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Short-Term Traffic Flow Prediction Based on Ga-Bp Neural Network

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Abstract: In response to the short-term traffic flow prediction, it is more sensitive in the short-time traffic flow prediction, and a short-time traffic flow prediction method optimized by genetic algorithm optimizes BP Neural Network is proposed. The weight and threshold of the BP Neural Network are processed by the genetic algorithm, and the BP Neural Network optimization is applied to adjust the real-time data predictive value. The experimental results show that the average absolute error of the algorithm is reduced by 9.1998% compared to the BP Neural Network, and the mean square error is reduced by 0.092. The average absolute error of the algorithm is reduced by 3.7229% compared to the wavelet Neural Network algorithm, and the mean square error is reduced by 0.0573. Compared to the above two algorithms, the GA-BP Neural Network algorithm has a better predictive effect, and provides a certain reference value for short-term traffic flow forecasting.

1. Introduction

Traffic flow prediction is an important bridge to build an intelligent transportation system. Real-time and accurate prediction of traffic flow is an important means to realize traffic flow distribution in road networks, ensure traffic flow control and conduct traffic guidance. Short-time traffic flow forecasting models include nonlinear models such as neural network models [1] and linear models such as Kalman filters [2] and autoregressive integrated moving average (ARIMA) models [3]. Lippi and Bertini applied Box-Jenkins time series analysis to predict freeway traffic flows and found that the ARIMA(0,1,1) model was the most statistically significant for all predictions [4]. To improve the prediction accuracy, several ARIMA variants have been proposed [5], such as KohonenARIMA (KARIMA), subset ARIMA, ARIMA with explanatory variables (ARIMA), vector autoregressive moving average (ARMA) and spatio-temporal ARIMA, seasonal ARIMA (SARIMA), etc., In addition to the above methods, Okutani and Stephanedes proposed Kalman filter model to predict traffic flow [6]. However, all these models are linear time series models, which do not respond well to external system changes and cannot handle the nonlinearity in traffic flow dependencies. Moreover, due to the stochastic and nonlinear nature of traffic flow, machine learning has been widely used in traffic flow prediction and has achieved good performance. El Faouzi developed a kernel smoother for short-time traffic flow prediction on autoregressive functions, and in [7] proposed an online learning weighted support vector regression (SVR) method for short-time traffic flow prediction. Zargari et al [8] developed different linear genetic programming, multilayer perceptron and fuzzy logic (FL) models to estimate the traffic flow at 5 and 30 minutes. Cetin and Comert [9] combined ARIMA models with expectation maximization and cumulative sum algorithms. Koesdwiady et al [10] proposed that fusing traffic and weather data with deep learning methods can improve the accuracy of traffic flow prediction. Vlahogianni et al. [11] combined artificial neural networks and genetic algorithms (GA) to predict short-term traffic flows.

2. Methodology

2.1 Overview of Bp Neural Networks

A BP Neural Network is a multilayer feedforward Neural Network with the ability to approach highly nonlinear functions by continuously updating the weights and thresholds of the network during the propagation of signals and errors.The network usually has three layers as shown in Figure 1: input layer, hidden layer, and output layer.

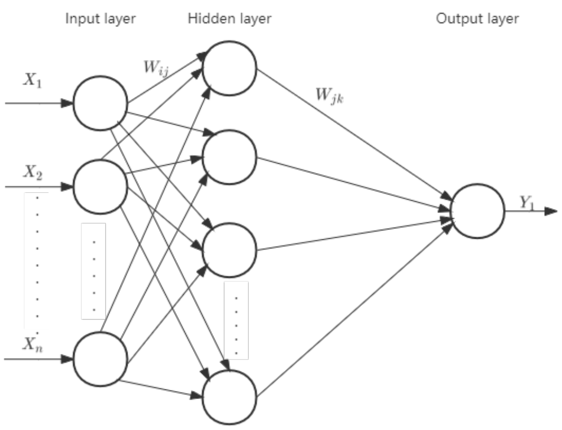


Fig.1 Bp Neural Network Topology Diagram

Suppose the sequence $X_i(i=1,2,3\cdots,n)$ is the input of the neural network system, and the sequence $Y_i(i=1,2,3\cdots,m)$ is the output of the neural network system, so that the input layer of the network has n neurons, the hidden layer of the network has p neurons, and the output layer 1 of the network has one neuron, so the final output sequence can be rewritten as Y_1

