Error Correction and Wavelet Neural Network Based Short-term Traffic Flow Prediction

Yulin Pan, Dong Wang, Xiaohong Li, Zhu Xiao
College of Information Science and Engineering
Hunan University
Changsha, China
wangd@hnu.edu.cn

Abstract—**Real-time and accurate short-term traffic flow prediction is an important part of intelligent transportation system research. Wavelet neural network is a preferable method for predicting traffic flow. However, its performance is not satisfactory since it's easy to fall into local optimum. This paper proposed an Error Correction Wavelet Neural Network prediction method (EC-WNN) to predict short-term traffic flow. First, we use Wavelet Neural Network to predict the traffic flow, and build the error prediction model of Auto-Regressive Integrated Moving Average (ARIMA) based on the error series. Then we use the prediction errors to update the prediction results. Finally, the real detected traffic data are used to evaluate the precision of the model, the results show that EC-WNN is superior to traditional WNN in accuracy of prediction.**

Keywords-traffic flow prediction; wavelet neural network; ARIMA; error correction;

I. INTRODUCTION

With transportation industry continuously progressing and the increasing of people's demand for traveling, traffic system faced with great pressure. For reducing the traffic accidents, easing the environmental pollution and improving the efficiency of traffic system, developing the intelligent transportation system (ITS) [1] has become the most effective and achievable solution. While, the premise and key to achieve traffic guidance are real-time and accurate traffic flow prediction.

Existing studies of short-term traffic flows prediction can be classified into three categories in transportation literature: (1) mathematics statistics model, such as Kalman Filtering Model [2] and Auto-Regressive Moving Average Model(ARMA) [3]. (2) Nonlinear system theory based model, such as Wavelet Analysis [4], and Chaos Theory [5]. (3) Knowledge discovery based intelligent model, such as Neural Network [6], Nonparametric Regression [7], and Support Vector Machine [8].

At present, Wavelet Neural Network WNN [9] has been widely used because of its excellent capability of self-learning, self-organization and nonlinear approximation. However, since the weights connect each layer along with the wavelet basis function are fixed after sample training, once the training falls into local optimum, the precision of prediction will be deteriorative. In order to solve the problem and improve the precision of prediction based on WNN, we proposes an error correction based method which combines WNN with ARIMA model.

II. RELATED THEORIES

A. Wavelet neural network

Wavelet neural network (WNN) is based on BP neural network combined with wavelet analysis theory and artificial neural network. With signal forward propagation and error back propagation characteristics, WNN uses wavelet basis function as a network hidden layer node to transfer function. The structure of WNN is shown in Figure 1. X1, X2, … , Xm are the system input sequence; Y1, Y2, … , Yn are prediction value.

wavelet basis function
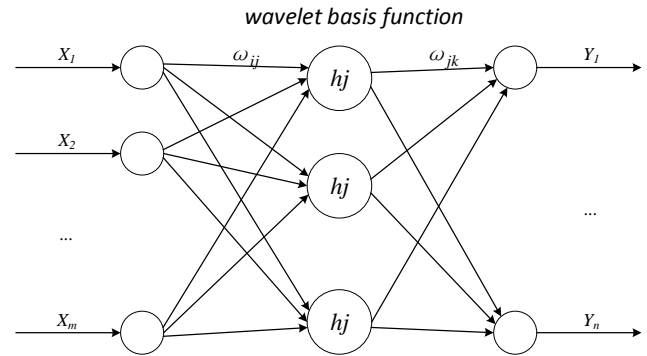

Figure 1. Structure of the wavelet neural network

When the input sequence is $x_i (i = 1, 2, ...m)$, the j-th node's output of the hidden layer is shown in (1), a_j and b_j are the scale factor and shift factor of the wavelet basis function h_j, ω_{ij} are the weights from the input layer to the hidden layer. L is the number of hidden nodes.

$$h(j) = h_j [\frac{\sum_{i=1}^{k} \omega_{ij} x_i - b_j}{a_j}] \qquad j = 1, 2, ...L \quad (1)$$

Here, h_j is Morlet wavelet basis function, which is shown in (2):

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

The output of wavelet neural network model is (3):

$$y(k) = \sum_{j=1}^{k} \omega_{jk} h(j) \qquad k = 1, 2, \ldots n \qquad (3)$$

In (3), ω_{jk} represents weight from hidden layer to output layer, j represents the node number of the hidden layer, k is the output node number.

Steps of training wavelet neural network are as follows:

- Initialization of Network: Initializing the connection weights ω_{ij} and ω_{jk}, the scale parameter a_j and the translation parameter b_j of the wavelet function by using random number.
- Output Prediction: Enter the training sample, calculate the output of the network according to (3), and calculate the error between real value and prediction value according to (4):

$$e = \sum_{k=1}^{m} yreal(k) - y(k) \qquad (4)$$

$yreal(k)$ is the real value of output, $y(k)$ is the prediction value.

