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How to accurately predict the congestion situation of urban rail transit from the perspective of public policy

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Abstract

From the perspective of public policy, it is crucial to accurately predict the congestion situation of urban rail transit. In this paper, a new predicting method for the congestion situation of urban rail transit is provided. Firstly, analyze three topological structural features and determine the characteristics of urban rail transit from the perspective of public policy by calculating the degree value, average value, actual number of edges between adjacent stations, and connectivity. Secondly, determine the key parameters of urban rail transit congestion situation and determine the impact parameters of urban rail transit congestion situation; Finally, combining the genetic algorithm and association rule algorithm, the operator is assigned congestion situation impact parameters, and precise prediction rules for urban rail transit congestion situation are set. With the congestion situation impact parameters as input and traffic congestion situation as output, a congestion situation prediction model for urban rail transit is constructed. The test results indicate that the proposed method can improve the accuracy of predicting urban rail transit congestion situation and effectively improve rail transit accessibility.

Keywords - public policy perspective, urban rail transit, congestion status, connectivity, genetic network planning algorithm, association rules

1. Introduction

With the continuous acceleration of urbanization, the scale of cities has also expanded, and the accompanying problems such as traffic congestion, environmental pollution, and traffic accidents have become increasingly serious. Developing urban rail transit has become an important way to solve the traffic problems brought about by the aforementioned urbanization process and plays an important role in the efficient operation of the city. With the complexity of urban rail transit network structure, the network characteristics are becoming increasingly obvious, and the passenger flow it carries is also increasing rapidly. At the same time, due to the openness of urban rail transit system, it is affected by various events and other factors under its operating conditions, leading to the problem of traffic congestion in urban rail transit [6]. In order to alleviate the pressure of urban commuting passenger flow, while the investment in urban rail transit construction is gradually increasing, the efficiency of rail transit is also widely concerned. Among them, improving the congestion problem of urban rail transit is the key to improving its operational efficiency. From the perspective of public policy, the improvement of the operational status and traffic congestion of urban rail transit is the most important way. The operation of urban rail transit is different from general transportation, as its network is relatively clear and complex [10]. However, due to various external factors, congestion in urban rail transit occurs, which greatly affects people's travel efficiency and reduces the working efficiency of this transportation mode [18].Therefore, from the perspective of public policy, how to accurately predict the congestion situation of urban rail transit has become a hot topic in current rail transit research. Relevant researchers have designed various prediction methods for the congestion situation of urban rail transit to improve the congestion situation of urban rail transit from the perspective of public policy and enhance the efficiency of rail transit work.

Chen et al. [5] proposed a method for predicting rail transit congestion situation based on a recursive mixed density network. The method points out that traffic situation awareness is the key factor of intelligent transportation system and smart city. The prediction of traffic congestion situation is one of the challenging tasks of traffic situation perception, which is very useful for route planning, alleviating traffic congestion, and reducing emissions. Due to the nonlinearity and randomness of short-term traffic flow, traditional parameterization methods cannot obtain accurate predictions. Deep learning methods have been widely studied in the field of short-term prediction. These non parametric methods have yielded promising results in practical experiments. Inspired by the current research status, a prediction method based on a combination of recursive mixed density networks, recurrent neural networks, and mixed density networks is proposed. This method has been implemented on actual traffic flow data, demonstrating significant advantages. Gao and Hong [6] designed a congestion prediction method for urban rail transit based on deep LSTM networks. Traffic congestion is a huge problem faced by road travelers worldwide. Timely and accurate prediction of upcoming traffic congestion can be reduced by actively planning routes. In urban areas, traffic lights, weather conditions, urban events, accidents, and people's habits can have a significant impact on traffic flow based on the structure of the road network. Therefore, a mechanism is needed to extract traffic data by capturing images from route planners' websites to predict traffic congestion. A fuzzy logic and random estimation algorithm was designed to detect the degree of road congestion. Then, combined with online training, a deeply stacked Long short-term memory network is constructed for multi-point future congestion prediction. The data predicted by this method is relatively comprehensive, but the model constructed during the prediction process is complex and not suitable for widespread use. Afrin and Yodo [1] studied the method of using Bayesian networks to predict traffic congestion probability. To ensure a strong traffic management system, it is crucial to monitor traffic conditions in a timely manner by estimating congestion levels. The current measurement can only represent changes in specific standard parameters, without considering probability characteristics. This article proposes a probabilistic congestion estimation method based on Bayesian networks. The proposed BN based method considers measurements related to speed and traffic, and provides probability estimates of possible congestion states. Two different BN models were developed for recurrent and non recurrent congestion and implemented in real-time datasets. The prediction method of this design considers the probability estimation of traffic congestion in real-time environments, achieving effective prediction, but there is a significant error in probability calculation.

On the basis of the precise prediction method for urban rail transit congestion situation mentioned above, this article proposes a new method for accurately predicting urban rail transit congestion situation from the perspective of public policy. The main characteristics of this method are as follows:

Characteristic 1: Abstraction the three topological structures of urban rail transit, analyze the characteristics of the three topological structures, and determine the characteristics of urban rail transit from the perspective of public policy by calculating the degree and average of urban rail transit stations, the actual number of edges and connectivity between adjacent stations.

Characteristic 2: Utilizing the traffic wave model to analyze the operational situation of urban rail transit in general, based on this, determine the key parameters of urban rail transit congestion situation, namely: congestion spread, diffusion speed, total queue length of the road network, and congestion rate of the road network, to determine the impact parameters of urban rail transit congestion situation.

Characteristic 3: Using genetic network planning algorithm to select the optimal operator for predicting the impact parameters of urban rail transit congestion situation. By combining genetic network planning algorithm and association rule algorithm, the operator is assigned congestion situation impact parameters, precise prediction rules for urban rail transit congestion situation are set, and the prediction parameter rule pool is updated to construct an urban rail transit congestion situation prediction model. The impact parameters are input into the model to achieve the final prediction.