To determine the output value of the hidden layer, the Sigmoid function is chosen as the excitation function under this BP neural network, and the expression of the Sigmoid function is

$$g(x)=\left(1+e^{-x}\right)^{-1} \tag{1}$$

Further, with the help of the weights ω_{ij} connecting the input layer and the hidden layer of the BP neural network and the threshold α_j of the hidden layer, the output values of the neurons of the hidden layer p can be calculated as

$$b_j = \left[1+\exp\left(-\sum_{i=1}^{n}\omega_{ij}x_i+\alpha_j\right)\right]^{-1},\ j=1,2,\cdots,p$$	(2)

The predicted output value R of the output layer of the BP neural network can be obtained based on the output value b_j of the implicit layer and the weights ω_{jk} and threshold b of the output layer.

$$R=\sum_{j=1}^{p}b_j\omega_{jk}-b$$	(3)

After the above steps to calculate the predicted output value R of the BP neural network, in order to determine whether R is within the target range, an error determination is required, and the error value d of the BP neural network algorithm is calculated by the following formula.

$d=Y_1-R$	(4)

2.2 Wavelet Neural Network

The wavelet neural network algorithm has a similar topology to the BP neural network algorithm, the difference is that when the signal is propagated forward to the implicit layer of the wavelet neural network algorithm, the wavelet basis function is used as a fixed transfer function of the nodes in the implicit layer, and the common wavelet basis function expression h_j is.

$$y=\cos(1.75x)e^{\frac{-x^2}{2}}$$	(5)

When a sequence $X_i(i=1,2,\cdots,n)$ of signals is input to the network with weights ω_{ij} connecting the input and hidden layers to an input layer with n neurons, a hidden layer with p neurons, and an output layer with 1 neuron, the output value of the hidden layer of this wavelet neural network algorithm can be calculated at this time by the following equation.

$$h(j)=h_j\left(\frac{\sum_{i=1}^{n}\omega_{ij}x_i-d_j}{c_j}\right)\quad j=1,2,\cdots,p$$	(6)

where $h(j)$ is the output value of the jth node of the hidden layer; c_j is the translation factor of the wavelet basis function h_j; d_j is the scaling factor of the wavelet basis function h_j.

3. Short-Time Traffic Flow Prediction Model

3.1 Defects of BP Neural Network

Although BP neural network has advantages such as strong nonlinear mapping ability, but because its initial weights and thresholds are randomly generated, resulting in poor network performance of this algorithm, which is easy to fall into the trap of local optimum due to error squared and the generation of local minima of the function, leading to bias in prediction. In addition, in the face of a large training set, the learning rate of BP neural network learning process is unstable and the convergence rate will be very slow, leading to a large error between the network and the actual system.

3.2 Improvement of BP Neural Network Defects

To address the limitations as well as the shortcomings of the BP neural network algorithm, this paper decides to improve the shortcomings and defects of the BP neural network algorithm with the aid of the genetic algorithm that has outstanding effects in the global optimal solution search process. Genetic algorithm (GA) is a population parallel stochastic search algorithm based on the principles of natural selection and genetic genetics, and the use of genetic algorithm to optimize BP neural network can avoid the bias of prediction caused by the randomly generated weights and threshold values of BP neural network itself. The specific steps of GA-BP neural network are shown in Figure 2.

