Prediction of urban traffic congestion time by BPneural network

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***Abstract*—This paper studies the time prediction of traffic congestion, through the real-time speed of the car, The free flow speed, the morning and evening peaks, the number of weeks, the average speed of the car in this section are used as independent variables, and the time of traffic congestion is studied as a dependent variable.Through the MATLAB R2014a numerical simulation software for BP neural network operation, the neuron input layer is the real-time speed, free flow speed, morning and evening peak, week number, and average vehicle speed factor of the car after processing. The prediction result is good, which proves that the model is effective and reliable, and can estimate the time of the vehicle passing through the crowded road section.**

Keywords- Quantization processing, BP neural network, time prediction of crowded road sections, R- squared

I. INTRODUCTION

The problem of traffic congestion has always plagued the development of the city.Accurate prediction of traffic congestion in traffic can effectively improve the capacity of existing road networks[1]. It is currently predicted that traffic congestion is generally acquired GPS real-time data, but this is not accurate enough, and the required time and prediction time vary greatly[2].This paper seeks a large amount of information for data support, based on matlab and Excel software, selects appropriate evaluation index system, and builds a mathematical model for predicting traffic congestion time based on BP neural network. Taking the mathematical model of traffic congestion time as the leading analysis, starting from the objective influencing factors, the impact of appearance factors on traffic congestion time is studied from different angles, and then the traffic congestion time is predicted, and a new solution to solve the huge challenges of actual traffic congestion is provided[3].

II. DATA PREPROCESSING

2.1Description of the original data

The time range is one month in September 2018. The data used in this study is derived from real-time GPS location data of 15,000 car navigation software in Beijing. The time range is one month in September 2018. The data includes the following information, car ID information, GPS time, GPS longitude, GPS latitude, GPS speed, GPS direction. The car ID information refers to the unique ID number of each car. GPS time, longitude, latitude, speed, and azimuth refer to the instantaneous coordinate position and speed angle of the vehicle.

2.2Preprocessing of data variables

Through a large amount of literature, previous research on problems, and this problem need to predict the time of congestion, GPS data has been obtained, and we choose: time through traffic congestion, real-time speed of the car, free-flow speed, morning and evening peak, The number of weeks and the average speed of the car on this section are studied as variables. In addition, we quantify the variable data.

1)Free flow speed

According to the real-time speed data of the car, the speed of the car in the whole day and the speed of the floating car in the night (22:00-6:00) period can be separately found, which can be clearly found from 2:00 every day to 6:00 the next morning. In the meantime,the proportion of speed above 50km/h is obviously improved. Therefore, in this study, nighttime data should also be considered[4]. By including nighttime data into the statistical category, the traffic speed of the road network in the non-crowded state is extracted, that is, free flow. Speed, recorded as the congestion severity by comparing the current speed with the free flow speed.

2)Average speed of the car on the road

Through the real-time GPS position data of the car navigation software in Beijing, we divide the area into zones according to the GPS longitude. For the Beijing road network, if you select a grid larger than 500 meters wide, there will be two parallel expressways or main roads in the same grid containing the same direction, that is, the first type of problem mentioned above occurs. The grid does not reflect the traffic status of the expressway passing through the grid. If you choose a small size grid, such as 50 meters, there may not be high-density GPS data falling into the grid in a 10-minute interval, and even the size of the grid will be smaller than the width of some roads in Beijing. Based on the above considerations, in the preliminary grid model study, a grid of about 100 × 100 square meters was selected for research. Calculate the average speed of the car in the fixed area, ie

$$V_a = \frac{\sum_{1}^{n} V_i}{n}$$

Where n is the number of cars in the zone and Vi is the real-time speed of the car in the zone.

3)Real-time speed of the car

Monitor the car through GPS and get the real-time speed of the car, recorded as Vi

Based on the free-flow speed, the average speed of the car on the road section, and the real-time speed data of the car, we perform a standard 0-1 transformation on the three variables. For the variable xj.

