Travel time prediction of urban road based on BP neural network

Fangyi Deng¹, Pei Su¹, Bingxue Luo¹, Peng Wu¹, Yan Guo¹ *

¹College of Information Engineering, Sichuan Agricultural University, Yaan, Sichuan, 625000, China.
*guoyan@sicau.edu.cn

Abstract. In view of the diversity and complexity of the existing travel time prediction methods, travel time is an important indicator to quantify the state of road traffic congestion. In this paper, based on the analysis of various travel time prediction methods, a network model based on the idea of BP algorithm is constructed by SPSS software, and the method of travel time prediction of urban road is studied by combining BP neural network with three indexes affecting vehicle speed. Firstly, taking Jinshui road of Zhengzhou as the research object, this paper obtains the data of three factors that affect the vehicle speed, namely, vehicle spacing, flow and density; then, it constructs the neural network model and analyzes the data with the help of SPSS; finally, the experimental results are obtained, and the analysis shows that the error between the predicted speed and the real speed is very small, the average predicted error value is 0.3, and the average error rate is 2.35%, the result has better accuracy and feasibility, which can further realize the effective prediction of the travel time of the car. The model established in this paper has better practicability for travel time prediction, and the data can be used as reference value for travel time prediction of intelligent transportation system and other systems.

1. Introduction
At present, as one of the main research contents of traffic flow guidance system and road information integration, travel time prediction must complete more accurate, reliable and timely prediction based on traffic condition data collection technology, and provide strong data support for vehicle guidance. At present, many scholars have studied the travel time prediction from different perspectives and methods, such as the theory of using Kalman filter, markov chain, support vector machine for the travel time prediction principle and algorithm, and the distribution prediction of vehicle travel time on the signal control road section by using the macro delay model, the travel time analysis and prediction model based on multiple regression. However, the above theories and models have strong comprehensiveness and need to calculate a large number of traffic parameter data. Therefore, in this paper, the distance between vehicles, flow and density that affect the travel time are combined with BP neural network to accurately predict the time needed to pass the urban traffic section.

2. Overview
2.1. BP neural network
BP neural network is a multilayer feedforward network trained by error back propagation. Its basic structure consists of an input layer, an output layer and any number of hidden layers [1], as shown in Figure 1:
The relevant mathematical theory has confirmed that BP neural network has the performance of realizing any complex nonlinear mapping, making it particularly suitable for solving the internal mechanism complicated problems. But there are still some problems in the practical application of BP neural network, such as local small, slow convergence and so on. For this reason, Pan Wenchan put forward a research scheme of improving BP neural network, applying dynamic learning rate in traditional BP neural network, and combining parameter adjustable activation function to improve BP neural network, which greatly improved training speed and prediction accuracy [2], and greatly avoided the previous defects of BP network.

2.2. Research status of traffic prediction
With the development of social economy, the number of private cars is increasing rapidly, and traffic congestion has become a common problem for people to travel. In order to alleviate this kind of phenomenon, Zou, Weidong, et al proposed a bi-directional extreme value prediction model based on bp-belelm, which accurately predicted the traffic flow and reduced the travel delay time [3]. Moreira Matias et al proposed a new expressway automatic event prediction (AID) model: drive3flow, which uses ARIMA and ETS to generate traffic/occupancy prediction [4]. Li Songjiang et al established a travel time prediction model based on clustering analysis, and used the system clustering method to classify the historical travel data set according to the characteristics of vehicle type and time segment, and accurately predicted the travel time [5]. Yang Minhui proposed a road travel time prediction algorithm based on online sequence limit learning machine, which ensures the real-time prediction [6]. Because of the constant changes of road network parameters, the prediction of road travel time must meet the requirements of real-time. Jiang Zho et al established a dynamic prediction model of travel time by using Kalman filter theory, and determined the travel time of the path [7]. In order to predict the travel time, Ding Hongfei effectively predicted the travel time by combining BP neural network and support vector machine according to the characteristics of the license plate recognition data and the information that can be extracted [8]. Based on the above research methods and objects of travel time prediction, this paper fully considers the three factors that affect the travel distance, flow and density, and uses BP neural network prediction model to predict the travel time accurately.

To sum up, neural network is a new mathematical modeling method, with the characteristics of identifying complex nonlinear. Neural network has successfully realized the neural expert system, solving combinatorial optimization problems, etc. In addition, under the condition of increasingly serious urban traffic congestion, more and more scholars apply neural network to the prediction of travel time, trying to get accurate travel time prediction value for people's reference, so as to reduce the travel frequency of urban traffic congestion.

3. Model building
Multi-layer perceptron is an extension of single-layer perceptron, which can successfully solve the nonlinear separability problem that single-layer perceptron can not deal with. As shown in Figure 2 is a typical three-layer perceptron structure:
The hidden elements in the hidden layer are represented by \( b_i \), where \( i = 1, 2, p \) is the sequence number of the hidden unit. \( b_i \) also represents the actual output value of the hidden unit. Generally, \( r_i \) is used to represent the threshold value of the \( i \)-th hidden element. All thresholds form a threshold vector.

