Short-time Traffic Flow Prediction Based on Wavelet Neural Network

Li Liu, Peipei Wu, Xinzhe Wang

College of Physics and Electronic Information, Hulunbuir University, China
hlbeliuli@sina.com, 57683624@qq.com, 15237565@qq.com

Abstract

With the rapid development of social economy, traffic congestion, frequent traffic accidents, and traffic pollution have become the focus of attention. As an important part of intelligent transportation system, traffic guidance system and traffic control system play a great role in improving road congestion, Therefore, the short-time traffic flow prediction is of great significance to urban traffic system. Based on the investigation of traffic flow characteristics, we analyze the advantages and disadvantages of available short-time traffic flow forecasting methods. In view of the nonlinear, time-varying and uncertain characteristics of traffic flow, wavelet neural network is selected as the traffic flow forecasting model combining the self-learning and self-adaptive characteristics of neural network. To solve the problem of short-time prediction and accuracy of traffic conditions, wavelet basis is used as the characteristic function of pattern recognition to optimize the parameter and error space of traditional BP neural network, the short-time prediction of traffic state is realized. In this paper, the wavelet neural network model is established, the traffic flow sample set is constructed, the sample data is trained to convergence, and a certain number of sample data are selected for testing. The test results show that the wavelet neural network not only has high prediction accuracy but also has fast convergence speed, good real-time performance, and has certain application value.

Keywords: Short-time traffic flow, Wavelet analysis, Neural network

1 Introduction

With the development of intelligent transportation system [1], short-time traffic flow forecasting, as an indispensable key technology, has attracted increasing attention. Moreover, the change process of urban traffic flow is a real-time, complex and nonlinear stochastic process, which is greatly affected by traffic environment, traffic accidents and weather changes. Therefore, how to improve the prediction accuracy and to ensure the universality of the model is an important research topic. With the rapid growth of car ownership and urban population, the existing road network capacity can no longer meet the increasing traffic demand. Following the serious urban traffic congestion, frequent traffic accidents, automobile noise pollution and exhaust emissions caused by environmental pollution become more and more serious. Great material and economic losses have been caused due to people's lives [2]. The traditional way to solve traffic problems is to build roads and transportation facilities. However, there is less and less space to build roads. In addition, it is difficult to solve the problem from the vehicle or road aspects alone due to the complexity of the traffic system. Since the limited urban land resources limit the need to meet the growing traffic demand by simply expanding the scale of the road network, it is necessary to increase the capacity of the existing network in order to ease traffic jams, reduce traffic accidents, and improve the environmental problems caused by vehicle exhaust emissions [3-4]. Since the 1980s, the developed countries, represented by the United States, Japan and Europe, have effectively and comprehensively applied information technology, sensor technology, computer technology and data communication technology to transform the traditional transportation industry. Intelligent transportation system (ITS) has emerged with the need of the times. It is a real-time, accurate and efficient ground transportation management system. Its objective is to resolve the contradiction between the increasing traffic demand and the limited road resources, finally realizing the full utilization of road resources, improvement of the people's travel efficiency and travel safety [5]. According to the United States National ITS, the research content of its intelligent transportation system includes 7 basic systems and 29 user service functions [6]. The core problem of traffic guidance is real-time dynamic traffic flow assignment, that is, dynamic and random traffic flow in the road network allocation problem. However, in order to realize the dynamic assignment of traffic flow, it is necessary not only to have real-time traffic flow data, but also to predict the traffic flow data in a short time. Therefore, short-time traffic flow prediction

*Corresponding Author: Li Liu; E-mail: hlbeliuli@sina.com
DOI: 10.3966/160792642019072004022

is an important prerequisite for traffic control and guidance, and its prediction performance is a key to the effective realization of traffic flow guidance system. Figure 1 shows, Urban Road GPRS Intelligent Monitoring system.