2. Accurate prediction of urban rail transit congestion situation from the perspective of public policy

2.1. Analysis of the characteristics of urban rail transit from the perspective of public policy

In predicting the congestion situation of urban rail transit from the perspective of public policy, it is first necessary to understand the characteristics of urban rail transit and conduct further analysis and research based on its characteristic structure. The characteristics of urban rail transit are similar to those of general transportation, but there are also significant differences. Urban rail transit is generally more common in large cities, with fixed tracks and specific rules for vehicle operation time [1]. In this analysis of this feature, the main focus is on analyzing the characteristics of the urban rail transit network, based on its road network topology structure. The urban rail transit network is mainly composed of station stations and rail lines, and its Abstraction topology includes three types, as shown in Figure 1. From Figure 1, it can be seen that in the topology structure of urban rail transit network 1, the network is complicated into network nodes, and the inter station intervals are described as boundaries, highlighting the direct connection relationship between urban rail transit.

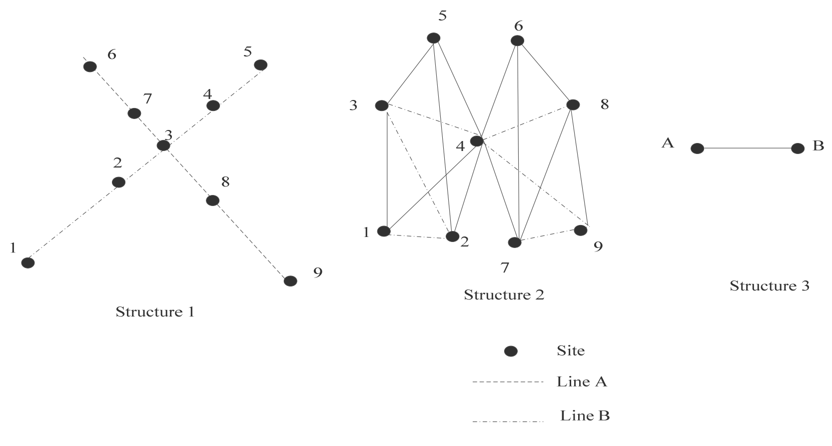

Fig. 1 - Topological structure diagram of urban rail transit network

The urban rail transit network topology structure 2 also abstracts it as a node, but its stations on the same track all have connection relationships, indicating the crisscrossing relationship between rail transit. The topology structure 3 of the urban rail transit network directly reflects the entire rail connection state, which means that transfers can be made directly under this structure, but only reflects the line transfer relationship.

According to the analysis of urban rail transit network structure, in order to highlight the characteristics of urban rail transit, this article first calculates the moderate value of the rail transit, which mainly reflects the characteristics of the station. The station occupies a key position in the occurrence of congestion in urban rail transit. Generally, the larger the station degree value, the higher its importance [3]. By measuring this value, it is determined whether there is a direct relationship between congestion and the station. The calculation formula for the station degree value of urban rail transit is:

$$D_i = \sum d_{ij} \tag{1}$$

where D_i represents the degree value of urban rail transit stations, and d_{ij} represents the connectivity coefficient from station to station j. When two sites are connected, $d_{ij} = 1$, and vice versa, $d_{ij} = 0$.

By determining the average degree of all urban rail transit stations, the average degree of urban rail transit stations is obtained, and the result is:

$$\overline{D_\iota} = \frac{1}{n} \sum_{i=1}^{N} k_i \tag{2}$$

where $\overline{D_\iota}$ represents the average value of station degree, and k_i represents the average Degree distribution function of urban rail transit station network.

On the basis of analyzing the degree value of urban rail transit stations, if the path of rail vehicles in the urban rail transit network is the minimum value between stations, it reflects the closeness between two stations [17]. The actual number of side changes between adjacent stations is also the key to reflect whether urban rail transit is accessible. The ratio result is:

$$c_i = \frac{2a_i}{k_i(k_i-1)} \tag{3}$$

where c_i represents the tightness between urban rail transit stations, and a_i represents the actual edge relationship that exists.

In addition, the analysis of urban rail transit characteristics can also highlight its characteristics through connectivity. Connectivity, as a global parameter for determining whether rail transit is congested, is crucial in the entire feature analysis [13]. When the connectivity value of urban rail transit is higher, it indicates that there are more idle nodes in the entire transportation, and there will be no congestion problem. The calculation formula for this parameter can be expressed as:

$$r_i = \frac{b}{3n-m} \tag{4}$$

where r_i represents the connectivity of urban rail transit, b represents the number of rail transit sides, n represents the total number of stations, and $3n - m$ represents the maximum number of connecting sides of the rail transit track.

In the analysis of the characteristics of urban rail transit from the perspective of public policy, Abstraction the three topological structures of urban rail transit, analyze the three topological structure characteristics, and determine the characteristics of urban rail transit from the perspective of public policy by calculating the degree value, average value, the actual number of edges and connectivity between adjacent stations of urban rail transit, Based on this, conduct subsequent research on congestion situation.

2.2. Determination of parameters influencing the congestion situation of urban rail transit from the perspective of public policy

On the basis of the above analysis of urban rail transit characteristics, in order to achieve accurate prediction of congestion situation in the future, it is necessary to further determine the key factors that cause congestion problems in urban rail transit, namely the influencing parameters, before making predictions. The operation of urban rail transit is quite similar to the general mode of transportation, and there may also be problems such as accidents and vehicle congestion during its operation [14]. Therefore, in the determination of situational impact parameters, the main analysis is the congestion caused by rail transit accidents. In the determination of this parameter, there are mainly two key parameters: congestion spread and diffusion speed.

Before determining key parameters, it is necessary to analyze the operational situation of urban rail transit in general. This analysis introduces the traffic wave model to analyze the operational situation of urban rail transit in general. The traffic wave model is a relationship of urban rail transit under the premise of traffic flow conservation rules [15]. Suppose that there are two areas with different traffic densities in a straight urban rail transit section, and the vertical division plane of these two traffic density areas is the Wavefront, as shown in Figure 2.