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4)Morning and evening peaks

At the same time, the time series of the average speed of the vehicle (the data with the rejection speed of 0, and the vehicle that can be stopped for rest) can be simply analyzed. As shown in Figure 5- 1, in the morning and evening peak hours, that is, between 7:00-9:00 and 17:00-19:00.

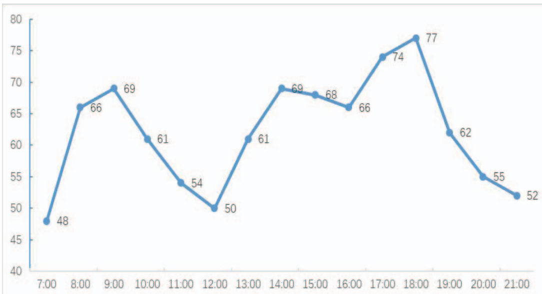

Figure 2-1 Vehicle quantity sequence diagram

5)Number of weeks

Through the GPS system to monitor the car, the GPS time is used to judge whether the vehicle is in the weekend and working day time period, and according to the data characteristics of the morning

Through the GPS system to monitor the car, the GPS time is used to judge whether the vehicle is in the weekend and working day time period, and according to the data characteristics of the morning and evening peaks and the number of weeks, the interval type attribute is transformed to facilitate the later calculation[5].

6)Time through traffic congestion

The GPS system reflects the vehicle's driving characteristics as the real-time speed of the vehicle. By comparing the real-time speed of the fixed vehicle with the free-flow speed, it depicts whether it passes through the congested road section, taking into account the timeliness of real-time data. We establish a time-coded data set for each vehicle separately, and further calculate the sampling rate for the reorganized data set. The sampling result is shown in Figure 5-2. It can be clearly seen that the sampling rate has a certain floating range. Mainly concentrated in the two intervals of 9S-15S and 53S-57S. The proportion of data lessthan 15s is greater than 73%. This part of the data can be used as the preliminary data for accurately extracting the trajectory. The data with the sampling rate in the range of 53S-57S can be used as supplementary data to supplement the calibration of the trajectory. Through the change of real-time speed, til is the

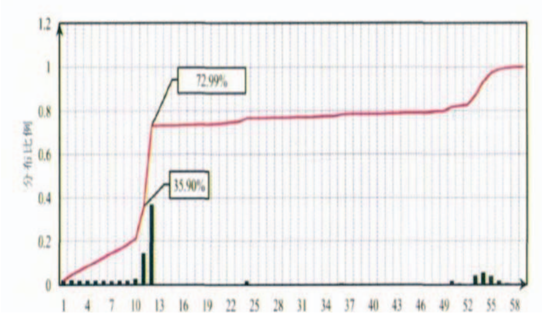

Figure 2-2 Sample data sampling frequency histogram

time when the speed of i car is significantly reduced to 80% of the free-flow speed, and Ti2 is the time when the speed of i car is significantly restored to 80% of the free-flow speed. which is the time of traffic congestion:

$$T_i = T_{i2} - T_{i1}$$

Normalize the time through traffic congestion.

III. BP NEURAL NETWORK ALGORITHM

BP neural network is a multi-layer neural network with three or more layers. Generally, the learning algorithm of the BP network can be described as follows:

Let the input of $x = (x_1, x_2, ..., x_n)^T$ the network, the hidden layer has h units, its output layer $v = (v , v ,...,$ $v)^T$, the output layer has m units, the output is $z = (z_1 ,$ $z_2 ,..., z_m)$

the target output isthe transfer function from the hidden layer to the output layer is f, and the transfer function of the output layer is g, then there are:

$$y_j = f\left(\sum_{i=1}^{n} w_{ij} x_i - \theta\right) = f\left(\sum_{i=0}^{n} w_{ij} x_i\right)$$

