a comparative analysis is conducted using an illustrative example. The research results indicate that this method can effectively describe the overall macro operational state of the road network and the congestion interference and infiltration phenomenon caused by congested space queuing. However, after allocating traffic flow through this method, the road network capacity still cannot meet actual needs. Xu et al. [17] proposed a random network path selection and traffic flow allocation model design method that considers decision inertia, analyzes the inertia behavior and influencing factors in traveler path selection, and describes the traveler's decision inertia through a variable reliability value coefficient. Through analysis, it is found that the Decision model of route selection considering decision-making inertia established in this paper is general and can consider the impact of multiple Bounded rationality factors on the path selection of travelers, but there is a problem of high traffic congestion index.

Aiming at the problems of high traffic congestion index and poor road network capacity existing in existing methods, a new real-time allocation method of urban dynamic traffic flow in social governance is proposed. The case proves the effectiveness of the traffic flow allocation method proposed in this paper. This method can reduce the traffic pressure, improve the operation efficiency of the traffic system, and improve the social governance effect according to the actual situation and needs of the city.

## 2. Real time collection and dimensionality reduction processing of urban dynamic traffic flow data

Social governance refers to a comprehensive and long-term work in which the government and various aspects of society jointly manage social affairs, maintain social order, public safety, and social stability. In practice, social governance faces many difficulties and challenges, among which traffic problem is a difficult problem in social governance. When using existing technologies to collect traffic flow data, there are problems such as incomplete data and high latency [11, 9, 6]. Therefore, this article adopts wireless sensor networks for real-time traffic flow data collection. Wireless Sensor Network (WSN) is a wireless communication technology that can deploy a certain number of sensor nodes on the road to monitor real-time traffic flow, speed, density, and other information, and transmit it to a central server for processing and analysis. Compared to traditional traffic flow data collection methods, WSN has lower deployment and maintenance costs, which can effectively save costs and human resources. And WSN adopts a distributed structure, even if a single node fails, it will not affect the operation of the entire system, and has high reliability and fault tolerance. Figure 1 shows the schematic diagram of real-time traffic flow data collection using wireless sensor networks.

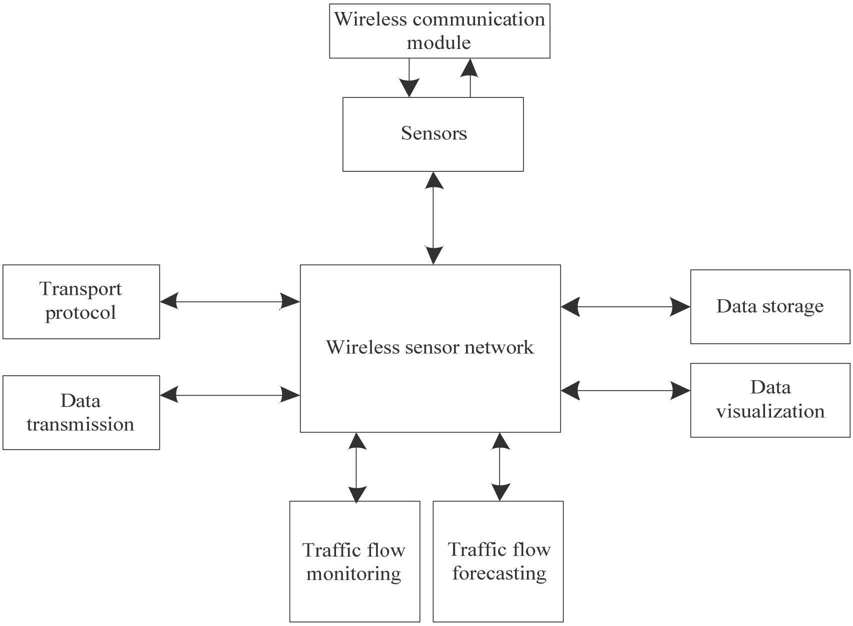


Fig. 1 - Schematic diagram of the principle of real-time traffic flow data collection using wireless sensor networks

The specific steps for real-time collection of traffic flow data using wireless sensor networks are as follows:

(1) Deployment and configuration of sensor nodes: Fully consider factors such as the number, location, communication distance of sensor nodes, as well as issues such as accuracy and real-time data collection. Arrange a certain number of sensor nodes on the road, each equipped with sensors and wireless communication modules, which can collect real-time traffic flow, speed, density and other information.

(2) Data collection and transmission: Sensor nodes transmit the collected data to the central server through wireless communication modules. During the data collection and transmission process, parameters such as data format, transmission protocol, and network bandwidth need to be considered.

(3) Data processing and analysis: The central server analyzes and processes the collected data, adjusts the timing and phase of traffic signals based on traffic conditions, and optimizes vehicle traffic efficiency and safety. In the process of data processing and analysis, data processing algorithms, data storage methods, Data and information visualization and other factors need to be considered.

(4) Real time monitoring and prediction: By monitoring changes in traffic flow, predict the likelihood of traffic congestion and accidents, and take timely measures to avoid traffic accidents. In the process of real-time monitoring and prediction, factors such as the time interval of data collection, the speed and accuracy of data processing need to be considered [2].