BP algorithm includes two processes of signal forward propagation and error back propagation. The specific steps are as follows:

a) Initialization, set all adjustable parameters to a small value of uniform distribution.

b) The following forward and reverse calculations are performed for each input sample.

c) In forward computing, a training sample is \((x(n), d(n))\), the input vector \( x(n) \) points to the input layer of the sensing node and the expected response vector \( d(n) \) points to the output layer of the computing node. The activation function \( V_j^{(L)}(n) \) of neuron \( j \) in \( L \)-th layer is

\[
V_j^{(L)}(n) = \sum W_{ji}^{(L)}(n)y_i^{(L-1)}(n)
\]

Where \( y_i^{(L-1)}(n) \) is the output signal of neuron \( i \) in the front \( L-1 \)-layer when iterating \( n \), and \( W_{ji}^{(L)}(n) \) is the weight of neuron \( j \) from neuron \( I \) in the \( L-1 \)-layer to that in the \( L \)-layer. When \( i = 0 \), \( y_0^{(L-1)}(n)=1 \), and \( W_{j0}^{(L)}(n)=b_j^{(L)}(n) \) is the bias of neurons in the \( L \)-th layer. The output signal of neuron \( j \) in layer \( L \) is \( y_j^{(L)}=\varphi(V_j(n)) \). If neuron \( j \) is in the first hidden layer \((L = 1)\), set \( y_0^{(0)}(n)=X_j(n) \), where \( X_j(n) \) is the \( j \)-th element of input vector \( x(n) \). If the neuron \( j \) is in the output layer \((L = L)\), let \( y_j^{(L)}(n)=O_j(n) \), calculate the error signal \( e_j(n)=d_j(n)-o_j(n) \), where \( d_j(n) \) is the \( j \)-th vector of the expected response vector \( d(n) \).

d) Backward computing, computing the \( \delta \) (local gradient) of the network, defined as

\[
\delta_j^{(L)}(n)+\eta\delta_k^{(L+1)}(n)y_j^{(L)}(n) = \begin{cases} 
E_j^{(L)}(n)\varphi'(V_j^{(L)}(n)) & \text{For output layer } L \\
\varphi'(V_j^{(L)}(n))\sum \delta_k^{(L+1)}(n)w_{kj}^{(L+1)}(n) & \text{To the hidden layer } L 
\end{cases}
\]

Where, \( \varphi'(\cdot) \) is the differential of independent variable. According to the generalized delta rule, the synaptic weights of the \( L \)-layer are adjusted

\[
w_{ji}^{(L)}(n+1)=w_{ji}^{(L)}(n) + \eta \delta_j^{(L)}(n)y_j^{(L)}(n)
\]

(Where \( \eta \) is the learning rate.)

e) \( n = n + 1 \), input new samples until EA meets the predetermined requirements.

f) Error calculation in algorithm flow:

1. Initialize \( V, W \); counter \( q=1, p=1 \);
2. Input samples, calculate the output of each layer:

\[
Y_j=f(V_j^{(L)}X_j) j=1,2,\ldots,m \quad \text{O}_k=f(w_j^{(L)}Y_j)k=1,2,\ldots,L
\]
3. Calculate output error:

\[
E^P=\sqrt{\sum_{k=1}^{L} \sum_{j=0}^{m} \delta_j^{(L)}(n)^2}
\]

4. Calculate the error signal of each layer:

\[
\delta_k^0=(d_k-O_k)(1-O_k)k=1,2,\ldots,L \\
\delta_j^y=\begin{cases} 
(S\delta_k^0w_{kj}) (1-y_j) & y_j j=1,2,\ldots,m \\
0 & \text{else} 
\end{cases}
\]

5. Adjust the error signal of each layer:

\[
W_{kj} \leftarrow W_{kj} + \eta \delta_k^0y_j \\
V_{ij} \leftarrow V_{ij} + \eta \delta_j^yX_i \\
\]

(Where \( x=0,1,2,\ldots,n \))
6. End, output results.

4. Experiment

4.1. Collection of experimental data
Taking Jinshui road of Zhengzhou as the research object, this paper collects the data of vehicle spacing, traffic flow and density on the traffic road and establishes BP neural network model. 70% of the obtained travel data is used as the training set to train the BP neural network model, and some of the training data are shown in Table 1:

Table 1. Original data

| Vehicle_Spacing(m) | Flow(veh/h) | Density(veh/km) | Speed(m/sec) |
|--------------------|-------------|-----------------|--------------|
| 8.458              | 972.307     | 59.118          | 5.0          |
| 14.807             | 2441.372    | 33.768          | 20.0         |
| 11.133             | 2546.483    | 44.912          | 16.0         |
| 13.469             | 2425.570    | 37.122          | 18.0         |
| 14.144             | 1726.061    | 35.351          | 14.0         |
| 16.813             | 1591.768    | 29.739          | 15.0         |
| 13.750             | 2250.065    | 36.364          | 17.0         |
| 15.331             | 1905.786    | 32.614          | 16.0         |
| 16.813             | 1803.640    | 29.739          | 17.0         |
| 12.504             | 2250.000    | 39.987          | 16.0         |