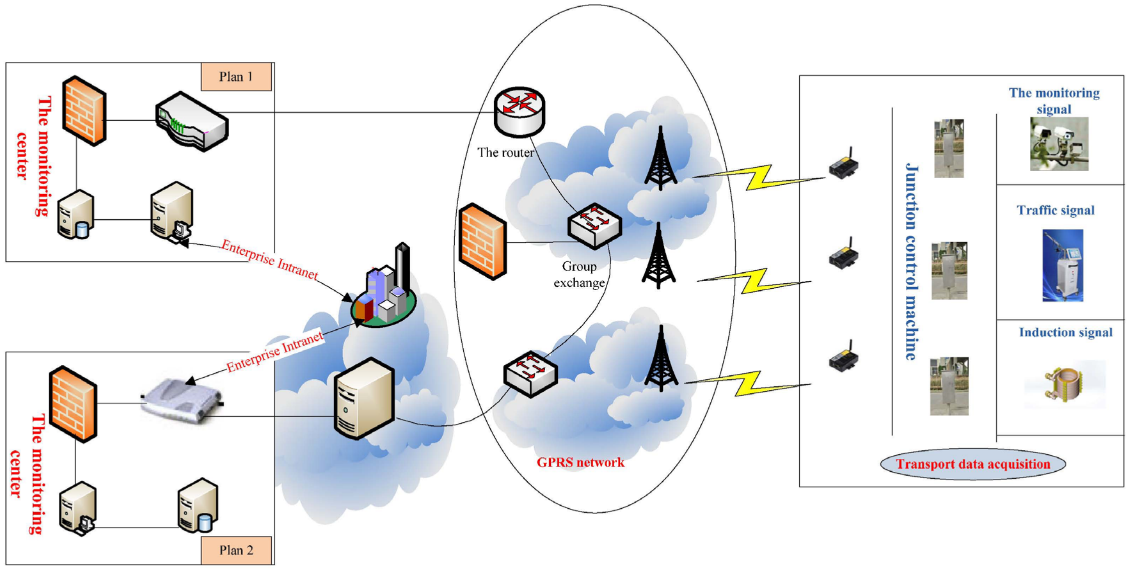

Figure 1. Urban Road GPRS Intelligent Monitoring system

To sum up, the study of short-time traffic flow forecasting method is of great significance to the research of ITS. Its significance has been mainly reflected in the following three aspects: (a) Short-time traffic flow prediction can provide future traffic data for traffic guidance system so as to provide effective real-time traffic diversion and control and reduce traffic congestion and delay [7]. (b) Predicting the future state of traffic flow can provide a reference for people to choose their travel path so as to save travel time and reduce energy consumption (c) Traffic flow forecasting lays the foundation for traffic event detection, so it can improve the ability of road network traffic incident forecast, reduce traffic accident and reduce the harm caused by traffic accident to the society. During the past decades, short-time traffic flow forecasting methods, proposed by experts from all over the world, have exceeded more than 200 kinds [8]. Early in the prediction study, there are several simple linear prediction models, such as historical average model, time series model [9], linear regression model. Most of these models use the least square method to estimate the parameters, exhibiting the advantage of simple calculation. However, these models cannot reflect the nonlinear and uncertain characteristics of traffic flow, and cannot meet the accuracy requirements of short-time traffic flow prediction [10]. The current prediction models can be divided into the following three categories: the prediction model based on traditional mathematical statistics, the prediction model based on nonlinear theory, and the prediction model based on intelligent method [11].

1.1 Prediction Method Based on Traditional Mathematical Statistics

Historical average model. The historical average model takes the average value of historical traffic at the same time as the predicted time for several days as the predicted value. It is a static prediction model.
Time series model. According to the observed time series data, a statistical series with time variation is formed. The mathematical model is established by curve fitting and parameter estimation, and the model is predicted in the future.
Kalman filter model. The state space model composed of state equation and observation equation is used to describe the traffic system and to predict the short time traffic flow. Because the Kalman filter model is based on the linear theory [12], it is flexible in use and easy to realize on-line prediction.

1.2 Prediction Method Based on Nonlinear Theory

Non-parametric regression method. The nonparametric regression method assumes that the intrinsic relationship of all factors in the system is embedded in historical data [13]. By looking for the nearest neighbor point similar to the current point in the historical data, the next moment data of the nearest neighbor similarity point is used as the prediction value.
Wavelet analysis. Wavelet analysis has good time-frequency localization and can focus on any local details of the signal. Because the wavelet analysis is good at amplifying signal, de-noising and focusing, in recent years, most studies have combined them with

other methods such as neural network model, non-parametric regression model, support vector machine model, time series model, to predict short-time traffic flow [14-18].

Chaos theory. Chaos theory deals with the chaos of nonlinear dynamical systems [19]. The Chaos is a seemingly irregular motion in a deterministic system. It is not caused by random external causes, but is directly obtained by deterministic equations.

1.3 Intelligent Prediction Method Based on Knowledge Discovery

Artificial neural network. Neural network prediction uses a large number of historical data samples to train the neural network model to obtain the input-output mapping relationship. This method does not need any empirical formula, even if the internal mechanism of the prediction problem is not clear, as long as there are a large number of input and output samples.

Support vector machine. Support vector machines are based on statistical learning theory [20]. Traffic forecasting technology is based on advanced traffic condition monitoring means [21]. It can achieve the future traffic road short-time prediction by real-time extraction of existing traffic road traffic parameters and combination with real-time forecasting model [22]. The statistical analysis method is relatively simple, but can not reflect the dynamic characteristics of traffic state change [23]. In this paper, the traffic flow at a certain intersection in a certain city is selected as the data source, and the short-time traffic flow is predicted by wavelet neural network [24]. The aim is to improve the convergence rate of training and the accuracy of prediction. The simulation results show that the proposed method is effective in traffic flow prediction. In this paper, wavelet neural network is used to predict the short-time traffic flow in order to improve the prediction accuracy.

The rest of this article is organized as follows. The second section introduces the related research of short-time traffic flow forecasting theory. The third section introduces the research of short-time traffic flow forecasting based on wavelet neural network. The fourth section introduces the flow of short-time traffic flow forecasting. In the fifth section, the experimental results are given to confirm our proposal, and the conclusions are summarized in the last section.

2 Related Works

2.1 Basic Concept of Short-time Traffic Flow Prediction

Traffic flow refers to the number of vehicles passing through a certain place, section or lane in a selected time period, which is also called traffic volume. It is one of the important parameters to describe the characteristics of traffic flow. Traffic flow forecasting [25] refers to the estimation of traffic flow in a certain period of time based on some historical traffic flow data provided by traffic flow acquisition equipment. According to the forecast period length of traffic flow, the forecast can be divided into long-term and short-time forecast. short-time prediction refers to cases in which the interval and prediction period of time series data are shorter, usually not exceeding 15 minutes.

2.2 Traffic Flow Characteristic Analysis

The road traffic system is a huge system with participation, time-dependence and complexity. The traffic flow [26] and its distribution have the characteristics of changing with time and space, so the traffic flow is time-dependent, random and uncertain [27]. Because the behavior of travelers is influenced by personal travel habits and traffic rules of urban road network, the traffic flow presents certain rules, mainly in periodicity. There are many uncertain factors in the traffic flow [28].

2.3 Modeling Principle of Short-time Traffic Flow Prediction

Real-time. The ultimate purpose of flow forecasting is to act on traffic guidance system and traffic control system to provide traffic flow future state data at the moment, so the predicted data information is required to be very real-time.

Accuracy. The purpose of short-time traffic flow forecasting is to serve traffic control system and traffic guidance. Only if the forecast result of traffic flow meets certain precision requirements and has certain accuracy, can it be applied.