A large amount of traffic flow data has been obtained through wireless sensor networks, but due to the large amount of data, it can reduce the efficiency of subsequent traffic flow allocation. Therefore, principal component analysis is used to reduce the dimensionality of the above data. The dimensionality reduction method for traffic flow data refers to the process and analysis of traffic flow data, converting high-dimensional traffic flow data into low-dimensional feature vectors [5, 14] for subsequent traffic flow allocation.

Standardize real-time traffic flow data to ensure that each variable has the same scale and variance:

$$x_i' = \frac{x_i - \bar{x}}{\sigma} \tag{1}$$

where $x_i$ represents the i-th sample; $\bar{x}$ represents the Sample mean; $\sigma$ represents the standard deviation of the sample.

The covariance matrix is calculated according to the standardized data to measure the correlation between different variables:

$$\mathrm{S} = \frac{1}{\mathrm{n}-1}\sum_{\mathrm{i}=1}^{\mathrm{n}}(x_i' - \bar{x})(x_i' - \bar{x})^{\mathrm{T}} \tag{2}$$

where n represents the number of samples; T represents a constant.

The covariance matrix is decomposed into eigenvalues to obtain eigenvalues and corresponding eigenvectors:

$$\mathrm{S}\nu = \lambda\nu \tag{3}$$

where $\lambda$ represent characteristic values; $\nu$ represents the corresponding feature vector.

According to the size of eigenvalues, select the eigenvectors corresponding to the first k largest eigenvalues as the principal components, project the original data onto the principal components, and obtain new low dimensional eigenvectors:

$$y_i = W^T x_i' \tag{4}$$

where $W$ is the matrix composed of the first k feature vectors selected.

PCA converts high-dimensional traffic flow data into low-dimensional feature vectors, reducing the dimensionality of the data and facilitating subsequent urban dynamic traffic flow allocation.

## 3. Real time allocation method of urban dynamic traffic flow

In social governance, urban dynamic traffic governance has problems such as traffic congestion, low traffic Factor of safety, and difficulty in public parking. Therefore, real-time allocation of urban dynamic traffic flow is needed to alleviate traffic congestion [7, 3]. Based on the real-time collection and dimension reduction results of urban dynamic traffic flow data, Generative adversarial network (GAN) is used to predict urban dynamic traffic flow. GAN can learn traffic flow patterns and laws from a large number of historical data and predict future traffic flow. Compared to traditional prediction methods, GAN can obtain more accurate prediction results, and has advantages such as high accuracy, real-time, scalability, and visualization in traffic flow prediction. It can effectively improve the efficiency and quality of urban traffic management [13, 18].

After dimensionality reduction processing, a GAN model is constructed using two modules: a generator and a discriminator. The generator is used to generate traffic flow prediction results, and the discriminator is used to evaluate whether the output results of the generator are true. The GAN model is:

$$\mathrm{V}(D, G) = E_{x\sim pdata}\big(logD(x)\big) + E_{z\sim pz(x)}\Big(log\big(1 - G(z)\big)\Big) \tag{5}$$

where $G$ represents the generator; $D$ represents discriminator; $z$ represents noise data; $pdata$ is the distribution of real data; $pz(x)$ is the distribution of noise data; $D(x)$ is used to convert random noise into traffic flow prediction results; $G(x)$ is used to evaluate the authenticity of traffic flow prediction results.

The Loss function is introduced to train the GAN model, and the parameters of the generator and discriminator are constantly adjusted, so that the generator can generate more accurate traffic flow prediction results, and the discriminator can better evaluate the authenticity of these results. The Loss function is as follows:

$$L_G = -E_{z\sim pz(x)}\left(logD\left(G(z)\right)\right) \tag{6}$$

$$L_D = E_{x\sim pdata}\left(logG\left(D(x)\right)\right) \tag{7}$$

$$\mathrm{L} = L_G + \lambda L_D \tag{8}$$

where $L_G$ represents the generator Loss function; $L_D$ is the discriminator loss function; $\mathrm{L}$ is the total Loss function.

The meaning of this Loss function is to minimize the competition between the generator and maximize the discriminator, so that the generator can generate more realistic sample data, and the discriminator can better distinguish between real data and generated data. Specifically, the first term of the Loss function is used to train the discriminator so that it can better identify the real data; The second item is used to train the generator to generate more realistic data.

Based on the prediction results of urban dynamic traffic flow, the shortest path algorithm is used for real-time allocation of urban dynamic traffic flow. The shortest path algorithm has low Time complexity, and can calculate the shortest path of the vehicle in a short time. It can calculate the shortest path of vehicles based on the topological structure and traffic status of the road network, allocate vehicles to different roads, and achieve optimal allocation of traffic flow [4, 15]. The specific steps to use this algorithm for real-time allocation of urban dynamic traffic flow are as follows:

Abstract the urban road network as a graph, with each intersection and road corresponding to the nodes and edges in the graph. Determine the starting and ending points based on the departure and destination of the vehicle. Set the distance from the starting point to all other nodes to infinity: $\mathrm{dist}[v] = \infty$, where $v$ is any node in the graph. The distance from the starting point to itself is set to 0: $\mathrm{dist}[s] = 0$, where $s$ is the starting point.

Select the node closest to the starting point as the current node, mark it as visited, and find the node closest to the starting point among the unreachable nodes:

$$\mathrm{u} = min_{v\in V} dist[v] \tag{9}$$

where $\mathrm{V}$ represents the set of nodes.

