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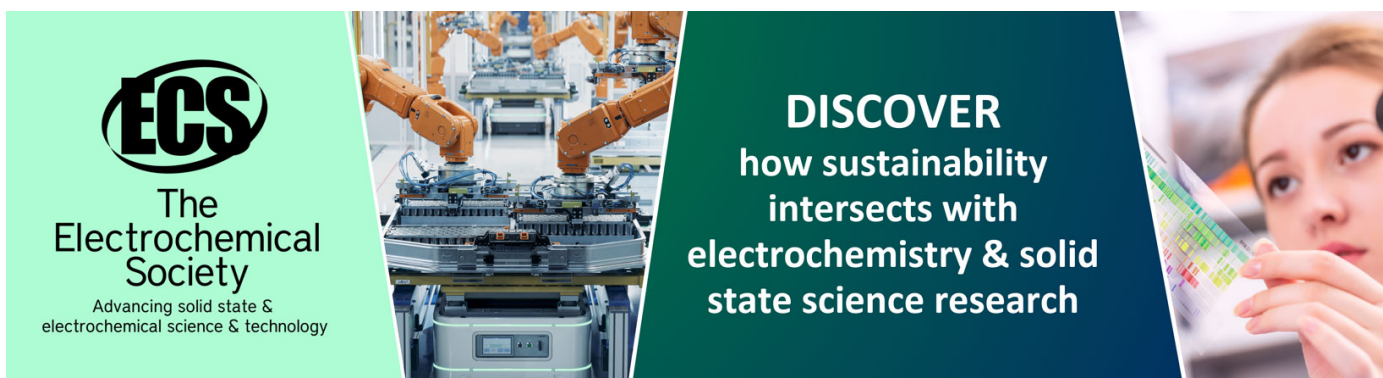
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Research on Urban Short-term Traffic Flow Forecasting Model

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ABSTRACT: Short-term traffic flow forecasting is one of the key technologies of ITS, and it is also the basis of traffic control and road navigation. According to the characteristics of short-term traffic flow, combining with the actual traffic flow data of an intersection in Hefei City, a prediction model based on BP neural network is constructed. The experimental results show that the model reflects the change rule and trend of short-term traffic flow, and the prediction accuracy is high.

1. Introduction

With the gradual improvement of people's living standards, people's demand for travel tools is also increasing, rapid growth of automobile traffic, urban roads have been unable to fulfil the rapid growth of vehicle demand, therefore, road congestion and frequent traffic accidents are becoming more and more serious. In order to solve the above problems, Intelligent Transportation System (ITS) has been applied, which can effectively alleviate road traffic problems[1]. ITS is a complex giant system, which consists of many parts. Traffic control and traffic guidance are the core subjects of ITS system research [2]. At the same time, the dynamic analysis and prediction of road traffic flow is also one of the important research topics fields in the field of transportation. Predicting traffic flow quickly and accurately provides travelers with timely road traffic conditions and dynamic planning of traffic routes with to provide information guarantee.

Traffic flow forecasting is mainly based on historical traffic data to predict the next period of traffic flow. According to the time span of forecasting, it can be divided into long-term, medium-term and short-term[3] flow forecasting. Short-term traffic forecasting is defined when the time span is not more than 15 minutes or even less than 5 minutes. It is the core of ITS research field and the research foundation of other subsystems. Short-term traffic flow forecasting always has been paid much attention by many scholars and researchers. In their own research field, they use their own professional knowledge to research and develop a variety of prediction models. Including Kalman filter model as the representative of the prediction model based on statistical methods; Wavelet theory as the representative of the non linear prediction model, and BP neural network as the representative of the prediction model. BP neural network has the ability of self-learning and approaching any non-linear system, as well as better adaptability and stability, which can meet the requirements of self-learning and self-adaptive in the process of traffic flow prediction. Therefore, this paper uses BP neural network model to analyze and study the short-term traffic flow prediction.