Dynamic feedback. Because the traffic flow is random and complex, its law cannot be fixed. In order to get a better prediction result, the prediction model should be able to dynamically feedback to the calculation model to adjust according to the actual situation once the traffic flow is abnormal.

Portability. The research and development of traffic flow forecasting model need time and money as the support. If a forecasting model is only suitable for a specific time or section of the road, it cannot be widely popularized. Therefore, only if the model is portable in time and space, can the cost be reduced and widely used, thus promoting the development of traffic control system.

2.4 Comparison and aDaptability Analysis of Traffic Flow Forecasting Methods

Common methods and comparative analysis of traffic flow prediction. By overview of the research of traffic flow prediction in recent years, the advantages and disadvantages and the using range of each model are summarized [29], As shown in Table1 and Table 2.

Table 1. Method based on linear system theory

model	merit	shortcoming	scope of application
Historical average	Simple principle Fast operation	Low prediction accuracy Can only be used for traffic flow changes A more stable section of the road	A stillness that does not require high precision State traffic prediction system
linear regression	Strong adaptability	Unable to correct errors in time, It can't reflect the nonlinear change of short-time traffic flow	Static traffic forecasting system
time series	Simple modeling Good real-time performance Stability is good	The accuracy of prediction depends too much on the number of samples, Unable to dynamically feedback real time adjustment model	A road with little fluctuation in traffic flow section
Kalman filtering [30]	Forecasting smooth traffic flow, Wide applicability	Prediction accuracy depends on linear characteristics of traffic flow	Linear nonreal-time online intersection General prediction system

Table 2. Methods based on nonlinear system theory

model	merit	shortcoming	scope of application
non parametric regression	High prediction accuracy, You can mine information from a history database, Algorithm transplantable	The matching complexity of nearest neighbor pattern is high, Low computational efficiency, Rely on a lot of historical data [31]	Suitable for traffic system impact factors Prime region
wavelet analysis	High prediction accuracy Strong adaptability	The mathematical theory of the algorithm is complex, and the calculation amount is large	Suitable for complex nonlinear intersection General prediction system
nerve net	Without clearly predicting the problem Internal mechanism, Self-learning and self-learning Adapt, Universal prediction accuracy tall	Insufficient data or noise will lead to large deviation of prediction results. Early training process recovery Miscellaneous, general stability [32]	Suitable for complex and variable nonlinear Traffic flow prediction based on
Support Vector Machine SVM	High precision, real time and stability Better qualitative	Model parameters and kernel functions have great influence on prediction accuracy [33]	Suitable for complex and changeable traffic Flow prediction

Applicability analysis of wavelet neural network in traffic flow prediction. As is aforementioned, the traffic flow presents the uncertainty, randomness, complexity and uncertainty. The algorithm based on statistical theory is difficult to solve due to the complexity of modeling process and the requirement of high precision. Therefore, the prediction method based on linear system theory is not suitable for short time interval and uncertain short time traffic flow, and is more suitable for medium and long time traffic flow prediction.

2.5 Evaluation Index of Short-time Traffic Flow Prediction

In order to obtain the best prediction results, it is often necessary to evaluate them according to the corresponding evaluation indexes. Several common short-time traffic flow prediction evaluation indicators are as follows. Suppose $Y_p(t)$ to predict the traffic flow at t time, $Y_r(t)$ is the actual traffic flow at t.

Mean Square Error.

$$MSE = \frac{1}{N}\sqrt{\sum_t (Y_p(t) - Y_r(t))^2} \tag{1}$$

This index reflects not only the magnitude of the traffic flow prediction error but also the discrete distribution of the error. The smaller the value, the smaller the error dispersion and the better the prediction effect.

Mean absolute error.

$$MAE = \frac{1}{N}\sum_t \left|Y_p(t) - Y_r(t)\right| \tag{2}$$

The average relative error reflects the absolute value of the error between the forecast value of traffic flow and the real value, and the smaller the value is, the better the prediction effect is.

Mean relative error.

$$MRE = \frac{1}{N}\sum_t \left|\frac{Y_p(t) - Y_r(t)}{Y_r(t)}\right| \quad t = 1,2,...,N \tag{3}$$

The average relative error reflects the degree of deviation between the predicted value of traffic flow and the real value, and the smaller the value is, the better the prediction effect is.

Fitness.

$$EC = 1 - \frac{\sqrt{\sum_t (Y_P(t) - Y_r(t))^2}}{\sqrt{\sum_t (Y_p(t))^2} + \sqrt{\sum_r (Y_r(t))^2}} \quad \textbf{(4)}$$

Maximum mean relative error.

$$MXMAE = \max(\frac{1}{N}\sum_t \left| \frac{Y_p(t) - Y_r(t)}{Y_r(t)} \right|) \qquad t = 1, 2, ..., N \quad \textbf{(5)}$$

2.6 Wavelet Analysis

Wavelet analysis [34-35] overcomes the defects of Fourier processing of non-stationary signals, It can not only obtain the frequency component of a signal, but also construct a flexible time-frequency window using a finite length of attenuated wavelet basis. The formula is:

$$WT(a,\tau) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} f(t) \times \psi(\frac{t-\tau}{a}) dt \quad \textbf{(6)}$$

The scale controls the scaling of the wavelet function, and the translation τ controls the translation of the wavelet function.

2.7 Feedforward Neural Network

Feedforward neural networks are used to deal with complex nonlinear classification. In complex nonlinear classification, the combined high-order input will appear, while the feedforward neural network [36-40] uses the parameter matrix determination method to predict the samples, and obtains the classification results of the samples. Figure 2 intuitively shows an example of a typical three-layer neural network model propagating forward.