Relax all neighboring nodes of the current node. If the distance from the starting point to the neighboring node is less than the original distance of the neighboring node, update the distance of the neighboring node to a smaller value.

Traverse all neighboring nodes $\mathrm{v}$ of the current node $\mathrm{u}$, update the distance of neighboring nodes, and calculate the shortest path of the vehicle based on the topology and traffic status of the road network:

$$\mathrm{dist}[v] = min\{dist[v], dist[u] + \omega(u,v)\} \tag{10}$$

where $\omega(u,v)$ represents the weight of edges $(u,v)$.

Based on the calculation results of the shortest path, while considering factors such as road capacity and speed, allocate vehicles to different roads to achieve optimal allocation of traffic flow.

## 4. Experimental analysis

In order to verify the effectiveness of the method proposed in this article, an experimental verification was conducted using city A as an example.

### *4.1. Research subjects*

The road density in city A is very high, but due to the extensive use of alleys and alleys in the urban construction process, Figure 2 is a schematic diagram of the local transportation network in the city. In the context of imbalanced regional development, the traffic capacity of local areas is severely insufficient, leading to increased traffic congestion and accident rates. Moreover, due to population growth and urban expansion, the public transportation network in city A is facing increasing transportation demand, and cannot meet the travel needs of passengers during peak hours. The lack of supporting parking lots also leads to a rebound in self driving traffic, which puts pressure on road traffic. At the same time, the number of private vehicles in city A has exceeded 6 million, exacerbating the level of urban traffic tension. In summary, the current situation of traffic flow in city A is quite complex, with narrow roads, excessive traffic flow, and complex environmental factors posing serious challenges to traffic management and overall planning. Therefore, real-time allocation of dynamic traffic flow in city A has certain practical significance.

Taking the city as the research object, the method proposed in this article is applied to allocate its traffic flow. The road network capacity and traffic congestion index are used as test indicators to compare the operating status of the city's traffic flow after the application of this method with before the application of this method.

(1) Road network capacity: Refers to the capacity of the road network to accommodate vehicle traffic demand, generally measured by indicators such as road width, number of lanes and vehicle speed.

(2) Traffic congestion index: Usually, indicators such as congestion speed and vehicle congestion time are used to reflect the situation of urban congestion. Real time data can be obtained through traffic flow monitoring equipment, and user experience of congestion can also be obtained through survey questionnaires.

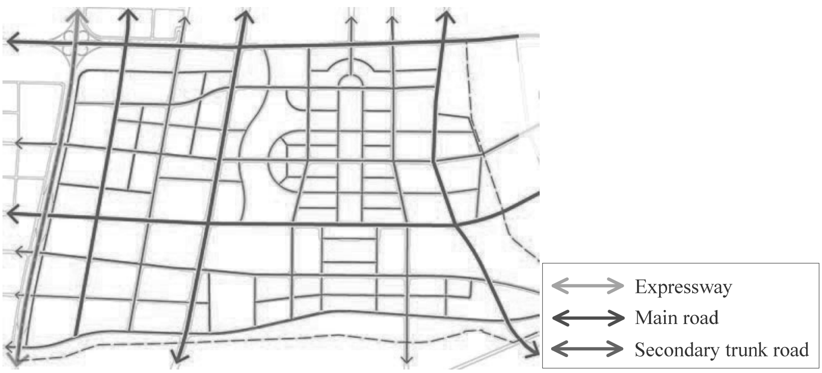


Fig. 2 - Schematic diagram of local transportation network in city A

### *4.2. Result analysis*

(1) Road network capacity

Using vehicle speed as an indicator to measure the traffic capacity of the road network, a comparison was made between the operating status of the city's traffic flow after the application of the methods in this paper, literature [8] and literature [19], and before the application of the above methods. The results are shown in Table 1.

From the data in Table 1, it can be seen that after applying the method proposed in this article, the vehicle speed in city A has been significantly improved on both the main and secondary roads, with the main road 1 having the most significant improvement effect. After applying the method proposed in this article, the vehicle speed has increased by 5.2 km/h compared to before. After the application of the methods in Long et al. [8] and Yue et al. [19], the traffic capacity of the road network is not significant. Therefore, it can be seen that the application of the method in this article to allocate traffic flow in city A improves the speed of vehicle traffic, which plays an important role in promoting the implementation of the sustainable development strategy of the city. This case demonstrates the advantages and feasibility of the method in this article.

(2) Traffic congestion index

Using vehicle congestion time as an indicator to measure the traffic congestion index, a comparison was made between the operating status of the city's traffic flow after applying the methods presented in this article, Long et al. [8] and Yue et al. [19], and before applying the above methods. The results are shown in Table 2.

From the data in Table 2, it can be seen that after applying the method proposed in this paper, the congestion time of vehicles has been significantly reduced. Among them, the congestion time control effect of vehicles on main road 2 is the most obvious.

