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REVIEW

Time Prediction Through A Congested Road Section

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ABSTRACT

First, the cellular automaton was used to simulate a "T" junction, and the correlation analysis was performed by combining the traffic pattern and the corresponding data to obtain the reason for the inaccurate prediction time of the navigation software. The collected data is preprocessed to obtain the driving time of multiple road vehicles in a week, and this is used as the influencing factor. Reuse the collected information: the length of the intersection, the average speed of real-time vehicles at the intersection, and the length of the intersection. The first two processes of the three pre-processing processes are considered together to obtain a time-dependent factor. The correlation factors and the duration of the intersections are used to predict the results of neural network training. Based on the analysis and prediction of the data, the causes of urban traffic congestion are analyzed, and measures to reduce urban congestion are proposed.

1. Introduction

With the acceleration of urbanization and the rapid growth of urban vehicle ownership, traffic congestion is becoming serious. Navigation software mainly considers speed limits and average speed when predicting transit time. However, in the case of traffic congestion, the predicted time differs greatly from the actual time. Therefore, it is of great significance to establish of a traffic congestion prediction model which accurately predicts the time to pass the traffic jam.

2. Determine the Relationship

2.1 Road Traffic Simulation Model

Study the relationship among traffic flow, traffic density, and average vehicle speed.

The relationship between traffic density (p) and traffic flow (N) is:

$$P = \frac{N}{L}$$

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Where L is the length of each lane in three directions.

The relationship between average speed (v) and vehicle flow (N) is:

$$v = \frac{Sum(v_i)}{N}$$

Where v_i is the speed of each car?

2.2 Cellular Automaton

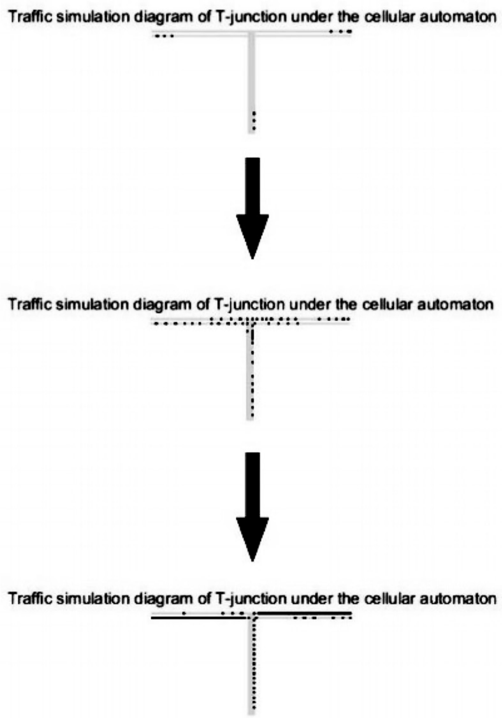

Figure 1. Traffic simulation

As shown in the figure, the road in three directions is regarded as a one-dimensional discrete lattice chain. The simplified vehicle driving rules are: Black cell indicates a car and white cell indicates a car-free. If there is a car in the front square, stop; if there is no car in the front square, move a grid forward.

2.3 Experimental Simulation

2.3.1 Experimental Parameters

Based on the actual situation of the road, visualize roads in MATLAB by defining the matrix. In this experiment, the road length L is 80m. Vehicle speed is a random distribution within 0-2. Vehicles turning at intersections are randomly distributed events. The number of simulation steps is 1000, and the unit step time is 0.01.

2.3.2 Analysis of Results

Some traffic flow, average speed and traffic density data are as follows.

Table 1. Partial data of experimental results

Serial Number	Vehicle Flow(N)	Average Speed($\bar{v}$)	Traffic Density(p)
1	5	0	0
2	5	0	0.0001
...	...	...	...
1000	106	0.6567	0.385

Perform a single factor analysis with considering the impact of traffic density on average vehicle speed. The results are shown in the figure:

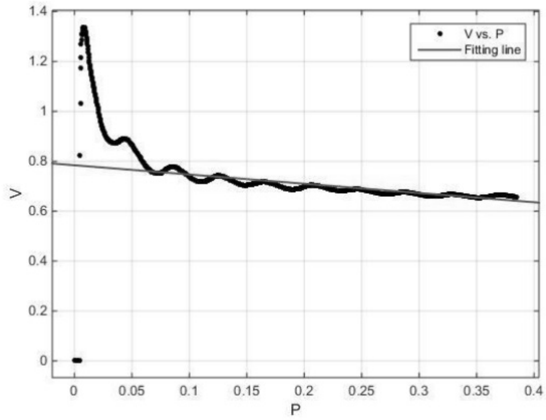

Figure 2. Fit renderings

Correlation coefficient is 0.04831. It can be seen that when the traffic density is 0-0.05, the curve fitting effect is poor and the correlation is not high; when the traffic density is more than 0.05, the curve fitting effect is good and the correlation is high.