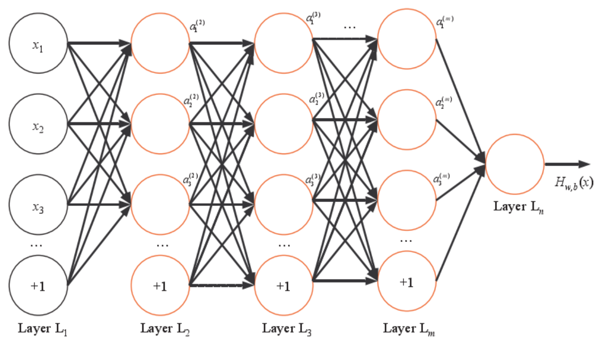

Figure 2. Typical neural network model

The most typical neural network is the BP neural network. Its input and output mapping relationship is:

$$f(z) = \frac{1}{1+\exp(-z)} \quad \textbf{(7)}$$

Among them, $z = \sum_{i=1}^{n} w_i x_i + b$

The essence of reverse computation is to adjust the weights and thresholds of neural networks through the neurons of the hidden layer according to the total error between the output layer and the actual results. So the algorithm flow of reverse computation is described as follows:

The feedforward propagation calculation is carried out, and the forward propagation formula is used to obtain the L1, L2, and L3. The activation value of the Ln (output layer). In order to simplify the model, the forward propagation calculation method with a layer of hidden layer is described below. The expression of n neurons in the hidden layer is:

$$\begin{cases} a_1^{(2)} = f(W_{11}^{(1)}x_1 + W_{12}^{(1)}x_2 + W_{13}^{(1)}x_3 + ... + W_{1n}^{(1)}x_n + b_1^{(1)}) \\ a_2^{(2)} = f(W_{21}^{(1)}x_1 + W_{22}^{(1)}x_2 + W_{23}^{(1)}x_3 + ... + W_{2n}^{(1)}x_n + b_2^{(1)}) \\ a_3^{(2)} = f(W_{31}^{(1)}x_1 + W_{32}^{(1)}x_2 + W_{33}^{(1)}x_3 + ... + W_{3n}^{(1)}x_n + b_3^{(1)}) \\ ... \\ a_n^{(2)} = f(W_{n1}^{(1)}x_1 + W_{n2}^{(1)}x_2 + W_{n3}^{(1)}x_3 + ... + W_{nn}^{(1)}x_n + b_n^{(1)}) \end{cases} \quad \textbf{(8)}$$

The neuron expression of the output layer is:

$$\begin{aligned} h_{w,b}(x) &= a_1^{(3)} \\ &= f(W_{11}^{(2)}a_1^{(2)} + W_{12}^{(2)}a_2^{(2)} + \\ &\quad ... + W_{1n}^{(2)}a_n^{(2)} + b_1^{(2)}) \end{aligned} \quad \textbf{(9)}$$

Then, if there is a neural network with multiple hidden layers, the steps of feedforward propagation are:

$$\left.\begin{aligned} z^{(l)} &= W^{(l-1)}a^{(l-1)} + b^{(l-1)} \\ a^{(l)} &= f(z^{(l)}) \end{aligned}\right\} \Rightarrow \quad \textbf{(10)}$$
$$z^{(l)} = W^{(l-1)} f(z^{(l-1)}) + b^{(l-1)}$$

Set the objective function, given a training set that contains a sample, and the objective function is:

$$\begin{aligned} J(W,b) &= \frac{1}{m}\sum_{i=1}^{m} J(W,b;x^{(i)},y^{(i)}) + \frac{\lambda}{2}\|W\|_2^2 \\ &= \frac{1}{m}\sum_{i=1}^{m} (\frac{1}{2}\|h(x^{(i)}) - y^{(i)}\|^2) \\ &\quad + \frac{\lambda}{2}\sum_{i=1}^{n_j - 1}\sum_{i=1}^{s_j}\sum_{j=1}^{s_{j+1}} (W_{ji}^{(l)})^2 \end{aligned} \quad \textbf{(11)}$$

The gradient descent method is used to minimize J (WGB), and the parameters are updated as follows:

$$\begin{aligned} W_{new}^{(l)} &= W^{(l)} - \alpha \times \frac{\partial J(W,b)}{\partial W^{(l)}} \\ &= W^{(l)} - \alpha \sum_{i=1}^{m} \frac{\partial J(W,b;x^{(i)},y^{(i)})}{\partial W^{(l)}} - \lambda W \end{aligned} \quad \textbf{(12)}$$

$$b_{new}^{(l)} = b^{(l)} - \alpha \times \frac{\partial J(W,b)}{\partial b^{(l)}} \\ = b^{(l)} - \alpha \sum_{i-1}^{m} \frac{\partial J(W,b;x^{(i)},y^{(i)})}{\partial b^{(l)}} \quad \textbf{(13)}$$

The key to weight and threshold updating for reverse calculations is:

$$\frac{\partial J(W,b;x^{(i)},y^{(i)})}{\partial W^{(l)}} \text{ and } \frac{\partial J(W,b;x^{(i)},y^{(i)})}{\partial b^{(l)}},$$

According to the chain rule:

$$\frac{\partial J(W,b;x,y)}{\partial W^{(l)}} = (\frac{\partial J(W,b;x,y)}{\partial z^{(l+1)}})^T \frac{\partial z^{(l+1)}}{\partial W^{(l)}} \quad \textbf{(14)}$$

Among them,

$$\frac{\partial z^{(l+1)}}{\partial W^{(l)}} = \frac{\partial \left[W^{(l)} \times a^{(l)} + b^{(l)} \right]}{\partial W^{(l)}} = a^{(l)}$$

The residual is defined as:

$$\delta^{(l)} = \frac{\partial J(W,b;x,y)}{\partial z^{(l)}} \quad \textbf{(15)}$$