Tab. 1 - Achievement test results of road network (km/h)

| Road | Before application | After the application of the method in this article | After the application of Long et al. [8] method | After the application of Yue et al. [19] method |
|---|---|---|---|---|
| Expressway | 64.1 | 68.7 | 65.2 | 67.1 |
| Main Road 1 | 20.3 | 25.7 | 21.5 | 23.0 |
| Main Road 2 | 24.1 | 28.9 | 25.2 | 27.5 |
| Main Road 3 | 20.8 | 23.6 | 21.9 | 22.6 |
| Secondary Main Road 1 | 22.5 | 26.0 | 24.3 | 24.9 |
| Secondary Main Road 2 | 18.7 | 19.4 | 19.7 | 19.0 |

Tab. 2 - Traffic congestion index test results/min

| Road | Before application | After the application of the method in this article | After the application of Long et al. [8] method | After the application of Yue et al. [19] method |
|---|---|---|---|---|
| Expressway | 10.2 | 5.6 | 8.7 | 7.0 |
| Main Road 1 | 39.7 | 21.5 | 30.2 | 28.8 |
| Main Road 2 | 40.2 | 20.1 | 31.8 | 29.3 |
| Main Road 3 | 27.5 | 19.2 | 20.7 | 20.1 |
| Secondary Main Road 1 | 11.5 | 6.3 | 7.4 | 10.3 |
| Secondary Main Road 2 | 9.7 | 5.0 | 6.4 | 8.1 |

After applying the method proposed in this paper, the congestion time of vehicles has been reduced by 20.1 min compared to before applying the method. After applying the methods in Long et al. [8] and Yue et al. [19], although the traffic congestion index has been reduced, the decrease is not as significant as the method in this paper. This indicates that the method in this paper achieves real-time monitoring of roads and real-time allocation of traffic flow, and can adjust the cycle of traffic lights according to the actual situation, in order to quickly solve the congestion problem, thus effectively reducing the occurrence of traffic congestion.

## 5. Conclusion

Traffic flow allocation is one of the important links in social governance, which has significant implications for achieving sustainable urban development and improving transportation efficiency. Therefore, a new real-time allocation method of urban dynamic traffic flow in social governance is proposed. Compared with the traditional prediction methods, GAN can obtain more accurate prediction results by using the generative adversarial network to predict the urban dynamic traffic flow. GAN has the advantages of high precision, real-time, scalability and visualization in traffic flow prediction. According to the test results, the vehicle speed on main road 1 has increased by 5.2 km/h, indicating that the application of this method has effectively improved the traffic capacity of the road network. The shortest path algorithm is used for real-time allocation of urban dynamic traffic flow, which has low Time complexity and can calculate the shortest path of vehicles in a short time. According to the test results, it can be seen that the congestion time of vehicles on Main Road 2 has been reduced by 20.1 min, indicating that the traffic congestion index has been significantly reduced after the application of this method. From this, it can be seen that the traffic flow allocation effect of this method is good, effectively improving the traffic capacity of the road network, reducing the traffic congestion index, and playing an important role in improving urban traffic efficiency and reducing congestion.

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*Advances in Transportation Studies an international Journal* 2023 Special Issue, Vol. 2

ISBN 979-12-218-0834-6 – ISSN 1824-5463 – DOI 10.53136/97912218083462 – pag. 13-28

# Safety distance detection of highway vehicles driving under partial water skiing conditions

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**Abstract**

Accurate safety distance detection under humid road conditions is of great research significance for improving driving safety. In this paper, a novel safety distance detection of highways vehicles driving under partial water skiing conditions is proposed. Firstly, the mechanism of tire water skiing and the model of water film thickness were analyzed. Secondly, the car following behavior of vehicles is analyzed, and the safety car distance model is established; By introducing sufficient distance coefficient K, the accuracy of the minimum safe driving distance calculation is improved. Finally, based on the CarSim2016 AEB system, combined with the minimum safe driving distance obtained from the solution, the safe distance detection of highways vehicles driving on is achieved. The experiment results show that the minimum safe distance of the proposed method are basically consistent with the actual critical driving distance, with a detection accuracy of 99.3%, a detection time of 0.3 seconds, and a variance of 0.01. This indicates that the proposed method can accurately detect the safe distance of driving vehicles and is more reliable.

*Keyword - expressway, minimum safe driving distance between vehicles, following driving behavior, sufficient distance coefficient, safe distance detection*

## 1. Introduction

Since 2014, China's highway mileage has ranked first in the world, highlighting the outstanding achievements of China's highway transportation industry in the era of rapid transportation. Despite the increasingly balanced density of China's highway network and the continuous improvement of traffic efficiency, highways still have a high accident rate that does not match their level [2]. Freeways have the characteristics of high traffic flow and fast driving speed. When vehicles intentionally or unintentionally stop while driving, it can lead to traffic accidents [11]. For highway traffic accidents, rear end collision has always been the main type of accidents, most of which are caused by overspeed or failure to maintain Safety car distance. Under long-term high-speed driving conditions, there may be significant problems for drivers in subjectively judging the distance between vehicles. If the distance between the front and rear vehicles is too large, the road traffic volume will decrease, which cannot effectively play the role of the highway and does not meet the expectations of drivers; If the distance between cars is too small, there is a significant risk of rear end collision [6]. The speed control on highways is relatively mature, but the distance control measures are relatively lacking. Therefore, in the context of continuously improving vehicle performance, exploring the minimum safe driving distance on highways has important value, so that the distance control measures not only meet the requirements of safe driving, but also meet the expectations of drivers. By determining the minimum safe driving distance on highways to achieve safe distance detection for vehicles driving on highways, it serves as a reminder to drivers, improves traffic safety, and fundamentally improves the safety level and service quality of highways, which is of great significance for promoting the development of intelligent transportation.