Set the travel speed of urban rail vehicles on the plane to, and drive normally according to the fixed speed. According to the principle of conservation of traffic flow, move forward and backward along the abscissa direction on the Wavefront. If the change of rail vehicles is equal in two different areas, then the number of vehicles passing through the wavefront during the passage time is:

$$H_m = (u_1 - u_j)k_i T \tag{5}$$

where H_m represents the total number of vehicles passing through the wave front, u_1 represents the initial speed of the initial rail vehicle, and k_i represents the change of vehicles in the two regions.

According to the relationship between rail transit flow, speed, and density parameters, the calculation result of vehicle traveling wave speed is:

$$u_j = \frac{q_1 k_i - q_2 k_i}{k_i} = \frac{\Delta q}{\Delta k_i} \tag{6}$$

where q_1 and q_2 respectively represent the section flow of rail transit area, Δq represents the section flow difference, k_i represents the rail transit density, and Δk_i represents the Density contrast.

After analyzing the operational situation of urban rail transit in general, determine the influencing parameters of congestion situation in urban rail transit.

The speed of urban rail transit accident road congestion spread refers to the parameters that affect the normal operation of rail vehicles in the accident section. When the speed of congestion spread on a single accident road is obtained from the ratio of actual spread length to time, this parameter characterizes the speed of congestion spread along the accident road itself and reacts [7].

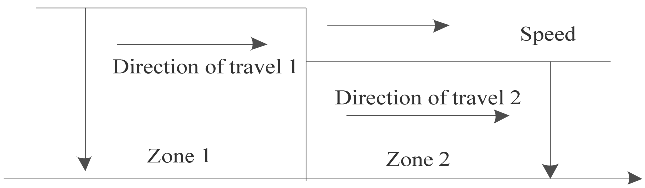

Fig. 2 - Schematic diagram of driving status in areas with different traffic densities

The calculation formula is:

$$V_i = \frac{L_i}{t} \tag{7}$$

where L_i represents the length of rail transit congestion spread at a certain moment in the accident section, t represents the duration of the rail transit accident, and V_i represents the speed of congestion spread in the rail transit accident section.

The road diffusion speed of urban rail transit accidents refers to the secondary congestion parameter that spreads to other rail transit road networks. The diffusion speed is the length of congestion that spreads from the accident location to the road network within a unit time, and its calculation formula is:

$$V_j = (\frac{1}{n}\sum_{i=1}^{n} u_i)/t \tag{8}$$

where u_i represents the distance between the location of the accident and the diffusion of congestion in the road network at a certain moment after the occurrence of a rail transit accident, n represents the number of sections where rail transit congestion spreads to the road network, and V_j represents the diffusion speed of urban rail transit accidents on the road.

After determining the two key parameters of congestion spread and diffusion speed, it is also necessary to clarify whether urban rail transit generally experiences congestion situations. Mainly reflected by the total queue length and congestion rate of the urban rail transit network [12].

When the urban rail transit accident occurs and the congestion spread lasts for a certain period of time, it will lead to the continuous increase of the total queue length of the road network. After the congestion status of its road sections is determined, the length can be calculated to reflect whether the urban rail transit has congestion. The calculation formula is:

$$G_m = \sum_{i=1}^{m} \frac{Q_i}{h_i} \tag{9}$$

where G_m represents the total queue length of the urban rail transit network, Q_i represents the number of rail vehicles queuing in the congestion time, h_i represents the number of the i congested sections, and m represents the number of congested sections on the network at the evaluation time.

According to the calculation results of the total queue length of the urban rail transit network, the congestion rate of the road network is calculated [8], and the calculation formula is:

$$\sigma_i = \frac{\gamma_i}{\gamma_{all}} \tag{10}$$

where σ_i represents the congestion rate of the road network, γ_i represents the congested road section, and γ_{all} represents the total mileage of the surrounding area of the accident location.

In determining the influencing parameters of urban rail transit congestion situation from the perspective of public policy, the traffic wave model is used to analyze the operating situation of urban rail transit in general. Based on this, key parameters of urban rail transit congestion situation are determined, including congestion spread, diffusion speed, total queue length of the road network, and road network congestion rate, to achieve the determination of the influencing parameters of urban rail transit congestion situation, As the basic data for predicting the congestion situation of urban rail transit from the perspective of subsequent public policies.

2.3. Accurate prediction model for congestion situation of urban rail transit from the perspective of public policy

How to accurately predict the congestion situation of urban rail transit from the perspective of public policy? Therefore, after determining the influencing parameters of urban rail transit congestion situation mentioned above, this article constructs an accurate prediction model of urban rail transit congestion situation from the perspective of public policy, and uses the influencing parameters as the input of the model for accurate prediction of urban rail transit congestion situation [4]. In this model construction, a combination of genetic network planning algorithm and association rule algorithm was used. The genetic network planning algorithm is a combination of the advantages of genetic algorithm and genetic programming algorithm, which is more effective in obtaining the behavior sequence of the research object [20]. Under the idea of iterative evolution, this algorithm predicts the research object through a directed graph structure, which can improve the efficiency of the research object. The basic structure of this algorithm is shown in Figure 3.

As shown in Figure 3, this algorithm connects each node and node during prediction, and during the connection process, it needs to process the judgment and calculation of nodes, which is the effective migration of nodes. The memory function of the algorithm is improved through connections between nodes, thereby improving the performance of the algorithm. Therefore, based on this algorithm, this article constructs an accurate prediction model for urban rail transit congestion situation from the perspective of public policy.