2. BP Neural Network Model

Being a multilayer feed forward neural network, BP Neural Network was proposed by Rumelhart et al.[7] in 1986, it is a multi-layer feedforward neural network. BP learning process is composed of forward propagation of input signal and back propagation of error information. When the input sample signal propagates forward, signals are input from the input layer and processed layer by layer through the middle layer (also known as the hidden layer, which can be either single or multi-layer) until the output layer. The state of neurons in each layer is only affected by the state of neurons in the upper layer. If the output layer does not get the desired output result, then the weights and thresholds of the network are adjusted according to the prediction errors, turning to back propagation, thus the network output approaching expectations. Therefore, BP network is divided into two stages: forwarding propagation of signals and reversing propagation of errors. A simple BP neural network structure is shown in Figure 1.

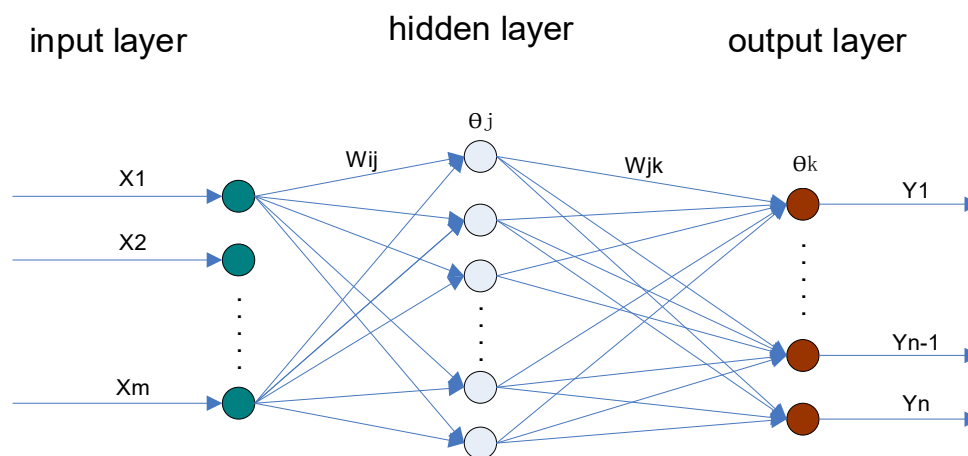


Figure 1. Structural Chart of BP Neural Network

Figure $X_1, X_2 \dots X_n$ is the input value of the network, $Y_1, Y_2 \dots Y_n$ is the output of the network, W_{ij} and W_{jk} are the weights of the network, and θ_j and θ_k are the thresholds of the network.

BP neural network training network before prediction, initial weights and thresholds of networks are random values in $[-1, 1]$ intervals. Through training, the network has the ability of memory and prediction, and the optimal weights and thresholds of the network are obtained for its later testing.

3. Establishment and Simulation of Short-term Traffic Flow Prediction Model Based on BP Neural Network

3.1. Data Sources

This paper is based on an intersection in Hefei from September 18, 2018 to October 17, 2018, samples of measured traffic volume (excluding weekends) for one month from 7 a.m. to 11 a.m. each day. A total of 51×22 sets of data were obtained every 5 minutes. In order to reduce the test error, 1173 sets of data are obtained after the data are processed iteratively, of which 1123 sets are used to train the network and 50 sets are used as test sets. After analyzing a large number of traffic data, it is found that traffic flow data has a strong regularity in time series: in a moment of t traffic flow and the intersection before the $t-i \times \Delta t$ ($i=1, 2, 3 \dots$) [8], traffic flow at time is highly correlated. Therefore, taking the traffic volume of $t-i \times \Delta t$ period as the input value of BP neural network, the output value of the network is the predicted traffic at t time. This paper uses the historical traffic information of the first 4 moments of the traffic flow forecasting t moment.