Therefore,

$$\frac{\partial J(W,b;x,y)}{\partial W^{(l)}} = (\delta^{(l+1)})a^{(l)} \quad \textbf{(16)}$$

Similarly：

$$\frac{\partial J(W,b;x,y)}{\partial b^{(l)}} = (\frac{\partial J(W,b;x,y)}{\partial z^{(l+1)}}) \frac{\partial z^{(l+1)}}{\partial b^{(l)}} \\ = \frac{\partial \left[W^{(l)} a^{(l)} + b^{(l)} \right]}{\partial b^{(l)}} \delta^{(l+1)} \\ = \delta^{(l+1)} \quad \textbf{(17)}$$

After updating the weight and threshold, the total error between the output layer and the actual result is less than the set condition, then the calculation is stopped, otherwise, the second step is returned to update the parameters until the condition is satisfied.

2.8 Wavelet Neural Network

According to the above analysis, the error space of P network is an extremely complex N-dimensional surface. The "height" of each point on the surface corresponds to the total error of the neural network. The coordinate vectors of each point correspond to the weights of N neurons. Fig.3 is a schematic diagram of a two-dimensional error space of a neural network. In view of the shortcomings of the neural network mentioned above, the wavelet basis function is used to replace the sigmoid function to optimize the network parameters and error space. Therefore, the input-output mapping of wavelet neural network can be expressed as follows:

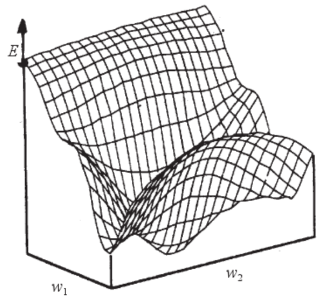

Figure 3. Neural network two-dimensional error space

$$\hat{y}_m = \sum_{i=1}^{N} w_i \psi(\frac{t - b_i}{a_i}) \quad \textbf{(18)}$$

Among them, $\psi(.)$ is the generating wavelet basis function of a function, scale a_i controls the scaling of wavelet functions, translation quantity b_i controls the translation of wavelet functions, w_i is the connection weight of a network neuron, and N is the number of mother wavelets.

3 Problem Solution

The flow chart of short-time traffic flow forecasting is shown in Figure 4. First of all, from the scene distributed on both sides of the road and intersection traffic flow collection device, as well as the traffic flow information collected by intelligent devices such as positioning devices installed on vehicles, sort out the traffic information that you need to predict, and then get a sample of the traffic flow forecast data, next, the traffic flow data sample is used as the input of the wavelet neural network. Trained to network convergence, finally, according to the input data, the prediction results of short-time traffic flow can be obtained.

The wavelet neural network training flow chart is shown in Figure 5. First, the wavelet neural network is constructed, then the parameters of the wavelet neural network [41] are initialized and trained. After the training, the network continues to train if the network does not converge, and it carries on the next step if the network converges. The wavelet neural network is tested and a certain sample data is selected to get the final prediction results.

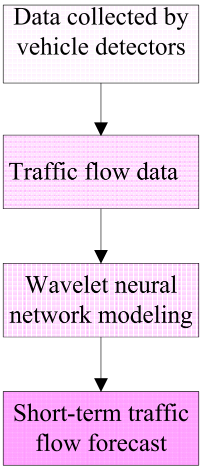

Figure 4. Flow chart of short-time traffic flow prediction

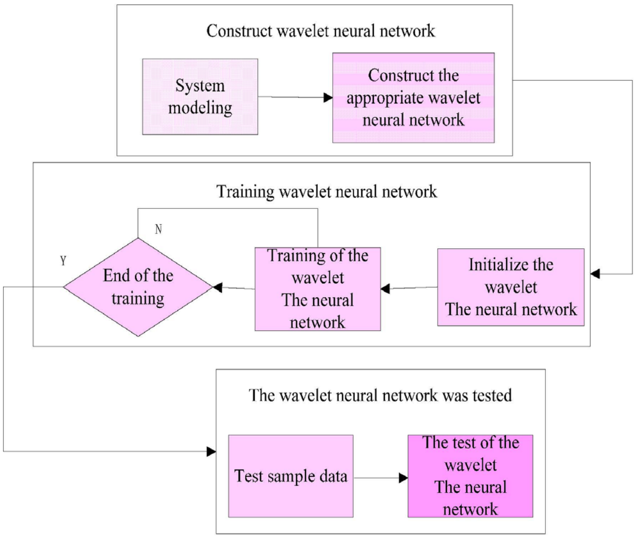

Figure 5. Wavelet neural network training flow chart

3.1 Data Processing of Short-time Traffic Flow

In short time traffic flow prediction, traffic flow sample data collected from intelligent devices such as traffic flow acquisition devices on both sides of roads and intersections and positioning devices installed on vehicles are numerous and inconsistent in size and size. So it is necessary to normalize the sample set.

$$X = \frac{X_i - X_{\min}}{X_{\max} - X_{\min}} \tag{19}$$

Among them, X For normalized sample values, X_i For the sample values before normalization, $X_{\max}$ and $X_{\min}$ Maximum and minimum values for each group of samples respectively.

3.2 Construction of Wavelet Neural Network

The construction of wavelet neural network is based on the characteristics of short-time traffic flow. According to the characteristics of short-time traffic flow, the wavelet neural network is selected as three layers: input layer, hidden layer and output layer. The input layer is the traffic flow of the first four time points of the current time point, and the data of 276 points are collected at each time point. Therefore, the input nodes of the wavelet neural network are 4. The original data of traffic flow at each point in time are shown in Figure 6.