The specific implementation process is as follows:

Process 1: Using genetic network planning algorithm to select the optimal operator for predicting the impact parameters of urban rail transit congestion situation. The operator is selected to ensure the stability of the parameters affected by urban rail transit congestion situation. The selection of this operator is mainly carried out under the corresponding screening rules, selecting the best individuals from the parent population for the inheritance of the next generation. In genetic network planning algorithms, operators are derived from both mutation and crossover individuals. Therefore, in this selection, it is necessary to calculate the individual fitness of the operator and determine the probability of individual genetic occurrence under the influence of fitness [11], in order to achieve the optimal operator selection.

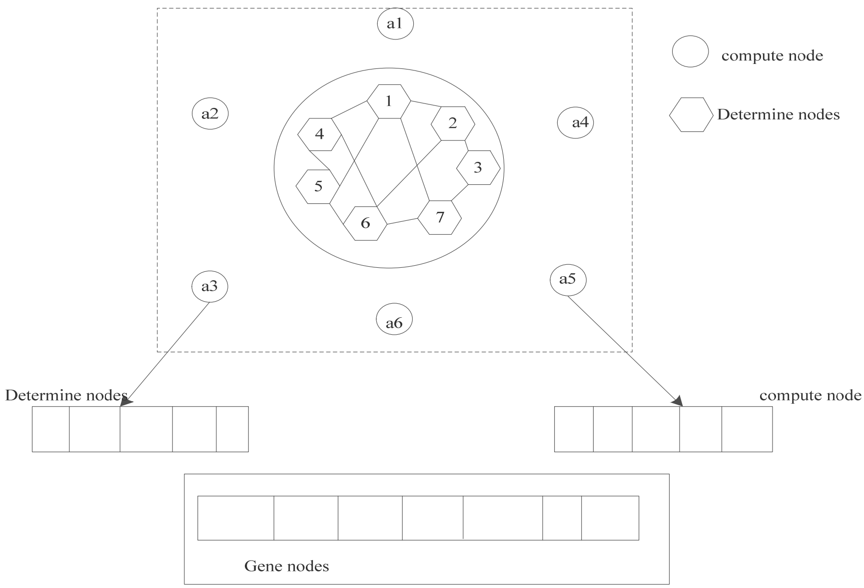

Fig. 3 - Basic structure of genetic network planning algorithm

The formula for calculating the fitness of operator individuals is expressed as:

$$f_i = \sum_{i=1}^{n}(f_{1i}, f_{2i}, \ldots, f_{ni})/y(x) \tag{11}$$

where f_i represents the fitness of the operator, and $y(x)$ represents the fitness function.

On this basis, by determining the probability of individual genetic occurrence and selecting the optimal operator, the results obtained are:

$$\mathrm{U(x)} = \mathrm{f_i}/\mathrm{n}\sum_{\mathrm{i}=1}^{\mathrm{n}}\mathrm{f(x_i)} \tag{12}$$

where $\mathrm{U(x)}$represents the probability of individual genetic occurrence, and $\mathrm{f(x_i)}$ represents the optimal operator.

Process 2: Combining genetic network planning algorithm and association rule algorithm, assign the operator to the urban rail transit congestion situation impact parameter. In this process, the combination of two algorithms is used to assign the above optimal genetic operator to the congestion situation impact parameter, so as to have the best chromosome and improve the accuracy of subsequent predictions [2]. By fusing the two pan elements into one cell element and assigning values, the impact parameters of urban rail transit congestion situation are obtained. The process is shown in Figure 4.

In this process, operator node $A_1 - A_3$ is represented as different node functions to record the time interval for determining the current congestion situation. The assigned results are represented as p_1 and p_2, and the assigned time is represented as T. In this process, the assigned results are represented as:

$$A_1 \rightarrow A_3 \wedge T(A_1 \rightarrow A_3)/N \tag{13}$$

where $\rightarrow$ represents the assignment process, and N represents the total number of parameters assigned.

Process 3: Set precise prediction rules for urban rail transit congestion situation. The setting of prediction rules helps to address the frequent occurrence of duplicate predictions in congestion situation prediction. In this rule setting, the calculation of the rule index is introduced, which is the key data in the association rule algorithm. Assuming that transaction X and transaction Y do not intersect, the calculation formula for this index with support is:

$$\gamma^2 = \frac{N(z-xy)^2}{xy(1-x)(1-y)} \tag{14}$$

where x represents rule support, y represents rule confidence, z represents data tuple, and γ represents rule index. When the index is 1, it indicates that the rule is valid when set, otherwise it is invalid.

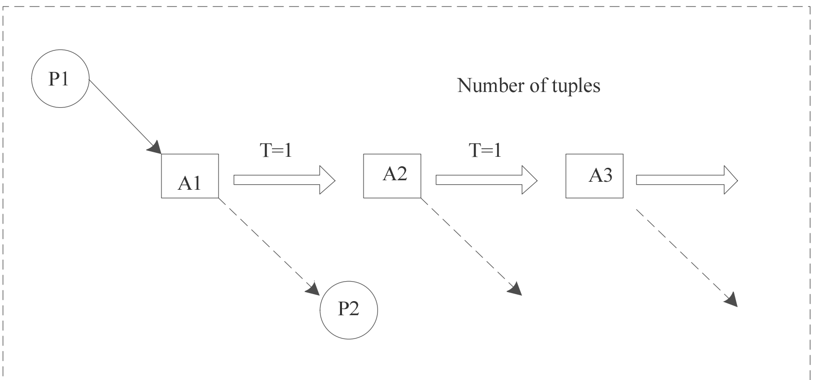

Fig. 4 - Assignment process of parameter operators for the impact of urban rail transit congestion situation

Process 4: Update the parameter rule pool for predicting the congestion situation of urban rail transit. Because the congestion situation parameters cannot always remain stable in this forecast, they need to be updated within a certain forecast interval. The update process is mainly through the update of the rule pool, which directly affects the Rate of convergence of the model in the forecast. The update result is shown as:

$$G = \sum_{r \in R}\{\gamma^2(r) + g(p_i - 1) + \alpha_i\} \tag{15}$$

where r represents the previous event after the rule pool update, g represents the weighted value, and α_i represents the event after the rule pool update.