Zhao et al. [20] proposed an improved secure distance model. Firstly, a two-dimensional extension set is established through the method of extension decision-making to achieve the division of dynamic security boundaries, and different braking modes are adopted in different domains. Secondly, based on the collision avoidance model, the ideal braking pressure is obtained and an improved safety distance model is constructed to achieve safe distance detection for driving vehicles. However, due to the poor accuracy of the minimum safe distance calculated by this method, the detection effect of safe distance is not satisfactory. Wang et al. [16] proposed a vehicle road visual collaborative driving safety detection method. First, the deep Convolutional neural network is used to complete the detection and tracking of the vehicles in front, and then a safety distance model is constructed to calculate the distance between vehicles. Finally, the safety distance detection is realized through the multi lane early warning model. However, this method cannot accurately detect the safe distance under some water skiing conditions, and the detection efficiency is not high. Zhang and Ma [19] proposed a detection method for active collision avoidance safety distance model based on trajectory weighted prediction. This method constructs a trajectory prediction model through a weight coefficient function that changes over time, and then constructs an active safety distance model to complete safety distance detection. However, due to the dependence of this method on accurate front vehicle trajectory data, if there are errors in the data, the minimum safety distance obtained may not be accurate enough, resulting in low accuracy of driving vehicle safety distance detection.

Based on the poor accuracy of the minimum safe distance calculation results of the above methods, which leads to low accuracy and efficiency of safe distance detection, a study on the safe distance detection of vehicles driving on highways under partial water skiing conditions is proposed. Firstly, the mechanism of tire hydroplaning and the model of water film thickness were analyzed to better understand the causes and influencing factors of tire hydroplaning, and to provide reliable information support for determining the minimum safe driving distance model of vehicles under humid road conditions in the future, in order to improve the accuracy of detection. Secondly, the basic section of the expressway is analyzed, and the car following behavior is analyzed under this section. Finally, combined with the mechanism of tire hydroplaning and the model results, the Safety car distance model is constructed to solve the minimum safe vehicle distance. And introduce the sufficient distance coefficient K value to ensure that the minimum safe distance between vehicles is not less than the actual critical distance between vehicles, in order to improve the accuracy of the minimum safe distance between vehicles and ensure the reliability of detection. Finally, based on the AEB system of CarSim2016 and combined with the research results of the minimum safe driving distance on highways in this paper, the safe distance detection of vehicles driving on highways is achieved.

## 2. Mechanism and model analysis of tire water skiing

To achieve safe distance detection for vehicles driving on highways under partial water skiing conditions, multiple factors need to be considered, among which tire water skiing is one of the important factors. By studying the mechanism of tire water skiing and the model of water film thickness, it is possible to better understand the causes and influencing factors of tire water skiing, and thus provide reliable information support for determining the minimum safe driving distance of vehicles under humid road conditions in the future, in order to improve the detection effect.

### *2.1. Mechanism analysis of tire water skiing*

When driving on waterlogged roads, there are three types of areas formed between the tires and the road: complete suspension area A, incomplete contact area B, and complete release area C, as shown in Figure 1. In area A, the dynamic water pressure is strong, making the tire completely separate from the road surface and unable to generate any braking or driving force [5]. And in this area, the water film formed by accumulated water on the road surface will be pushed by the tires on both sides, causing the thickness of the water film to become thinner, thereby reducing the tire's grip and prone to risks; In area B, the tires will discharge water from the convex areas of the road surface, forming a dry area, but there is still water in the concave areas; Zone C, in a nearly dry state, with the tread in full contact with the road surface, can generate forward driving force.

The adhesion between the tire and the road surface varies greatly in regions C and B, respectively. However, due to the compression of the tire, the water film generates a reaction force, causing the tire in region A to experience horizontal driving resistance and vertical buoyancy, resulting in complete separation between the tire and the road surface. Therefore, no adhesion is generated in this region, which is a partial water skiing state [8]. When the driving speed is low, Zone C will be longer and the vehicle can maintain a certain degree of maneuverability; When the vehicle speed reaches a certain critical value, the C-zone completely disappears, and the tire suspends on the water film, causing complete water skiing. At this point, the vehicle loses its maneuverability. Therefore, based on the above analysis, in region A, due to the complete separation of tires from the road surface, both braking and acceleration are ineffective. Drivers should avoid sudden braking or acceleration operations in this region. In Zone B, the tires only make partial contact with the road surface, so the braking and acceleration performance of the vehicle may be affected to some extent. Drivers should slow down appropriately and try to avoid handling actions such as sharp turns. In Zone C, the tires come into complete contact with the road surface, and the vehicle's braking and acceleration performance returns to normal, but caution is still required for driving. Therefore, in order to reduce the risk of driving on waterlogged roads, drivers should pay attention to these different contact areas and adjust their driving speed and handling actions appropriately. When driving at high speeds, it is particularly important to be alert to the appearance of Zone A, as this means that the vehicle is in an extremely dangerous state of complete water skiing.

Next, in order to better understand the mechanism of tire water skiing, respond to water skiing situations, provide reliable information support for subsequent safety distance detection, and reduce accident risk, based on the above analysis content, the stress condition of the tire during water skiing is analyzed, as shown in Figure 2.