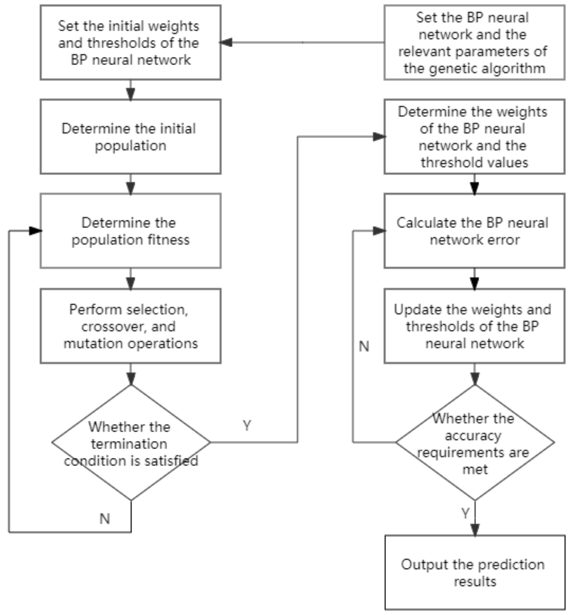


Fig.2 Ga-Bp Neural Network Optimization Steps

3.3 Overview of GA-BP Neural Network Algorithm

The GA optimization BP neural network algorithm consists of the following processes.

(1) Parameter initialization. Complete the settings of the BP neural network and the relevant parameters of the genetic algorithm [35].

(2) Creation of the neural network. According to the actual problem faced, determine the training samples as well as the learning samples, and input the training samples into the input layer of the neural network based on the normalization of the samples, after which the weights and thresholds of the initial network can be obtained and used as the initial population of the improved genetic algorithm.

(3) Determine the fitness function. In this paper, the reciprocal of the difference between the predicted and actual values of the BP neural network algorithm is used as the fitness function, so the following formula is the expression of the fitness function [36].

$$v = \frac{1}{\frac{1}{2}\sum_{m=1}^{M} E_k} \qquad (7)$$

where m is the number of samples trained and E_k is the training error of a given sample.

(4) Selection operation. The roulette wheel method is used as the selection algorithm, which satisfies the relation of equation (8).

$$P_i = \frac{v_i}{\sum_{i=1}^{n} v_i} \tag{8}$$

where $i = 1, 2, \cdots, n$, n is the population size.

(5) Crossover operation. The crossover process of the information W_{ij} at position j of the ith gene and the information W_{kj} at position j of the kth gene satisfies the relationship shown in equation (9).

$$\begin{cases} W_{ij} = W_{ij}(1-l) + W_{kj} \\ W_{kj} = W_{kj}(1-l) + W_{ij} \end{cases} \tag{9}$$

where l is a random number of [0,1].

(6) Mutation operation. The jth gene direction of the ith individual was selected for mutation, and the mutation operation was performed as shown in Equation (10).

$$a_{ij} = \begin{cases} a_{ij} + (a_{ij} - a_{\max}) \times f(g) \\ a_{ij} + (a_{\min} - a_{ij}) \times f(g) \end{cases} \tag{10}$$

where $a_{\max}$ is the upper bound of gene a_{ij}; $a_{\min}$ is the lower bound of gene a_{ij}; $f(g) = r_2(1 - g/G_{\max})^2$; r_2 is a random number; g is the current iteration number; $G_{\max}$ is the maximum evolution number; and r is a random number between [0,1].

(7) Build the model. The weights as well as thresholds obtained after the above steps are set as the optimal weights and optimal thresholds. On this basis, the optimal weights and optimal thresholds are assigned to the initial weights and chef thresholds of the BP neural network to complete the initial construction of the GA-BP neural network algorithm.

(8) Prediction step. After the training of the BP neural network, the prediction samples of the test set are predicted to obtain the final short-time traffic flow prediction values, and the accuracy as well as the relative error are calculated.

4. Experimental Simulation

4.1 Data Source

The traffic flow data of the sample were obtained from the observation records of the number of different types of traffic units on a road in Chengguan District of Lhasa City, and the data set was obtained from 7:00 to 12:00 and from 15:00 to 20:00 every day, with a total time of 10 hours. The data collected during the above time period can effectively include the morning and evening peak hours in the statistical scope, which makes the research process more reasonable and generalizable.The sampling interval of each group of data was 5 minutes, and the data were collected from November 12, 2020 to November 21, 2020, and a total of 1200 sets of data were recovered during these 10 days In this paper, 1080 sets of data from 9 days from November 12, 2020 to November 20, 2020 were used as the training data set, and 120 sets of data from 1 day on November 21, 2020 were used as the test data set.