Process 5: Build a prediction model for urban rail transit congestion situation. Based on the above process, a final urban rail transit congestion situation prediction model is constructed, and the influencing parameters are input into the model to achieve the final prediction. The constructed model is represented as:

$$\omega(x_i) = \frac{1}{m}\sum_{i=1}^{n} G \times \gamma^2 \int p_i/\beta_i \tag{16}$$

where $\omega(x_i)$ represents the predicted input model, and β_i represents the interference term in the model processing.

In the design of an accurate prediction model for urban rail transit congestion situation from the perspective of public policy, genetic network planning algorithm is used to select the optimal operator for predicting the impact parameters of urban rail transit congestion situation. By combining genetic network planning algorithm and association rule algorithm, the operator is assigned congestion situation impact parameters, precise prediction rules for urban rail transit congestion situation are set, and the prediction parameter rule pool is updated to construct an urban rail transit congestion situation prediction model. The impact parameters are input into the model to achieve the final prediction.

3. Experimental analysis

3.1. Experimental plan and parameter setting

In order to verify the feasibility of the prediction model designed in this article, this experimental study focuses on the rail transit in a certain city. The traffic data of the research object is real-time data, and the validation research is conducted from two perspectives: wide area and endpoint area. In data collection, taking into account peak work hours, real-time rail transit data is provided through a certain map software to balance the granularity of data collection and data analysis time for predicting regional rail transit congestion situation. The parameters in this experimental study are shown in Table 1.

Tab. 1 - Experimental parameters

Parameter	Content
Real time data collection period for rail transit	8:00-10:20
Number of collected road sections/piece	2500
Dataset dimension	30*2556
Real time rail transit data update duration/S	2
Congestion section length/m	500
Iterations	100
Experimental error/%	<1

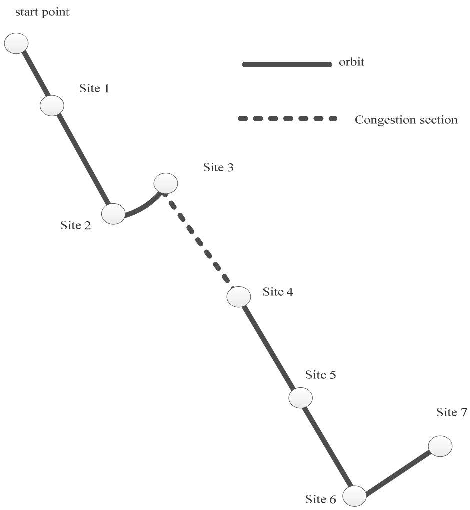

Fig. 5 - Schematic diagram of some congested sections of urban rail transit in sample cities

The schematic diagram of the congested sections of the urban rail transit selected in the test is shown in Figure 5.

3.2. Experimental methods and indicator settings

This experiment was conducted in a comparative manner, mainly comparing the proposed method, reference [5] method, and reference [16] method. In order to ensure the accuracy of the experiment, the experimental results have been verified and corrected multiple times. The experiment mainly tests the accuracy of three methods for predicting the congestion situation of selected urban rail transit and the error of rail transit congestion situation warning. Among them, the accuracy of urban rail transit congestion situation prediction directly reflects the feasibility of the method, while the error of rail transit congestion situation warning refers to the early understanding of congested sections in a certain state, which is convenient for taking certain measures.

3.3. Experimental results

The experimental analysis of the prediction accuracy of the selected urban rail transit congestion situation was conducted using the proposed method, method of Chen et al. [5] and Wang et al. [16], and the results are shown in Figure 6.

According to the analysis of the test results in Figure 6, it can be seen that the accuracy of predicting the selected urban rail transit congestion situation using the proposed method, method of Chen et al. [5] and Wang et al. [16] has changed to a certain extent with the change of prediction times. From the graph, it can be seen that the prediction accuracy of the proposed method is consistently higher than the other two methods, with a maximum of nearly 99.9%, indicating the feasibility of the proposed method.

Further experiments were conducted using the methods proposed, method of Chen et al. [5] and Wang et al. [16] to analyze the warning error of selected urban rail transit congestion situations. The results obtained are shown in Figure 7.

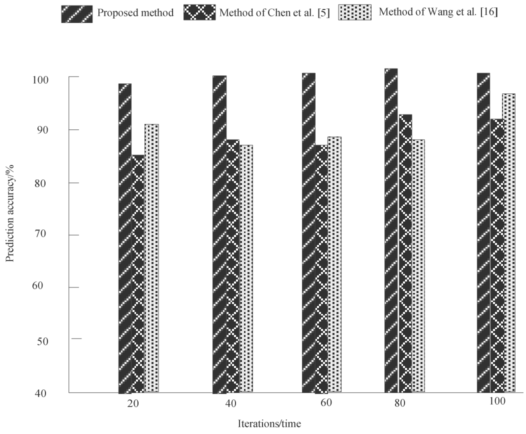

Fig. 6 - Accuracy of urban rail transit congestion situation prediction

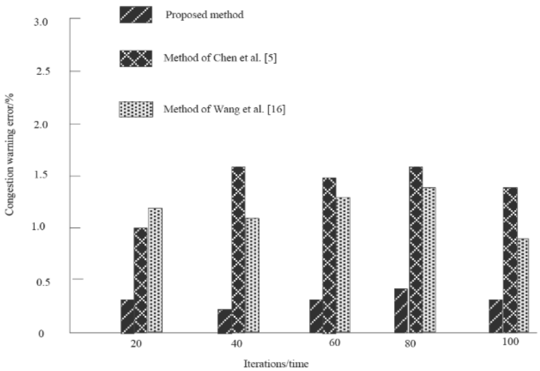

Fig. 7 - Warning error of urban rail transit congestion situation

According to the analysis of the test results in Figure 7, it can be seen that the method with the highest warning error for the selected urban rail transit congestion situation is the method of Chen et al. [5], followed by the method of Wang et al. [16], and the lowest is the proposed method. The error results of the three methods in predicting urban rail transit congestion show a decreasing trend, but the overall level of decline is average. However, the error of the proposed method is the lowest among the three methods, less than 0.5%, which is superior to the other two methods in comparison.