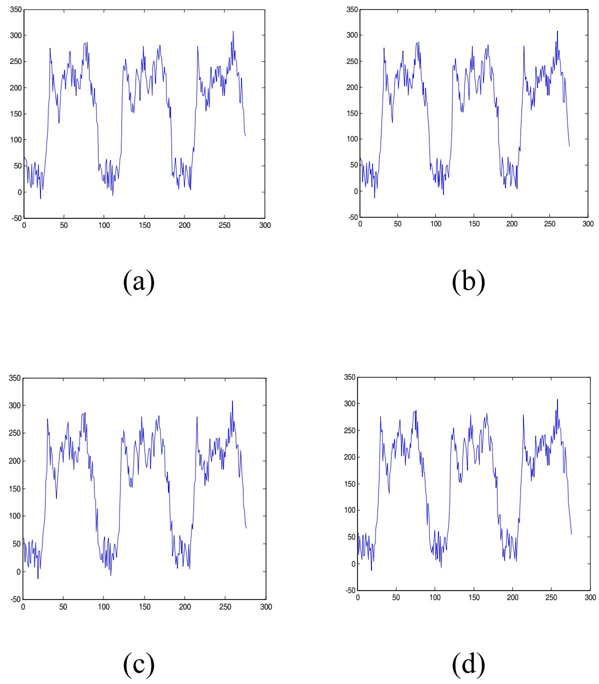

Figure 6. Original data map

According to the past experience, we can refer to the following formula design.

$$n = \sqrt{n_i + n_o} + a \tag{20}$$

in which n is the number of hidden layer nodes, n_i is the number of input layer nodes, n_o is the number of output layer nodes, and a is a constant between 1 and 10. According to formula (20), we can determine that the number of hidden layers is between 3~12. If the number of hidden layer nodes is too small, the fault tolerance of the network will be very poor, and the recognition rate of the samples will be greatly reduced. If there are too mang hidden layer points chosen, the network will become complex and the learning time will be too long. Therefore, the specific number should be determined according to the training times and errors of the network. Firstly, the number of hidden layer nodes is selected and then the number of hidden layer nodes is increased step by step in the case of sample number ratio. The neural network is trained by this method and the number of hidden layer nodes in the case of minimum error is finally selected.

4 Problem Solution

4.1 Wavelet Neural Network Prediction Results

The sample data are normalized and used as input to the wavelet neural network model. After inputting the sample set into the network, we begin to train the wavelet neural network. Because the hidden layer nodes range from 3 to 12, we first set the hidden layer number as 3, then gradually increase it to 12. The error of the network model is observed and the minimum error is obtained when the number of hidden layer nodes is 6. Therefore, the number of hidden layer nodes is 6. When the number of hidden layer nodes is 6, the training of wavelet neural network is shown in Table 3.

Table 3. Error analysis of network model

Hidden layer node number	3	4	5	6	7
MAE	50.0823	21.0852	21.6092	20.0912	79.6034
MSE	7.2137	2.6723	2.7129	2.5211	9.2780
MRE	0.1088	0.0108	0.0028	0.0114	0.0632
Hidden layer node number	8	9	10	11	12
MAE	22.2738	20.0410	20.9016	21.9713	25.9806
MSE	2.8746	2.5583	2.6142	2.7379	4.0243
MRE	0.0040	0.0139	0.0098	0.0188	0.0157

Figure 7, the blue curve is the actual traffic flow, and the red curve is the traffic flow curve predicted by the wavelet neural network. It can be seen from the diagram that the wavelet neural network can well predict the short-time traffic flow on the whole. Except a few time points, the prediction accuracy is very high in the whole trend.

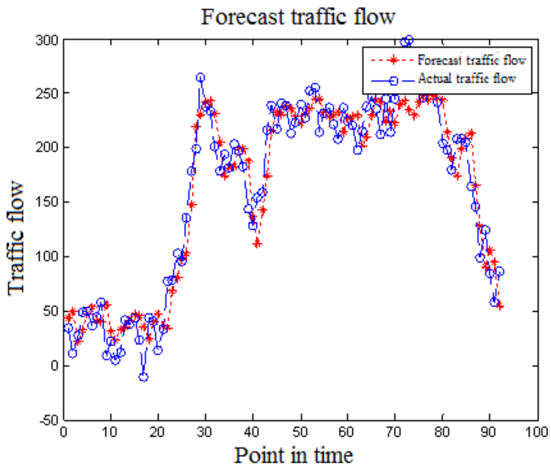

Figure 7. Short-time traffic flow prediction diagram based on Wavelet Neural Network

4.2 BP Neural Network Prediction Results

The sample data are normalized and used as inputs to the BP neural network model. After inputting the sample set into the network, we begin to train the BP neural network. The error of the network model is observed, and the error of the hidden layer node is finally obtained. As is shown in Figure 8, the blue curve is the actual traffic flow, and the red curve is the traffic flow curve predicted by the BP neural network.

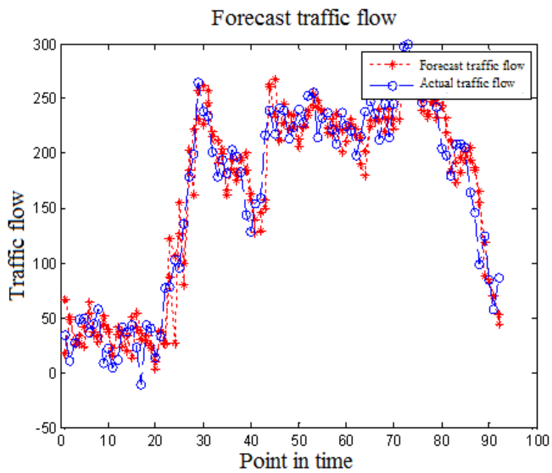

Figure 8. Short-time traffic flow prediction diagram based on BP Neural Network

4.3 Comparative Analysis of Prediction Performance

In order to further evaluate the prediction results of wavelet neural networks, in this paper we selects two most commonly used performance evaluation indicators: Mean square error (MSE) and mean absolute error (MAE) to analyze. The MSE and MAE of BP neural network and wavelet neural network are calculated respectively. The results are shown in Table 4.