4.2 Predicted Results

The GA-BP neural network algorithm used in this paper contains an input layer, an implicit layer and an output layer, in which the input nodes are determined by the data collection time, 10 in total, the output node is 1, the number of nodes in the implicit layer is set to 18, the learning rate of the BP neural network is set to 0.1, the target is 0.00001, the population size of the genetic algorithm is 100, the number of iterations is 50, the crossover probability is 0.4 and the variance probability is 0.2. The final prediction results of the GA-BP neural network algorithm are shown in Figure 3.

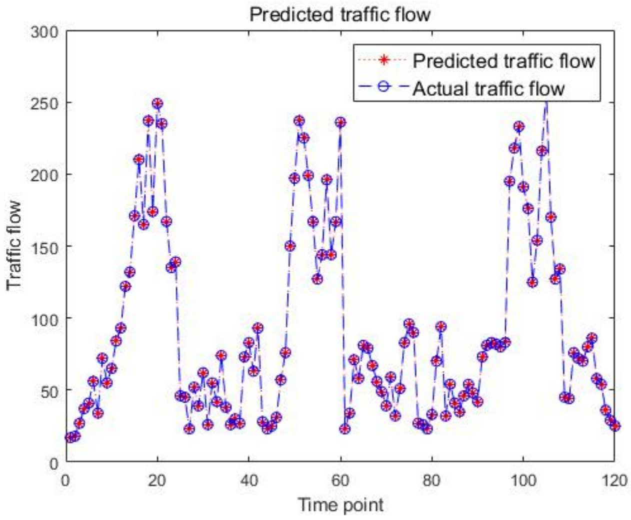


Fig.3 Comparison of Predicted and Actual Values

From Figure 3, it can be seen that the traffic prediction values basically match with the actual values, especially the traffic flow prediction during the peak hours appears to be more accurate. In order to understand the accuracy of GA-BP neural network in more details, the error variation of traffic flow prediction by GA-BP neural network is plotted as shown in Figure 4. From Figure 4, it can be seen that the prediction error of the traffic flow prediction model based on GA-BP neural network meets the model setting requirements, which verifies the robustness of the model. In addition, with the increase of the number of network training, the overall error decreases, indicating that this prediction model has strong reliability as well as accuracy.

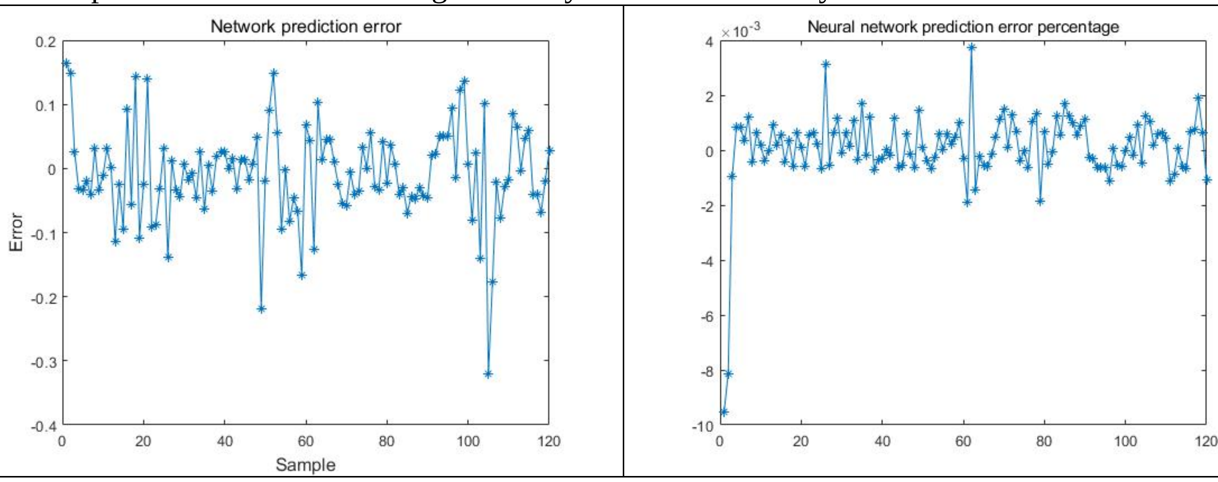
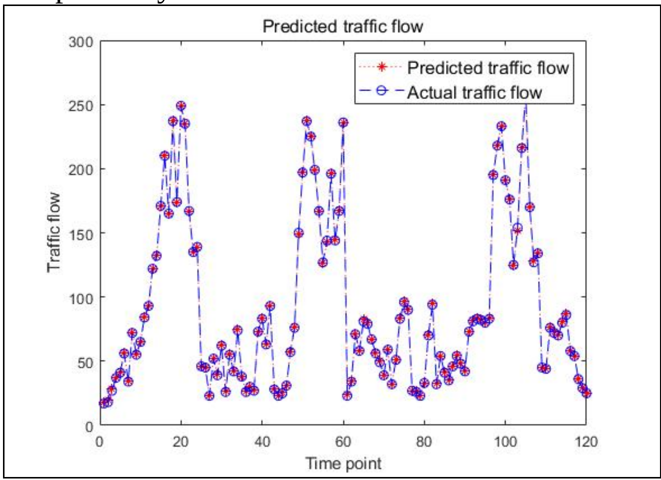