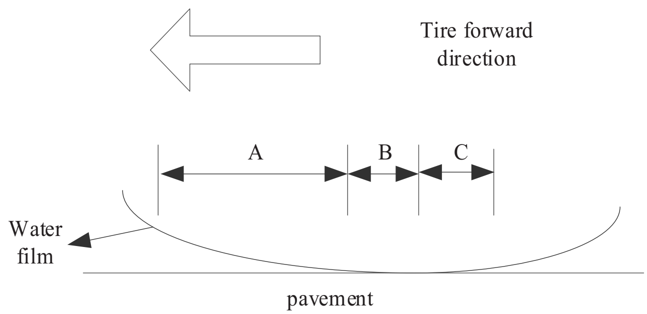


Fig. 1 - Schematic diagram of contact area

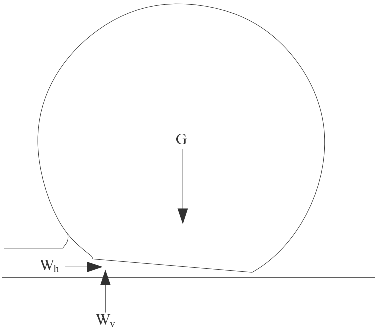


Fig. 2 - Schematic diagram of stress

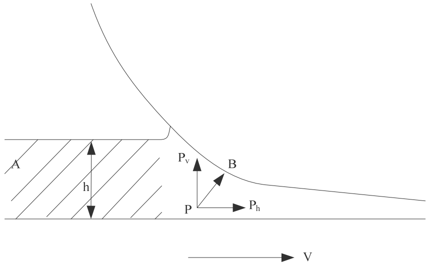


Fig. 3 - Schematic diagram of dynamic water pressure components

In Figure 2, the definitions of each letter are described as follows: $W_v$ and $W_h$ are the components of the hydrodynamic pressure in the vertical and horizontal directions, respectively. The vertical direction bears the tire load, the horizontal direction hinders the tire's forward movement, and G represents the load borne by the tire. Assuming the tire remains stationary and the water film moves relative to the tire at velocity V, establish a coordinate system with the tire center as the origin as shown in Figure 3.

In the figure, A and B are the two points of the water film, P is a point in the static water pressure space of the water film at point B, $p_h$ is the horizontal component representing the horizontal thrust of the water film on the tire, $p_v$ is the vertical component representing the vertical thrust of the water film on the tire. After establishing a coordinate system, it is possible to better describe and calculate the decomposition of the dynamic water pressure at a certain point on the tire in both horizontal and vertical directions. To analyze the relative motion between the water film and the tire, and further study the thickness changes of the water film in different contact areas and its impact on the tire, in order to determine the accurate water film thickness in the future and provide more accurate road condition information for solving the minimum safe driving distance in the future. The formula for calculating the components of dynamic water pressure in the horizontal and vertical directions is as follows:

$$W_h = \int_{S_w} p_h ds \tag{1}$$

$$W_v = \int_{S_w} p_v ds \tag{2}$$

where $S_w$ is the water film area that can generate dynamic water pressure.

According to the Euler equilibrium differential equation, the position function of point P [4] is known as:

$$\mathrm{p} = \mathrm{f}(\mathrm{x}, \mathrm{y}, \mathrm{z}) \tag{3}$$

During driving, the mass force on the liquid is only the relative pressure at any point within the liquid under gravity. When the thickness of the water film $h$ is too small, the hydrostatic pressure can be ignored. Therefore, the formula for calculating the relative pressure at a certain point in the liquid is:

$$p' = \gamma h \tag{4}$$

where $\gamma$ is the weight of the liquid.

Assuming that a certain micro element in the water film moves from point A to point B during water skiing, there will be no loss of kinetic energy along the way. When reaching point B, the velocity of the micro element is zero due to the water generated by water skiing [7], and due to the blocking effect of the tire, all the kinetic energy of the micro element water when it impacts the tire is converted into pressure. At this point, the pressure at point B of the water film can be calculated by the following formula:

$$p = \frac{\rho v^2}{2} \tag{5}$$

where $\rho$ is the density of water, and $v$ is the vehicle's driving speed. As a result, the vehicle experiences tire slippage under humid road conditions.

*2.2. Water film thickness model*

When driving on waterlogged roads, there is a certain relationship between the thickness of the water film and the deformation value of the tire. When the water film is thick, the tire will experience greater resistance when in contact with the road surface. In this case, the deformation of the tire will increase because the tire needs to adapt to the unevenness of the road surface and maintain contact with the road surface through deformation. However, it should be noted that excessive water film thickness may also cause the tire to lose effective contact with the road surface, thereby reducing the stability and grip of the vehicle. Therefore, determining accurate water film thickness to consider reducing the adverse effects of tire deformation and providing more accurate road condition information for the subsequent calculation of the minimum safe driving distance between vehicles. The calculation formula for water film thickness is as follows:

$$h = h_0 + h_1 \tag{6}$$

where $h_0$ is the height value of the low corner point when the tire surface forms a certain wedge angle with the road surface; $h_1$ is the deformation value of the tread in the vertical direction.

By studying the viscoelasticity of rubber materials, the calculation formula for $h_1$ can be obtained:

$$h_1 = \iint_{dA} \frac{p}{\pi \rho} \left[ \frac{1}{2q_0} - \frac{q_1 - q_0}{2q_0} e^{\left(-\frac{q_0 t}{q_1}\right)} \right] dxdy \tag{7}$$

where $dA$ is the unit grid area of the tread; $t$ is a time variable; $q_0$. $q_1$ is the calculation coefficient related to the elastic modulus of the tread unit and pavement material; $p$ is the vertical concentrated load.