4. Conclusion

The problem of urban rail transit congestion has become a key issue that needs to be addressed in current urban development. Predicting the congestion situation of urban rail transit can improve this problem. A new prediction method has been designed for this purpose. This method determines the characteristics of urban rail transit and key parameters of urban rail transit congestion situation from the perspective of public policy, and combines genetic network planning algorithm and association rule algorithm to construct a new urban rail transit congestion situation prediction model, achieving the final research. The research results indicate that the proposed method can improve the effectiveness of prediction and provide early warning of urban rail transit congestion situation.

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Collaborative lane change control method for multi lane vehicles considering driving characteristics

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Abstract

The collaborative lane change control effect of multi lane vehicles is of great significance for the safety protection of vehicle driving. In order to reduce the collision frequency of multi lane vehicle collaborative lane changing, a multi lane vehicle collaborative lane changing control method considering driving characteristics is proposed. This method utilizes a driving characteristic classification method based on the Newell model and BP neural network. After extracting the driving characteristic parameters of multi lane vehicles through the Newell model, backpropagation training is used to minimize classification errors. The interlayer connection threshold and bias of the BP neural network are set, and the extracted driving characteristic parameters of multi lane vehicles are input into a trained BP neural network model to classify and recognize different driving characteristics. Combining the characteristics of non driving, a multi lane collaborative lane change method based on driving characteristics is used to construct a multi lane model, analyze the status of one's own lane and target lane, and use satisfaction as the lane change indicator to control the collaborative lane change of multi lane vehicles. The experimental results indicate that the multi lane vehicle collaborative lane change method can effectively overcome the problem of lane change collisions and has high application value.

Keywords - consider driving characteristics, multiple lanes, vehicle collaboration, lane change control, newell model, bp neural network

1. Introduction

With the increasing demand for motor vehicle travel, in order to improve the traffic capacity of roads, the number of lanes in the transportation network has also increased [10]. The significant increase in traffic demand and the spatial limitations in the construction of the transportation road network cannot achieve synchronous development [12]. Therefore, traditional road traffic facilities and control methods need to be improved in order to meet the increasing traffic demand, solve the problem of road congestion, reduce economic losses in the transportation field, and reduce the probability of traffic accidents [3]. In this new traffic environment, only by using intelligent transportation technology, comprehensively and scientifically analyzing the road traffic potential, optimizing the management mode of road information diversification in complex traffic flow environment, and carrying out coordinated lane change control for multi lane vehicles, can the planning rationality of the traffic system be optimized [1]. In the collaborative lane changing control of multi lane vehicles, traffic participants consist of multiple individual vehicles, which interact with each other and become the core participants in the traffic road network [20]. In the transportation road system, urban motor vehicles have the characteristic of concentrated travel, and the growth rate of traffic flow is significant. As the number of lanes on a certain section increases, the traffic road system will frequently encounter negative factors such as chance, randomness, and uncertainty, which will affect the driving safety between individual vehicles [15, 9]. Therefore, it is necessary to explore the rational control of the influence relationship between vehicles during the collaborative operation of multi lane vehicles. Regardless of the traffic environment, vehicle driving safety is the most important research issue. Based on the information conditions, if the multi lane vehicles can combine the changes of driving characteristics, the traffic information of the current road section and the subsequent road sections, and scientifically and reasonably control the coordinated lane changing driving of vehicles before the danger occurs, the number of traffic accidents and the economic losses caused by traffic accidents can be reduced to a certain extent [5]. Therefore, the collaborative lane change control effect of multi lane vehicles is of great significance for the safety protection of vehicle driving.

In summary, whether it is the main trunk line of the city or the urban ring road traffic, when the number of lanes increases, the problem of vehicle coordinated lane changing becomes one of the core issues in the control of the traffic road system [16, 18]. If the driver cannot reasonably operate the vehicle to change lanes and maintain a reasonable driving distance in both horizontal and vertical directions, a traffic accident may occur. Based on current relevant information, it can be seen that the proportion of traffic accidents caused by improper driver operation is significant. Research on collaborative lane change control for multi lane vehicles is necessary to reduce the incidence of traffic accidents. When conducting vehicle collaborative control, the driving behavior of the control is mainly divided into vehicle following and lane changing, which are the core issues of multi lane vehicle driving. According to the lane changing problem in various traffic driving scenarios, the content of vehicle collaborative lane changing mainly includes the collaborative control of lane changing vehicles and vehicles before and after the current lane, as well as the collaborative control of lane changing vehicles and vehicles before and after the target lane. The use of such control technologies can optimize the safety of vehicles and thus optimize traffic efficiency [14]. Therefore, scholars from both domestic and foreign countries have paid more attention to the issue of vehicle collaborative control.

Lin et al. [17] studied the PSO fuzzy expert algorithm and proposed a driving style oriented adaptive control method for automotive driving. The first aspect of this method is to design a driving style recognition method using the fuzzy expert algorithm. Based on the collected real test data of driving behavior, the principal component analysis method is used to derive the four input parameters of the fuzzy expert system. Secondly, based on the Equivalent Consumption Minimization Strategy (ECMS) and combined with the Adaptive Equivalence Factor (EF), a new adaptive control method for driving style is proposed. Although this method has been proven to be feasible, it lacks analysis on the collision performance of multi lane vehicles in the collaborative control of multi lane changing, and its effectiveness still needs to be improved. Miranda et al. [11] studied an optimization method for electric vehicle power fuzzy controller, which improves the driving control effect of the vehicle from the perspective of controller optimization. However, this method requires analyzing the dynamic information of the actual driving conditions of the car, which is a complex analysis process and has a certain negative impact on the control effect of the car. Wang et al. [19] studied the elastic path tracking control method of autonomous vehicles. This method can control the vehicle to drive intelligently according to the planned path in complex working conditions, but the lane-changing behavior of the vehicle is random. If the vehicle needs to change lanes during intelligent driving, the lane-changing control effect of this method is not ideal.