Where is the jth neuron output of the hidden layer is represented,

$$w_{0j} = \theta, x_0 = -1$$

$$z_k = g\left(\sum_{j=0}^{h} w_{jk} y_j\right)$$

WhereZ_k refers to the kth neuron output of the output layer. At this point, the error between the network output and the target output is:

$$\varepsilon = \frac{1}{2}\sum_{k=1}^{m}(t_k - z_k)^2$$

Now we start to adjust the weights, the purpose of the adjustment is to make it ε smaller. Because the negative gradient direction is the fastest direction in which the function value decreases. Therefore, you can set a step size of η and adjust it each unit along the negative gradient direction, that is, each weight adjustment is:

$$\Delta w_{pq} = -n\frac{\partial \varepsilon}{\partial w_{pq}}$$

In the formula, ηrefers to the learning rate. According to this adjustment method, the error will become smaller and smaller, so the BP neural network (backpropagation) is adjusted in the order:

First adjust the weight of the hidden layer to the output layer, set as the input of the kth neuron of the output layer, then:

$$v_k = \sum_{j=0}^{n} w_{jk} y_j$$

Where U_i represents the input of the jth neuron of the hidden layer:

$$u_j = \sum_{i=0}^{n} w_{ij} x_i$$

Note: The jth neuron in the hidden layer is connected to Therefore, the iterative formula for weight adjustment from the input layer to the hidden layer is:

$$w_{ij}(t+1) = w_{ij}(t) + \eta \delta_j x_i$$

It is judged whether the error satisfies the requirement or reaches the maximum number of iterations it goes to step2 and continues to the next training period.

IV. SOLVING THE MODEL

The samples were divided into two groups, one for learning neural network algorithms and the other for verification of results. According to the BP neural network model, the input data and the target output are set by themselves. In order to improve the model and achieve the optimal prediction result, in this paper, the hidden layer is set to one layer, and the number of hidden layer nodes is nine. The time of traffic congestion is predicted.

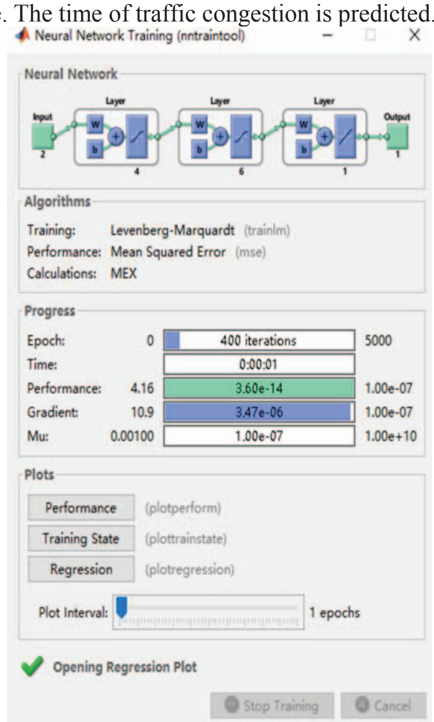

Figure 3-1 Neural network prediction model diagram

Obtain the error condition map and the frequency histogram. It can be seen from the error situation graph that the error of all data is less than 0.05. This indicates that the selection of the neural network prediction model is roughly consistent with our ideal. From the frequency histogram, it can be seen that there are only a few The data error is above 0.02, which proves the accuracy of our data prediction[6].