Table 4. Predictive performance analysis

prediction model	MAE	MSE	MRE
Wavelet neural network	20.0912	2.5211	0.00114
BP neural network	21.7464	2.7465	0.0156

As is shown in Table 4, the MSE, the MAE and the average relative error (MRE) of the wavelet neural network model are 2.5211, 20.0912 and 0.00114, respectively, which are much smaller than those of the BP neural network. It indicates that the wavelet neural network has a fast convergence speed and a high prediction accuracy. Therefore, the wavelet neural network is an effective forecasting method in short-time traffic flow forecasting.

5 Conclusion

Short-time traffic flow is highly time-varying, complex and uncertain, which is more difficult than medium and long-term traffic flow prediction. In this paper, the wavelet neural network is used to predict the traffic. The prediction results show that it can be used to predict traffic in short time, and its precision is very high. Therefore, it is expectable that the wavelet neural network should have potential applications in the future intelligent transportation system.

References

[1] S. Dai, J. Liu, J. Zhu, Urban Motorization Development and Policy in China, *Urban Transport of China*, Vol. 13, No. 2, pp. 42-56, March, 2015.

[2] J. Zhang, H. Song, S. Wang, J. Gu, Research on Framework of New Generation Intelligent Traffic Management System in Metropolitan Area of Chongqing, *China Railway Press*, Vol. 13, No. 4, pp. 156-161, February, 2015.

[3] Y. Liu, C. Tian, Analysis of Dynamic Characteristics of Urban Traffic Congestion Based on Specificity of Network Configuration, *China Journal of Highway and Transport*, Vol. 26, No. 1, pp. 163-169, June, 2013.

[4] F. Li, The Development Trend of Intelligent Transportation System in Foreign Countries, *Foreign Roads*, Vol. 19, No. 1, pp. 1-5, August, 1999.

[5] Filjar R, Dujak M, Drilo B, Intelligent Transport System, *Coordinates*, Vol. 5, No. 6, pp. 8-10, May, 2009.

[6] C. Dai, X. Liu, J. Lai, P. Li, H. C. Chao, Human Behavior Deep Recognition Architecture for Smart City Applications in the 5G Environment, *IEEE Network*, DOI: 10.1109/MNET.2019.1800310, May, 2019.

[7] L. Wei, H. Chen, L. Wang, Analysis of Key Factors Leading to Road Traffic Accidents, *Journal of Transport Information and Safety*, Vol. 33, No. 1, pp. 84-89, October, 2015.

[8] J. Yuan, B. Fan, Research Progress of Short-time Traffic Flow Prediction, *Urban Transport*, Vol. 10, No. 6, pp. 73-79, April, 2013.

[9] Akaike H, Canonical Correlation Analysis of Time Series and the Use of an Information Criterion, *Mathematics in Science and Engineering*, Vol. 126, pp. 27-96, January, 1976.

[10] H. Lu, Z. Sun, W. Qu, Real-Time Corrected Traffic Correlation Model for Traffic Flow Forecasting, *Mathematical Problems in Engineering*, Vol. 9, pp. 1-7, December, 2015.

[11] J. Xue, Z. Shi, Short-Time Traffic Flow Prediction Based on Chaos Time Series Theory, *Journal of Transportation Systems Engineering & Information Technology*, Vol. 8, No. 5, pp. 68-72, May, 2008.

[12] J. Sun, L. Zhang, Vehicle Actuation Based Short-Term Traffic Flow Prediction Model for Signalized Intersections Shenyang University of Technology, *Journal of Central South University of Technology*, Vol. 19, No. 1, pp. 287-298, April, 2012.

[13] Q. Shang, C. Lin, Z. Yang, A Hybrid Short-Term Traffic Flow Prediction Model Based on Singular Spectrum Analysis and Kernel Extreme Learning Machine, *PLOS ONE*, Vol. 11, No. 8, pp. 1-25, December, 2016.

[14] L. Wan, J. Yang, Application of Wavelet Neural Network in Short-time Traffic Flow Prediction, *Computer Simulation*, Vol. 29, No. 9, pp. 352-355, September, 2012.

[15] L. Zhang, Q. Liu, W. Yang, An Improved K-nearest Neighbor Model for Short-term Traffic Flow Prediction, *Procedia-Social and Behavioral Sciences*, Vol. 96, pp. 653-662, January, 2013.

[16] L. Kao, C. Chiu, C. Lu, A Hybrid Approach by Integrating Wavelet-based Feature Extraction with MARS and SVR for Stock Index Forecasting, *Decision Support Systems*, Vol. 54, No. 3, pp. 1228-1244, April, 2013.

[17] X. Yang, L. Xu, Y. Zhou, Research on Real-time Prediction Model of Road Traffic Flow Based on Wavelet Neural Network, *Technology of Highway and Transport*, Vol. 241, pp. 2088-2094, February, 2013.

[18] D. Huang, J. Song, D. Wang, Forecasting Model of Traffic Flow Based on ARMA and Wavelet Transform, *Computer Engineering and Applications*, Vol. 42, No. 36, pp. 191-194, December, 2006.

[19] X. Zheng, B. Han, D. Li, RBF Neural Network Based Urban Expressway Short-term Traffic Flow Prediction, *Shandong Science*, Vol. 25, No. 3, pp. 23-28, September, 2012.

[20] Y. Huang, Traffic Flow Forecasting Based on Wavelet Neural Network and Support Vector Machine, *Journal of Computational Information Systems*, Vol. 8, No. 8, pp. 3471-3478, January, 2012.