In addition to the above research methods, the current electronic stability control system and automatic braking anti-lock braking system used in vehicles can optimize the active safety and driving comfort of vehicles, and can provide information early warning in dangerous situations and directly start protection procedures. However, such a system can operate normally only when it reaches the threshold of security protection. In real life, everyone has different driving characteristics, so the warning of dangerous events is not applicable to every driver [13]. Therefore, when studying the problem of multi-lane vehicle collaborative lane change control, this paper takes the driving characteristics as the prerequisite and necessary condition of lane change control. Only after analyzing the driving characteristics of drivers can the targeted design of vehicle control be completed.

Driving characteristics indicate the driver's attitude and tendency towards the traffic network of the vehicle in a certain condition, which is closely related to the driver's gender, hobbies, mood and experience. When driving the vehicle, the driver needs to combine the traffic environment, clarify the driving intention of the car, and use the control behavior that best matches the current traffic state. Therefore, this paper proposes a multi-lane vehicle collaborative lane change control method considering driving characteristics. This method can analyze the running state of its own lane and the target lane after classifying and mastering the driving characteristics, and take satisfaction as an indicator to decide the lane change behavior of vehicles.

2. Collaborative lane change control method for multi lane vehicles based on driving characteristics analysis

2.1. Driving characteristic classification method based on Newell model and BP neural network

2.1.1. Method for extracting driving characteristic parameters based on Newell model

Newell model can combine the vehicle driving track with the Kinematics law to fit and analyze the vehicle driving law. Compared with other models, this model can set the vehicle acceleration as the output of the model, and with only a small number of parameters calculated, it can fully analyze the following state between multi lane vehicles and extract driving characteristic parameters [8]. Therefore, this article uses this model to extract driving characteristic parameters of multi lane vehicles during collaborative lane changing.

The Newell model is:

$$Y_{m+1}(T+\alpha) = min\{Y_{m+1}(T) + v\alpha, Y_m(T) - c\} \tag{1}$$

where $Y_{m+1}(T+\alpha)$ represents the displacement of the $m+1$ car at time $T+\alpha$, $Y_{m+1}(T)$ represents the displacement of the $m+1$ car at time T, v represents the driving speed of the car, α and c represents the minimum reaction time and safe following distance of the vehicle, respectively. For different drivers, there are differences in the reaction time and minimum safe distance values for following vehicles. $Y_{m+1}(T) + v\alpha$ and $Y_m(T) - c$ refers to the Free streaming and congestion flow of multi lane vehicles. The relationship between vehicle speed and following distance is shown in Figure 1.

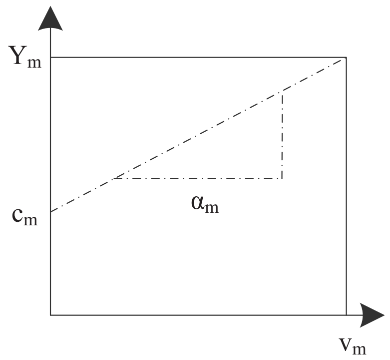

Fig. 1 - The relationship between vehicle speed and following distance

The relationship between vehicle speed and following distance shown in Figure 1 is Q_m:

$$c_m + v\alpha_m = Q_m \tag{2}$$

where c_m and α_m respectively represent the minimum safe distance between the m car and the preceding car, and the reaction time of the car following.

If the speed of the $m+1$ vehicle changes, the speed of the m vehicle in multiple lanes also changes accordingly, and c_m is fixed. At this point, the following state of the vehicles in multiple lanes becomes:

$$Y_m(T + \alpha_m) = Y_{m-1}(T) - c_m \tag{3}$$

Considering the randomness of the vehicle following process when driving on multiple lanes, the parameters describing the driving behavior characteristics of the vehicle will also dynamically change [7]. However, in real life, the distance interval consumed by the vehicle when restoring speed is relatively large compared to the deceleration interval. If this state is described by the velocity displacement curve, it will present a hysteresis state, as shown in Figure 2.

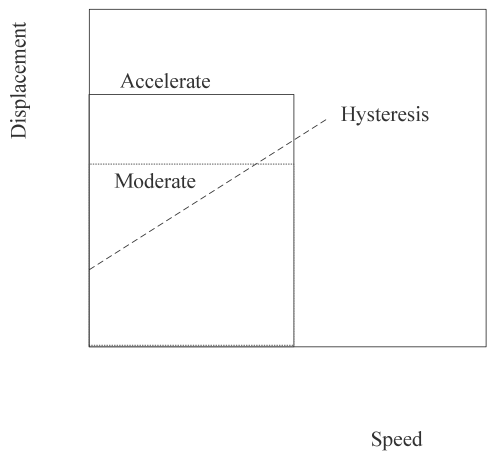

Fig. 2 - Details of the hysteresis status during the following process

There are differences in the hysteresis state of each vehicle, and there will be significant differences in the parameters α and c. Therefore, based on the hysteresis state, there is a significant transition problem in the instantaneous response time series of vehicles. During the vehicle start stop process, the more significant the instantaneous response time, the more significant the change in the following characteristics of the vehicle during start stop. To quantify this issue, the article uses the driving characteristic stability parameter β to express the vehicle acceleration and deceleration stability:

$$\beta = \frac{\alpha_{2-}\alpha_1}{\bar{\alpha}} \tag{4}$$

where $\bar{\alpha}$ and α_1 respectively represent the average reaction time and the reaction time before startup and shutdown, α_2 represents the reaction time after startup and shutdown. Therefore, this article sets the driving characteristic parameters as parameter group $z = (\alpha, c, \beta)$.