3.2. Hidden Layer Node Number

The determination of the number of hidden layer nodes is a very complicated problem [9], since it is closely related to the complexity of the problem, the number of nodes in the input layer and the

number of nodes in the output layer. Excessive number of nodes may reduce system error, but it will also lead to problems such as increasing training time, poor fault tolerance, weak generalization ability[10]. It is not only easy to fall into local minimum but also hard to get the optimal value. If the number of nodes is too small, the network may not be able to train or the performance of the network is poor. Therefore the number of hidden layer nodes is often determined by the designer based on experience or experimental conclusions.

This simulation experiment chooses the best range of hidden layer nodes by empirical formula.

$$L = \sqrt{(M + N)} + \alpha \quad (1)$$

In the formula, L is the number of hidden layer nodes, M is the number of input nodes, N is the number of output layer nodes, and α takes the constant in the range of [3,7].

3.3. Evaluation Index of Predictive Performance

In order to get the optimal prediction model, it is necessary to select performance evaluation indexes and to measure the quality of the prediction model in a quantitative way. This simulation experiment chooses the following three indicators to evaluate.

(1)MRE(Mean Relative Error,MRE)

$$MRE = \frac{1}{m} \sum_{i=1}^m \frac{|\Delta xi|}{xi}, i=1,2,\dots,m \quad (2)$$

Among them, m is the number of predicted samples, Δxi is the difference between the predicted value and the true value, and Xi is the true value. The smaller the MRE obtained from the experiment, the closer the predicted value is to the real value, and the better the predicted effect will be.

(2) EC (Equality Coefficient,EC)

$$EC = 1 - \frac{\sqrt{\sum_{i=1}^m (xi - yi)^2}}{\sqrt{\sum_{i=1}^m xi^2} + \sqrt{\sum_{i=1}^m yi^2}} \quad (3)$$

Among them, Xi is the true value and Yi is the predicted value. EC value reflects the fitting degree between predicted value and real value. Since value is between (0,1), the bigger the data value is, the better the fitting effect will be.

(3) Accuracy

$$Accuracy = \frac{1}{m} \sum_{i=1}^m \frac{xi}{yi} \quad (4)$$

The greater the accuracy, the higher the accuracy.

3.4. Simulation Verification

After the number of hidden layer nodes is obtained by empirical formula through a lot of experiments, the number of hidden layer nodes is finally determined from the above three evaluation index data, as is shown in Table 1.

Table1.Comparison Table of Results of Different Implicit Layers

index	Node number							
	5	6	7	8	9	10	11	12
MRE	0.2171	0.2121	0.2174	0.2171	0.2141	0.2209	0.2049	0.2090
Accuracy	0.7829	0.7879	0.7826	0.7829	0.7859	0.7791	0.7951	0.7910
EC	0.8868	0.8884	0.8843	0.8845	0.8854	0.8850	0.8877	0.8848

After comprehensive consideration of MRE, EC and Accuracy, a hidden layer is used in the simulation and verification experiment in this paper, which is mainly about BP network model with 11 hidden layer nodes. The mapping relationship between input and output of neurons uses the following sigmoid function:

$$f(x) = \frac{1}{1+e^{-x}} \quad (5)$$

To evaluate the model used in this experiment more comprehensively, using cross-validation, the MRE, EC and Accuracy data and average values of five experiments are given, as shown in Table 2.

Table 2. Prediction performance of BP model

Input Layer Node Points	Hidden Layer Node Number	EC	MRE	Accuracy
4	11	0.8877	0.2049	0.7951

It has been clearly seen from the table that the size of EC reflects the degree of forecasting effect. When the value of EC is greater than 0.85, it can be regarded as a good prediction result. Meanwhile, the EC value of this experiment is 0.8877, which shows that the prediction result of this model is good.

The traffic flow forecasting simulation obtained from this experiment is shown in Figure 2.