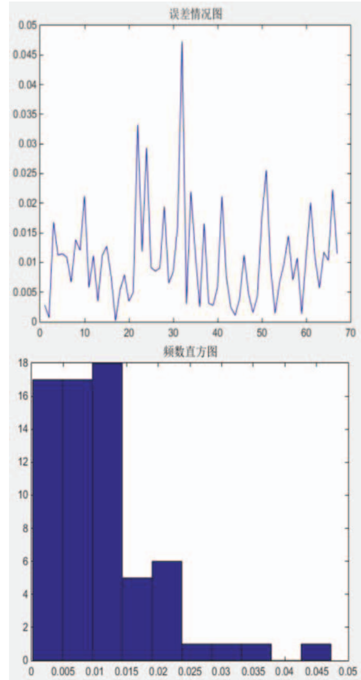

Figure 3-2 Model error analysis diagram

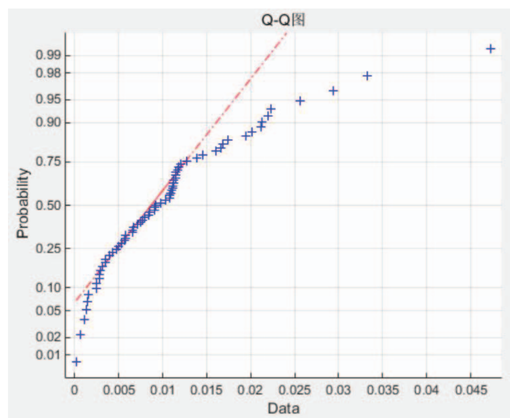

Figure 3-3 Test goodness of fit Q-Q diagram

The Q-Q diagram (Quantile-Quantile Plot) is a good method to test the goodness of fit. It is widely used abroad, and its graphic method is simple and intuitive, and easy to use.

For a set of observations x_1 , x_2 ,..., x_n , After the parameter θ of the distribution model is determined by the parameter estimation method, the distribution function $F(x;\theta)$ is known. Now I want to know how the observation data and the distribution model fit. If the fitting effect is good, the empirical distribution of the observed data should be very close to the theoretical distribution of the distribution model, and the quantile of the empirical distribution function should naturally be approximately equal to the theoretical quantile of the distribution model. The basic idea of QQ map is based on this point of view, the quantile of the empirical distribution function and the theoretical quantile of the distribution model are plotted as a pair of arrays on a Cartesian graph, which is a point, n observation data corresponding to n Point, if the n points look like a straight line, the observation data fits well with the distribution model.

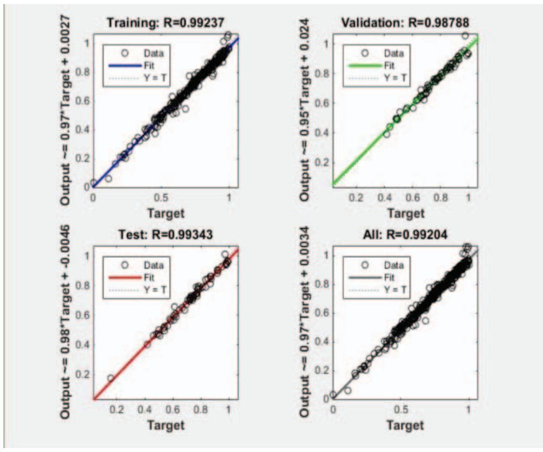

Figure 3-4 Training, Validation, Test, and All Fit

It can be seen from our Q-Q diagram that most of the data we predicted fall on a straight line, indicating that the fitting distribution is better.

The following training results are the fit relationship between our data and the predicted values in the training process, effectiveness, test, and all of them. R represents the fitted value, so that all the fitted values can be seen. Both are greater than 98%, and the fitting effect is better.

The final test set can be seen through the comparison of the time prediction results of traffic congestion. The fitting degree is better, and the true value and the predicted value are within the allowable range of the error. This also explains the correctness of the model from the side.

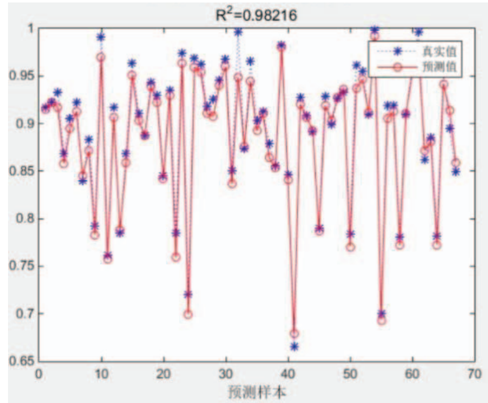

Figure 3-5 Comparison of raw data and simulation data

V. CONCLUSIONS

This paper combines urban traffic congestion research, based on BP neural network theory, integrates intelligent algorithm, uses MATLAB to realize engineering instance simulation and calculation, constructs traffic congestion prediction model, and obtains the results we need and utilizes The traffic dataset predicts the effectiveness of the model. The method is more comprehensive, more reliable, and more in line with the actual situation. It provides a reference method for traffic management.

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