2.1.2. Driving characteristic classification method based on BP neural network

Use the extracted driving characteristic parameters from section 2.1.1 as driving characteristic classification samples and input them into the BP neural network for classification and recognition. The common BP neural network belongs to a network structure of 3 layers or more. The driving characteristic classification method based on BP neural network studied in this article is shown in Figure 3.

As shown in Figure 3, in the driving characteristic classification method based on BP neural network, the neural network structure is divided into input layer, hidden layer, and output layer. The fully connected relationships between layers are mainly constructed by neurons, and there is no connection relationship between neurons within the layers. The BP neural network uses a guided learning mode to train the network structure. Simply put, it is through learning that the activation values of neurons are propagated from the input layer, hidden layer, to the output layer.

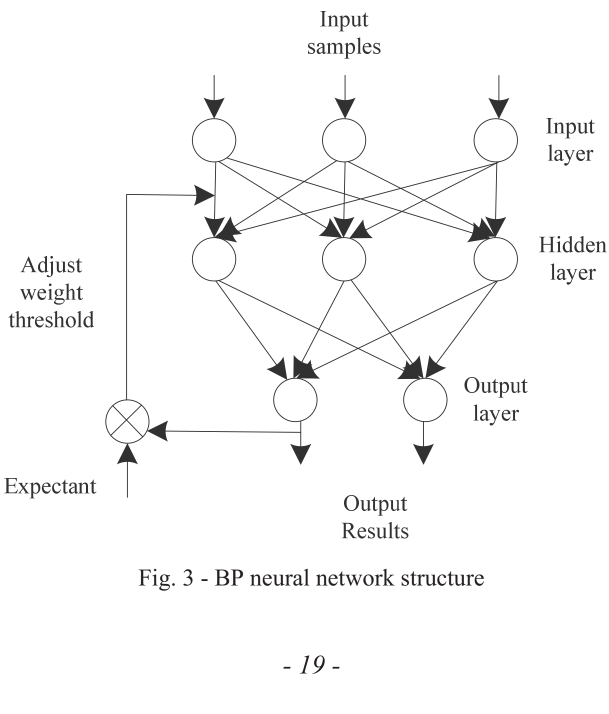

Fig. 3 - BP neural network structure

The neurons in the output layer can obtain the actual output response of the network. Compare the error between the output results of each neuron in the output layer and the expected value, with the aim of minimizing the error. Starting from the output layer, adjust the connection weight threshold layer by layer, and finally return to the input layer. This process is known as the backpropagation training process [2]. In the BP neural network, each neuron is activated using a nonlinear activation function, which is the sigmoid function γ. The relationship between the input driving characteristic parameter sample z_1 and the output driving characteristic classification result l_1 is:

$$\mathrm{z}_m = \gamma\left(\sum_{i=0}^{m-1} \varpi_{ij}'\, z_i' - \delta_i\right), i = 1,2,\dots,n \tag{5}$$

$$l_m = \gamma\left(\sum_{i=0}^{m-1} \varpi_{ij}'\, z_i' - \delta_j\right), j = 1,2,\dots,m \tag{6}$$

where ϖ_{ij}' represents the connection weight coefficient, z_i' represents the input i-th driving characteristic parameter sample, δ_i and δ_j represents the i-th and j-th neuron thresholds, respectively, m represents the total number of driving characteristic parameter samples. l_1 is the classification result of driving characteristics.

When training the BP neural network, the input driving characteristic sample is set as $\mathrm{z}_m = \{z_1', z_2', \dots, z_k'\}$, where k represents the number of learning modes, the expected value of the output result of the input layer is $W_m = \{W_1, W_2, \dots, W_p\}$, and where p represents the number of input layer units, The net input vector and output vector of the middle hidden layer are set to $\mathrm{R}_m = \{R_1, R_2, \dots, R_q\}$ and $\mathrm{A}_m = \{A_1, A_2, \dots, A_q\}$, where q represents the number of neurons in the hidden layer, The net input vector of the output layer and the actual output vector are $B_m = \{B_1, B_2, \dots, B_h\}$ and $l_m = \{l_1, l_2, \dots, l_h\}$, respectively, where h represents the number of neurons in the output layer. The connection weight between the input layer and the hidden layer, as well as between the hidden layer and the output layer, is ϖ_{ij}', and the threshold for each unit in the hidden layer and output layer is δ.

The training steps for the BP neural network used to classify driving characteristics are:

(1) In the BP neural network used to classify driving characteristics, the weights and threshold values of each layer are initially set to random values between -1 and 1.

(2) Use any driving characteristic parameter to train sample $[\mathrm{z}_m, y_m]$ into the network structure.

(3) The output of the input layer of the BP neural network structure is calculated, and each neuron in this layer does not have sample processing function. Only the input driving characteristic parameter samples are forwarded to the hidden layer, and the output vector of the input layer is set to be consistent with the input samples.

(4) Input and output of each unit in the hidden layer of operations:

$$\mathrm{R}_m = \sum_{j=1}^{m} \varpi_{ij}'\, \mathrm{z}_m - \delta \tag{7}$$

$$\mathrm{A}_m = \gamma(\mathrm{R}_m) \tag{8}$$

(5) Input of driving characteristic parameter samples for each unit in the operation output layer, and output of driving characteristic classification results:

$$B_m = \sum_{j=1}^{m} \varpi_{ij}'\, \mathrm{A}_m - \delta \tag{9}$$

$$l_m = \gamma(B_m) \tag{10}$$

(6) Calculate the correction error of each unit in the output layer by combining the expected driving characteristics classification results with the given values:

$$e_h = (W_m - l_m)\gamma(B_m) \tag{11}$$

(7) Correction error of each unit in the hidden layer of operation:

$$e_q = \left[\sum_{j=1}^{q} \varpi_{ij}'\, e_h\right]\gamma(\mathrm{R}_m) \tag{12}$$