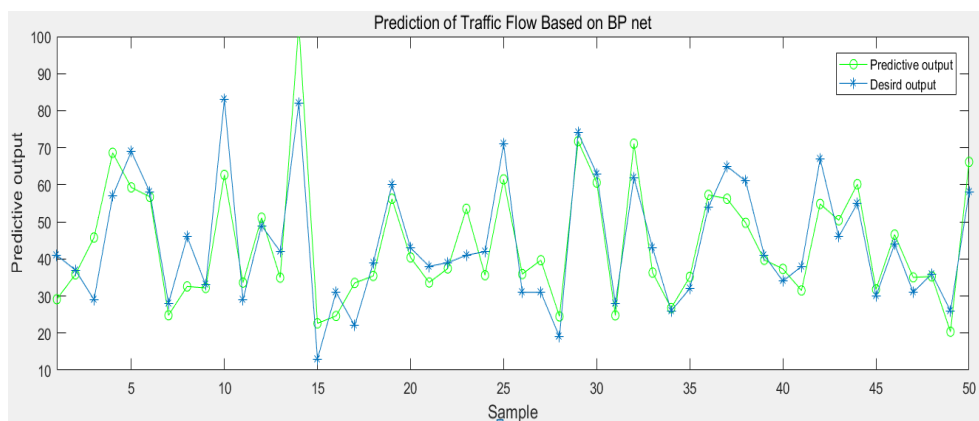


Figure 2. Short-term Traffic Flow Prediction Simulation Diagram

As you can see from Figure 4, the model better reflects the change rule and trend of short-term traffic flow, it also satisfies the requirement of short-term traffic flow forecasting.

4. Conclusion

In this paper, BP neural network is used to predict short-term traffic flow at a single intersection and verification with real data sets. The results show that the EC value and accuracy of the predicted results of the model are both high. But this experiment only uses the first four periods of the intersection to predict the traffic flow in the next period, the influencing factors of the upstream section of this intersection are not considered. At the same time, in data set selection, because the data samples are limited, the peak and non-peak periods of traffic flow in a day are not separated. Later stage needs to continue to collect basic traffic data on the basis of prediction over time intervals. Consequently, relevant factors such as traffic flow at relevant intersections need to be considered. Further experiments will have to be carried out to obtain better prediction results through the successive study.

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References

- [1] Yu Tao. (2018) Short-term traffic flow forecasting and Realization Based on SVM and BP neural network [D]. Nanjing University of Posts and Telecommunications, NanJin.
- [2] LuoXianglong. (2017) Jiao Qinqin, NiuLiyao, Sun Zhuangwen. Short-term traffic flow prediction based on in-depth learning [J]. Computer Applied Research, 34: 91-93+97.
- [3] Xiaolei Ma, Zhimin Tao, Yinhai Wang, Haiyang Yu, Yunpeng Wang. (2015) Long short-term memory

- neural network for traffic speed prediction using remote microwave sensor data[J]. *Transportation Research*, 3:158-162.
- [4] Xiangxue Wang, LunhuiXu.(2018) Short-term traffic flow forecasting based on in-depth learning [J]. *Transportation system engineering and information*, 18: 81-88.
- [5] Jing Li, Chupei Chen. (2016) Short-term traffic flow prediction based on improved variable learning rate BP algorithm [J]. *Automation and instrumentation*, 2: 182-184.
- [6] XinGuo. (2015) An improved short-term traffic flow prediction algorithm [J]. *Computer technology and development*, 25: 103-107+112.
- [7] Jianzhong Lu, Hao Cheng.(2015) Short-term traffic flow prediction based on improved GA optimized BP neural network [J]. *Journal of Hefei University of Technology (Natural Science Edition)*, 38: 127-131.
- [8] Yanliang Bi, Yinjie Lei, Wei Wang. (2016) BP neural network optimization based on improved genetic algorithm and its application in classification of red wine quality grade [J]. *Computer measurement and control*, 24: 226-228.
- [9] Song Li, Lijun Liu, ManZhai.(2012) Short-term traffic flow prediction based on BP neural network optimized by improved particle swarm optimization [J]. *Systems engineering theory and practice*, 32: 2045-2049.
- [10] Gaige Wang, LihongGuo, HongDuan.(2013) Target threat assessment using glowworm swarm optimization and BP neural network[J].*Journal of Jinlin University (Engineering and Technology Edition)*, 43:1064-1069.