Thus, the mechanism and model analysis of tire hydroplaning are completed to better understand the causes and influencing factors of tire hydroplaning, providing reliable and effective information support for the safety distance detection of vehicles driving on highways under certain hydroplaning conditions in the future.

## 3. Implementation of safe distance detection for automobiles driving on freeways under partial water skiing conditions

Next, in order to achieve accurate detection of the safe distance of vehicles driving on the expressway under partial water skiing conditions, first determine the basic section of the expressway to be studied, analyze it, then analyze the car following behavior under this section, finally combine the mechanism of tire water skiing and the model results, build a Safety car distance model, and introduce sufficient distance coefficient K to ensure the accuracy of the minimum safe distance calculation, To improve the reliability of detection and ensure driving safety.

*3.1. Overview of basic sections of highways*

The basic section of a highway is the main part of the highway, usually a straight or approximately straight section, without obvious turns or intersections, and vehicles can travel at higher speeds. The design of these sections takes into account the demand for high-speed driving, with larger lane widths and gentle slopes [18]. In addition, there is usually no impact of ramps or weaving sections on basic road sections, and vehicles can travel at relatively stable speeds and flows. Therefore, this study will focus on the basic sections of highways as the research environment. The schematic diagram is shown in Figure 4.

The basic road section range refers to the main road section from 150m upstream to 760m downstream of the on-ramp mainline connection, from 760m upstream to 150m downstream of the off-ramp mainline connection, and from 150m upstream of the intersection point representing the beginning of the weaving section to 150m downstream of the separation point representing the end of the weaving section.

### *3.2. Car following behavior*

Next, in the basic section environment of the highway mentioned above, the following driving behavior will be analyzed to provide rich information for subsequent safe distance detection of driving vehicles, thereby making the detection results more accurate and improving driving safety. Under high-density traffic flow conditions, driving behavior is mainly determined by the operating characteristics of the preceding vehicle [15].

Car following is a driving state where vehicles are arranged in a queue at a certain distance, which is particularly common in single lane situations such as highways. The principle of car following is shown in Figure 5.

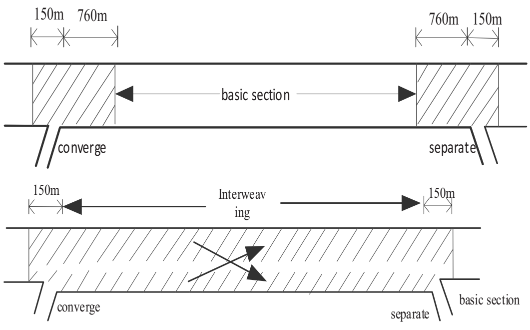


Fig. 4 - Schematic diagram of basic sections of highways

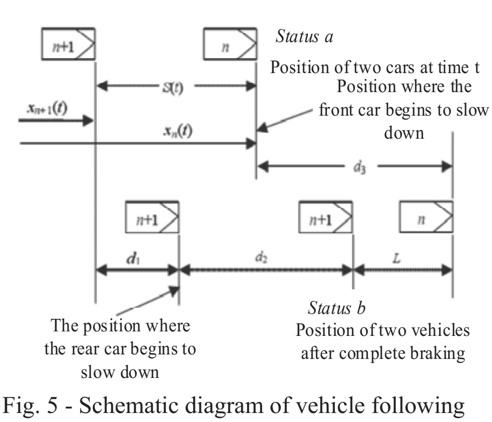


Fig. 5 - Schematic diagram of vehicle following

Next, based on the above schematic diagram, describe the operational characteristics of the fleet driving in a following state, as follows:

1) Restrictive

In the process of car following, an appropriate car following distance can provide enough reaction time and Braking distance for the driver to deal with emergencies or sudden braking of the car ahead. If the distance between vehicles is too small, the driver will not be able to react and stop in a timely manner, which can easily lead to collision accidents. In addition, the current large speed difference between the rear vehicles can easily cause a sharp decrease in vehicle spacing [14], increasing the risk of collisions. At the same time, the driver of the following vehicle also needs to pay attention to the space between the adjacent lane and the preceding vehicle when driving, in order to maintain stability and safety when following the vehicle. From this, it can be concluded that following distance, vehicle speed, and following requirements constitute the constraints of following driving [3].

2) Delayability

According to the above restrictive operating characteristics, when the current operating state of the vehicle changes, the driver of the following vehicle will experience continuous reactions of perception, recognition, judgment, and operation. Firstly, the perception stage refers to the driver perceiving a change in the running state of the preceding vehicle. The driver perceives the actions of the front car through visual, auditory, and other senses, such as the front car's brake lights coming on or making a braking sound. This is the first step for the driver to realize that there may be changes in the front car. Next is the identification stage, where the driver needs to determine what changes have occurred to the running status of the preceding vehicle. This may require observing the behavior of the preceding vehicle, analyzing the speed changes of the preceding vehicle, and paying attention to other traffic signals to confirm whether the preceding vehicle is urgently braking or slowing down. In the judgment stage, drivers need to evaluate the current traffic situation and the conditions of their own vehicles to decide what driving behavior to take. This may include selecting appropriate braking force, adjusting vehicle speed, or changing lanes to avoid collisions with the vehicle in front. Finally, during the operation phase, the driver will perform corresponding driving operations based on the judgment results. This may include pressing the brake pedal, adjusting the throttle or steering wheel, etc. to adapt to changes in the running status of the vehicle in front. Moreover, due to factors such as reaction time, there is a certain degree of delay in the changes in the running state of the rear vehicle [10].