[21] J. Liu, W. Guan, A Summary of Traffic Flow Forecasting Methods, *Journal of Highway and Transportation Research and Development*, Vol. 21, pp. 82-85, February, 2004.

[22] J. Xue, Z. Shi, Short-time Traffic Flow Prediction Based on Chaos Time Series Theory, *Journal of Transportation Systems Engineering and Information Technology*, Vol. 8, No. 5, pp. 68-72, December, 2008.

[23] X. Jiang, H. Adeli, Dynamic Wavelet Neural Network Model for Traffic Flow Forecasting, *Journal of Transportation Engineering*, Vol. 131, No. 10, pp. 771-779, April, September, 2005.

[24] M. Jun, X. Li, Y. Meng, Research of Urban Traffic Flow Forecasting Based on Neural Network, *Acta Electronica Sinica*, Vol. 37, No. 5, pp. 1092-1094, October, 2009.

[25] M. Zhang, Y. Zhen, G. Hui, G. Chen, Accurate Multisteps Traffic Flow Prediction Based on SVM, *Mathematical*

Problems in Engineering, Vol. 2013, No. 8, pp. 1-8, October, 2013.

[26] Y. Li, Urban Traffic Flow Prediction and Assignment with Dynamic Programming, *Journal of Transportation Systems Engineering and Information Technology*, Vol. 9, No. 3, pp. 135-139, September, 2009.

[27] D. Qu, D. Guan, Z. Liu, Study on the Characteristics of Mixed Traffic Flow in Chinese Cities, *Journal of Qingdao University of Technology*, Vol. 28, No. 3, pp. 81-86, February, 2007.

[28] G. Shen, X. Wang, X. Kong, Short-time Traffic Volume Intelligent Hybrid Forecasting Model and Itsapplication, *Systems Engineering-Theory & Practice*, Vol. 31, No. 3, pp. 561-568, January, 2011.

[29] B. L. Smith, M. J. Demetsky, Traffic Flow Forecasting: Comparison of Modeling Approaches, *Journal of Transportation Engineering*, Vol. 123, No. 4, pp. 261-266, April, 1997.

[30] Z. Yang, Z. Zhu, A Real-time Volume Predictio Model Based on The Kalman Filtering Theory, *China Journal of Highway and Transport*, Vol. 12, No. 3, pp. 63 -67, May, 1999.

[31] A. Abadi, T. Rajabioun, P. A. Ioannou, Traffic Flow Prediction for Road Transportation Networks with Limited Traffic Data, *IEEE Transactions on Intelligent Transportation Systems*, Vol. 16, No. 2, pp. 653-662, September, 2015.

[32] B. G. Çetiner, M. Sari, O. Borat, A Neural Network Based Traffic-Flow Prediction Model, *Mathematical and Computational Applications*, Vol. 15, No. 2, pp. 269-278, January, 2010.

[33] Q. Xu, R. Yang, Traffic Flow Prediction Using Support Vector Machine Based Method, *Journal of Highway and Transportation Research and Development*, Vol. 22, No. 12, pp. 131-134, September, 2015.

[34] Q. Li, G. Jiang, Bi-level Model of Multi-Step Forecasting For Short-time Data of Loop in Sydney Coordinated Adaptive Trafficsystem, *Journal of Jilin University (Engineering and Technology Edition)*, Vol. 43, No. 4, pp. 854-860, May, 2013.

[35] G. Marfia, M. Roccetti, Vehicular Congestion Detection and Short-term Forecasting: A New Model with Results, *IEEE Transactions on Vehicular Technology*, Vol. 60, No. 7, pp. 2936-2948, January, 2011.

[36] G. He, S. Ma, Y. Li, Study on the Short-Time Forecasting for Traffic Flow Based on Wavelet Analysis, *Systems Engineering-Theory&Practice*, Vol. 22, No. 9, pp. 101-106, September, 2002.

[37] H. Yin, S. C. Wong, J. Xu, C. K. Wong, Urban Traffic Flow Prediction Using a Fuzzy-Neural Approach, *Transportation Research Part C: Emerging Technologies*, Vol. 10, No. 2, pp. 85-98, February, 2002.

[38] S. Chen, W. Wang, G. Qu, Short-Time Traffic Flow Time Series Forecasting Based on Wavelet Analyses-Fuzzy Markov Prediction Model, *Journal of Southeast University (Natural Science Edition)*, Vol. 35, No. 4, pp. 637-640, April, 2005.

[39] G. He, S. Ma, Y. Li, A Study on Forecasting for Time Series Based on Wavelet Analysis, *Acta Automatica Sinica*, Vol. 28, No. 6, pp. 1012-1014, October, 2002.

[40] J. Oh, S. P. Washington, D. Nam, Accident Prediction Model for Railway-Highway Interfaces, *Accident Analysis & Prevention*, Vol. 38, No. 2, pp. 346-356, May, 2006.

[41] M. Lippi, B. Matteo, F. Paolo, Short-term Traffic Flow Forecasting: An Experimental Comparison of Time-series Analysis and Supervised Learning, *IEEE Transactions on Intelligent Transportation Systems*, Vol. 14, No. 2, pp. 871-882, February, 2013.

Biographies

Li Liu received a master's degree in engineering from Heilongjiang University in 2011. She is currently lecturer at Physics and Electronic Information college of Hulunbuir University. Her research interests include short-range wireless communications, Wavelet neural network and so on.

Peipei Wu is currently studying for a bachelor's degree at Hulunbuir University. Her research interests include mobile and Internet behavior analysis, 4G network technology and so on.

Xinzhe Wang is currently studying for a bachelor's degree at Hulunbuir University. Her research interests include wireless communication technology, transducer technology and so on.