30% is used as the validation set to verify the accuracy of the model. See Table 2 for some validation data

Table 2. Original data

| Vehicle_Spacing(m) | Flow(veh/h) | Density(veh/km) | Speed(m/sec) |
|--------------------|-------------|-----------------|--------------|
| 11.400             | 2102.684    | 43.860          | 13.0         |
| 13.274             | 1697.891    | 37.668          | 13.0         |
| 12.012             | 2329.121    | 41.625          | 16.0         |
| 15.780             | 1061.270    | 31.686          | 9.0          |
| 8.052              | 2249.916    | 62.094          | 10.0         |
| 16.230             | 1197.449    | 30.807          | 11.0         |
| 16.654             | 1702.942    | 30.023          | 16.0         |
| 11.567             | 2944.705    | 43.226          | 19.0         |
| 15.872             | 1332.308    | 31.502          | 12.0         |
| 15.124             | 1484.845    | 33.060          | 12.0         |

4.2. Experimental process
In this paper, the experimental data includes vehicle spacing, flow, density, using these three data to predict the speed. In order to solve this problem, a BP neural network prediction model is constructed, which combines the working principle of the perceptron. Using the BP neural network function of spss20, the prediction speed under different conditions is obtained.

Set the random value as the starting point; the calculation variable is: Section = 2* RV.BERNOULLI (0.7) - 1, when the value of the part is 1, the corresponding data is used as the training set, and when the value of the part is - 1, it is used as the verification set; select analyze -> neural networks -> multilayer perceptron, select the neural network function option, and predict the vehicle speed.

5. Experimental result
According to the above steps, according to the different values of the part, classify the results, get the predicted speed value, then compare the predicted value with the real speed value, and calculate the error rate and error value between the predicted value and the real value. After calculation, the average...
error value is 0.3, and the average error rate is 2.35%. The comparison effect between predicted speed and real speed is shown in Figure 3:

![Figure 3. Comparison of predicted value and real value of BP neural network](image_url)

6.Conclusion
This paper takes Jinshui road of Zhengzhou as the research object, obtains the traffic data of automobile, studies the three factors that affect the speed of automobile: the distance between vehicles, the flow and the density, designs the travel time prediction method of urban road based on BP neural network, and analyzes the data with SPSS software. The results show that the average prediction error value between the predicted speed and the real speed is 0.3, and the average error rate is 2.35%. Therefore, the more accurate prediction speed value can be obtained, which can further realize the effective prediction of the vehicle travel time, and the data can be used as the reference value of the intelligent transportation system travel time prediction. The weather, temperature, road visibility and other factors that affect vehicle driving are not considered in this study, which will be further explored and explained in the future study.

ACKNOWLEDGMENT
The authors are extremely grateful to the journal editorial team and reviewers who provided valuable comments for improving the quality of this article. This work was supported by Key Laboratory of Agricultural information engineering of Sichuan Province and Training Program of Sichuan Agricultural University (Research on plant disease recognition in complex environment based on machine learning algorithm 2020628).

Reference
[1] Dansonglin, Liu Shangqi, Luo Yanyan, Liang Guangyue, Yang chaopeng. Prediction of the effect of high aquifer on the development of SAGD based on BP neural network [J]. Daqing Petroleum Geology and development, 2019,38 (2): 73-80
[2] Pan Wenchuan, Liu Shangdong. Optimization research and application of BP neural network [J]. Computer technology and development, 2019,29 (5): 74-76
[3] Weidong Z, Yuanqing X. Back propagation bidirectional extreme learning machine for traffic flow time series prediction[J]. Neural Computing and Applications, 2018.
[4] Moreira-Matias L, Alesiani F. Drift3Flow: Freeway-Incident Prediction Using Real-Time Learning[C]// 2015 IEEE 18th International Conference on Intelligent Transportation Systems. IEEE, 2015.
[5] Li Songjiang, song junfen, Yang Huamin, Zhang Fengrong. Prediction of Expressway travel time based on cluster analysis [J]. Computer simulation, 2019 (2): 384-389
[6] Yang Minhui. An algorithm for road travel time prediction based on online sequential limit learning machine [J]. Electronic technology and software engineering, 2019 (18): 181-182
[7] Jiang Zhou, Zhang Cunbao, Xu Zhida, et al. Forecasting methods and models of urban road travel time based on real-time data [C] // the 8th China Annual Conference on intelligent transportation.
[8] Ding Hongfei, Li Yanhong, Liu Bo, et al. Research on combination prediction of Expressway travel time based on BP neural network and SVM [J]. Computer application research, 2016, 33 (10): 2929-2932