So, it is concluded that the vehicle speed is greatly affected by other factors such as subjective factors in the range of 0-0.05. Remove this part of the data, and perform correlation analysis again.

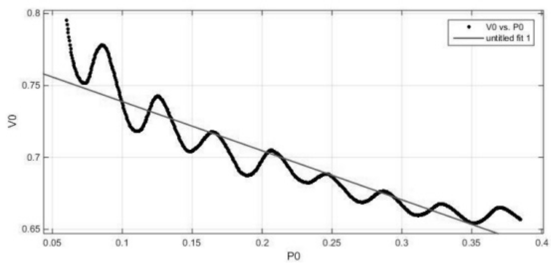

Figure 3. Fitting effect map after 0.05

The correlation coefficient is 0.87 and the correlation is good. It is concluded that when the traffic density is greater than 0.05, the traffic density becomes the main factor

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affecting the average speed.

Considering the impact of traffic flow and traffic density, perform a two-factor analysis on the intercepted data. The analysis results are as follows:

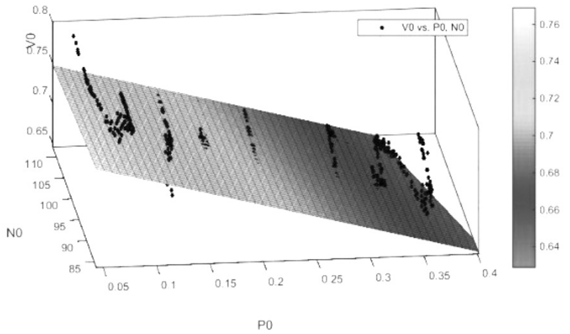


Figure 4. Fitting results of two factor analysis

The correlation coefficient is 0.8921. Therefore, the average speed is affected by traffic flow and traffic density.

3. Time Prediction through Congested a Road Cection

3.1 Establishment of BP Neural Network

Build a BP neural network model with time as the influencing factor. Perform correlation analysis and data image comparison based on 9951391、9981551、9996990、9997010、10355201、10355211、10355221、10387851、10390271、10403841 132456 traffic information flow in a week. The results are as follows:

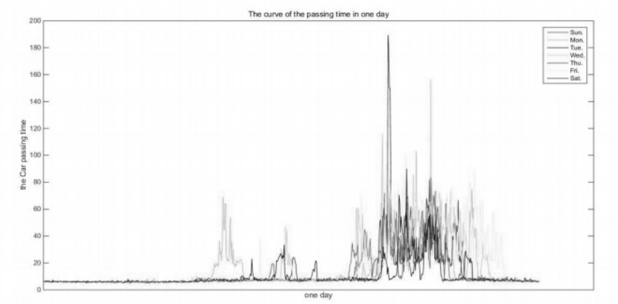


Figure 5. The results

Analysis shows that the rush hour is mainly concentrated in the late rush hour. Road length and average speed are direct factors, while time and week are indirect factors.

3.2 Traffic Time Prediction Model based on BP Neural Network

Preprocess the data used in this article and define the time factor that restricts vehicles from crossing the intersection as: $e_v = \frac{L}{v}$.

3.2.1 Network Construction

The input layer is $X = e_v = [e_{v1}, e_{v2}, \ldots]$. The output layer is $Y = T = [T_1, T_2, \ldots]$.

Input layer. The tree of neurons is equal to the number of dimensions of the input vector in the learning sample. Each neuron is a simple distributed hope that passes the input variables directly to the hidden layer.