Fig.4 Forecast Error and Forecast Percentage Error

4.3 Algorithm Accuracy Comparison

To better see the accuracy of the proposed model, the BP neural network algorithm and the wavelet neural network algorithm proposed in Chapter 1 are compared and analyzed, and the prediction results of BP neural network and wavelet neural network are shown in Fig. 5 and Fig. 6, respectively.



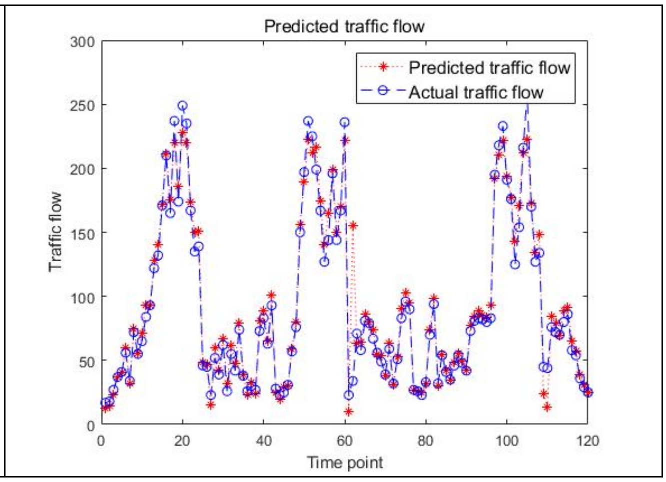


Fig.5 P Neural Network Prediction Results

Fig. 6 Wavelet Neural Network Prediction Results

In order to better understand the analytical results of the model, two error evaluation indicators, mean square error (MSE) and mean absolute percentage error (MAPE), were further calculated, which were calculated as follows.

$$MSE = \frac{1}{N}\sqrt{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \tag{11}$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100\% \tag{12}$$

Further, MSE as well as MAPE were calculated for each of the three models from the above two formulas, and the results are shown in Table 1.

Table 1 Ga-Bp Neural Network Prediction Results

Predictive Models	Evaluation Indicators	
	MSE	MAPE/%
BP Neural Network	0.1621	15.0674
Wavelet Neural Network	0.1274	9.5871
GA-BP Neural Network	0.0701	5.8642

From the above table, it can be seen that the GA-BP Neural Network prediction algorithm proposed in this paper has the lowest mean square error and percentage error compared with BP Neural Network algorithm and wavelet Neural Network algorithm, which means that the GA-BP Neural Network algorithm has higher accuracy in the process of traffic flow prediction.

5. Conclusion

This paper combines the genetic algorithm in heuristic algorithm with the BP Neural Network algorithm in machine learning, and proposes a short-time traffic flow prediction method using genetic algorithm to optimize the threshold value as well as the weight value of the BP Neural Network algorithm.By comparing the specific experimental results of BP Neural Network, wavelet

Neural Network and the algorithm proposed in this paper, GA-BP Neural Network can better approximate the real value in the traffic flow prediction process, i.e., GA-BP Neural Network algorithm has better prediction effect.

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