3) Transitivity

According to the definition of car following and the two operating characteristics mentioned above, it can be seen that during car following, the operating state of the preceding vehicle affects the motion state of the following vehicle. Once the first vehicle changes its operating state, the effect will gradually propagate until the last vehicle, which is called transferability [12]. Due to the reaction time of the driver and the dynamic characteristics of the vehicle, there is a delay in the transmission, which forms a damping wave for backward transmission. After receiving the information, no corresponding adjustments will be made immediately, but there is a certain lag.

### *3.3. Implementation of safe distance detection for vehicles driving on freeways*

#### 3.3.1. Determination of minimum safe driving distance between vehicles

On the basis of the above analysis, combined with the mechanism and model analysis of tire hydroplaning, a model of Safety car distance is constructed to solve the minimum safe vehicle distance, so as to realize the safe distance detection of vehicles driving on the expressway under partial hydroplaning conditions. Since the Safety car distance model is mostly derived from the analysis of the braking process [1], in order to calculate the safe distance more accurately, an improved algorithm for the Mazda safe distance model is selected, so as to improve the detection accuracy of the safe distance of driving vehicles, help drivers better control vehicles, and reduce traffic accidents. The algorithm is as follows:

$$D_s = \begin{cases} \frac{1}{2a_{max}}[v^2 - (v - v_{rel})^2] + v\left(t_x + t_a + \frac{1}{2}t_s\right) + d_0, Forward\ \ velocity \\ \frac{v^2}{2a_{max}} + v\left(t_x + t_a + \frac{1}{2}t_s\right) + d_0,\ \ Forward\ \ stop \end{cases} \tag{8}$$

where $a_{max}$ is the maximum braking deceleration; $v$ is the speed of the rear vehicle; $v_{rel}$ is the difference in speed between backward and forward ($v$-$v_q$), m/s; $t_x$ is the driver's braking response time; $t_a$ is the braking coordination time; $t_s$ is the growth time of braking deceleration; $d_0$ is the safe parking distance, usually taken as 2-5m. For $a_{max}$, ignoring the influence of the vehicle model and treating the deceleration of the front and rear vehicles as equivalent, $a_{max} = 7.5m/s^2$, $v$ is selected as 20m/s~36m/s, and only $v_{rel} \geq 0$ is considered; $t_x = 1.26s$; $t_a = 0.1512s$; $t_s = 0.175s$;$d_0 = 2m$.

When the number of vehicles driving on the highway reaches a certain level, a stable traffic flow will be formed, and vehicles will want to return to following. When the traffic volume increases again, it will cause vehicles to shift from weak following to strong following, until traffic congestion occurs. For the study of the minimum safe driving distance on highways in this article, it is aimed at the critical state of transitioning from weak following to strong following [13]. When vehicles follow in a stable traffic flow, in the event of emergency braking of the front vehicle, it is often caused by the factors of a certain vehicle in the convoy that the rear vehicles collide with each other. Based on the critical conditions of vehicle following, determine whether there is a potential risk of rear end collision when retreating. When the expected distance between the rear vehicles is lower than the critical safe driving distance, there is a high possibility of rear end collision. Due to the fact that the calculation of the minimum safe distance between vehicles is crucial for detecting the safe distance between vehicles, the accuracy of the calculation is directly related to the effectiveness of the detection and the safety of drivers. Therefore, in order to achieve accurate detection in the future, it is necessary to introduce a sufficient distance coefficient K value to ensure that the minimum safe distance between vehicles $D_s$ (i.e., the critical safe distance between vehicles) is not less than the actual critical distance between vehicles, in order to ensure the reliability of the detection, The specific formula is as follows:

$$D_s = D_{min} + K(D_{max} - D_{min}) \geq v \quad t_h - L \tag{9}$$

where A is the critical headway between the front car and the rear workshop,s; $L$ is the length of the front car 6m, with 6m for small cars and 12m for large cars.

When calibrating the K value, the critical headway $t_h$ is a crucial parameter that requires a large volume of vehicle headway samples and screening analysis to determine the critical threshold before it can be used to calibrate the K value. Through screening analysis, this article selects 2.35 seconds as the critical headway for low-speed driving on highways. And corresponding to the driver's braking reaction time mentioned earlier, there is a critical headway of 2.51s for medium speed and 2.64s for high-speed driving. The inequality for determining the sufficient headway coefficient K is:

$$\mathrm{K} \geq \frac{(vt_h - L) - D_{\min}}{D_{\max} - D_{\min}} = \frac{\mathrm{v}(t_h - t_R) + \frac{(v - v_{\mathrm{rel}})^2 - v^2}{2\mathrm{a}} - (L + d_{\mathrm{stop}})}{\frac{(v - v_{\mathrm{rel}})}{2a}} \tag{10}$$

where $t_R = t_r + t_a + \frac{1}{2}t_s$ represents the driver's total reaction time, and the rest are the same as before.