Hidden layer. The hidden layer output calculation formula is:

$$h(j) = h_j\left(\frac{\sum_{i=1}^{l} \omega_j x_j}{a_j}\right), (j = 1,2,\ldots,l)$$

Output layer. The neuron tree in the output layer is equivalent to the dimension k of the output vector in the learning sample. The output of neuron corresponds to the element of the estimation result. There is a calculation formula:

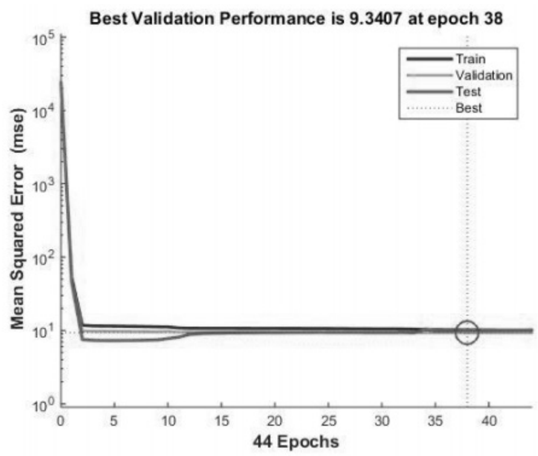
$$y(k) = \sum_{k=1}^{m} \omega_k h(j), (k = 1,2,\ldots,m)$$

The neural network model has a full-time pruning algorithm. The fine-tuning process is as follows:

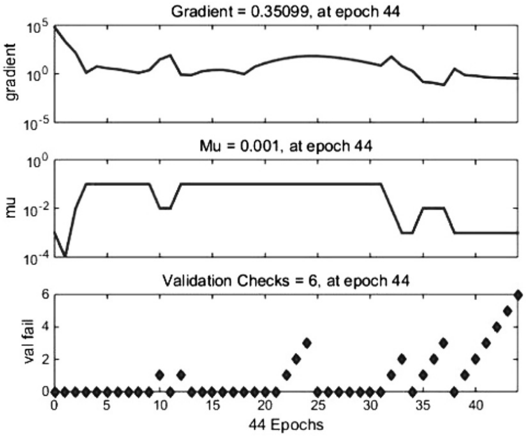
$$e = \sum_{k=1}^{m} yn(k) - y(k)$$

Where $yn(k)$ and $y(k)$ are the expected output and the output predicted by the neural network respectively.

3.2.2 Analysis of Prediction Results



The figure shows that after 44 data iterations, the optimal forecast value of project approval was obtained. The blue line is training data, the green line is validation data, and the red line is test data. In the above data, 70%: 15:%: 15% training mode is used to obtain the data to be predicted. A functional test of the gradient descent method was performed on the model, and the following results were obtained:



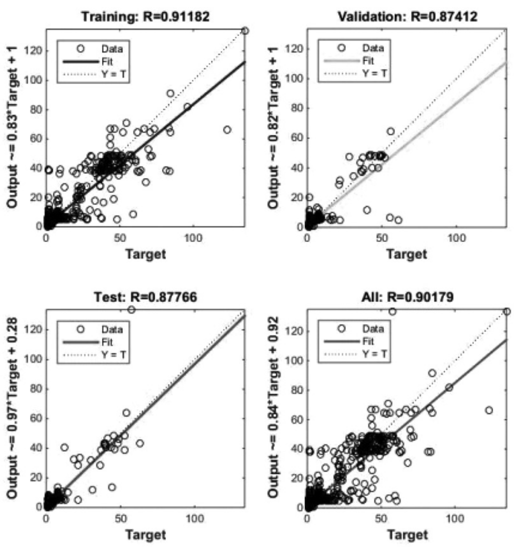
The gradient method is a function of the gradient descent method and has a good effect.

During the validation check training, the system will automatically input the sample data in the validation set to the neural network for validation each time the training is conducted. After inputting the validation set, you will get an error.

If the learning rate is high, the system may be unstable. If the learning rate is low, the training period is too long, and the required error cannot be achieved. In general, we tend to choose a smaller learning rate to keep the system stable and judge by observing the error decline curve.

A rapid decrease indicates that the learning rate is more appropriate, and a larger oscillation indicates that the learning rate is higher. So, due to different network scales, the choice of learning rate must be adjusted.

In order to prevent model training from overfitting, a test analysis was performed on the model. Give the result as follows:



R-squared of training data is 0.91182. R-squared of Validated date is 0.87412. R-squared of Tested data is 0.87766. R-squared for all data is 0.90179. By comparing the training results in this paper, we can see that this model is suitable for real-time road condition prediction.

4. Significance

It is concluded that the predicted time of traffic jam sections is affected by time, week, road length and real-time intersection speed by processing the data of Shenzhen's traffic condition information. In the perspective of big data, the causes of urban traffic congestion are analyzed. On this basis, propose measures for scientific planning to optimize layout and use big data to understand the city. It is of great significance to predict the crux of the traffic congestion problem and new direction of traffic management.

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