- Weights Adjusting: Adjust the weights of wavelet neural network and parameters of the wavelet function according to equations below. η_1, η_2 in the formula represents learning factor.

$$\omega_{nk}^{i+1} = \omega_{nk}^{i} - \eta_1 \frac{\partial e}{\partial \omega_{nk}^{i}} \qquad (5)$$

$$a_{k}^{i+1} = a_{k}^{i} - \eta_2 \frac{\partial e}{\partial a_{k}^{i}} \qquad (6)$$

$$b_{k}^{i+1} = b_{k}^{i} - \eta_2 \frac{\partial e}{\partial b_{k}} \qquad (7)$$

B. ARIMA Model

Auto-Regressive Integrated Moving Average (ARIMA) [10] model is proposed by Box-Jenkins, it has dominated many areas of time series forecasting, such as social, economic, engineering, and environmental problems. In ARIMA(p,d,q) model, the future value of a variable is assumed to be a linear function of several past observations and random errors. Where:

p : order of the autoregressive part of the model

q : order of the moving average part of the model

d : order of differencing

After d-order differencing of the past observations, the ARIMA(p,d,q) model turns to be ARMA(p,q) model. The expression of the model ARMA(p,q) is defined by:

$$y_t - \varphi_1 y_{t-1} - \varphi_2 y_{t-2} - \ldots - \varphi_p y_{t-p} = e_t + \theta_1 e_{t-1} + \theta_1 e_{t-2} + \ldots + \theta_q e_{t-q}$$

Where:

y_t : univariate time series under investigation

$e_i (i = t, t-1, \ldots, t-q)$: white noise series normally distributed with mean zero and variance σ^2

$\varphi_i (i = 1, \ldots, p)$: coefficients which reflects the relationship between y_t and the past value of the time series.

$\theta_i (i = 1, \ldots, q)$: coefficients which reflects the relationship between y_t and the residues

III. ERROR CORRECTION BASED WAVELET NEURAL NETWORK TRAFFIC FLOW PREDICTION

There are two reasons why we add the error correction into wavelet neural network. One is the weights connect each layer along with the wavelet basis function are fixed after sample training, also WNN is easily fall into local optimum. Once the training falls into local optimum, the model can not be dynamically adjusted. However, we can adjust the prediction value according to the former prediction error dynamically. Another one is that the traffic flow is not only related to former traffic flow values in the last few moments but also related to weather, working day or holiday and so on. Only using the WNN to learn the traffic information from traffic flow is not enough. Error correction method is a supplement of the WNN, with which we can improve the precision of prediction. The algorithm framework is in Figure 2, the specific steps of the method is shown below:

1) Training the wavelet neural network.

2) Checking stationary of the error time sequence, if the sequence does not satisfy the stationary conditions, do difference of the error sequence.

3) Calculating the autocorrelation coefficient and partial autocorrelation coefficient to describe the sequence characteristics and determine the order of p, q in ARMA model.

4) Estimate the parameters by using Least Squares Estimation [12] , build the ARMA(p,q) model.

5) Using wavelet neural network to calculate the output data of prediction $\dot{y}_i$.

6) Calculating the error before e_{i-1} . y_{i-1} is the real data at the i-1 moment.

$$e_{i-1} = y_{i-1} - \dot{y}_{i-1}$$

7) If the error e_{i-1} is very big, According to the error series $e_1, e_2 \ldots e_{i-1}$ rebuild the ARIMA model.

8) According to the error series $e_1, e_2 \ldots e_{i-1}$ using an ARIMA model to predict the new error e_i

9) Adjusting the prediction data. $\ddot{y}_i$ is the prediction value after error correction.
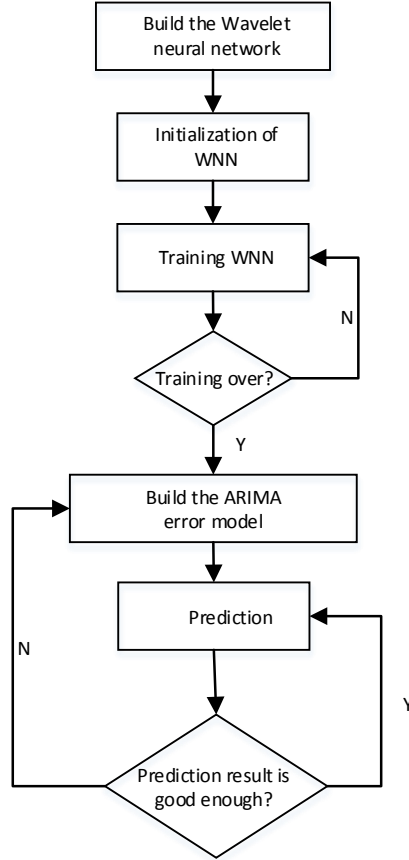
$$\ddot{y}_i = \dot{y}_i + e_i$$

Figure 2. The algorithmic framework of EC-WNN

IV. SIMULATION AND ANALYSIS OF MODEL

In order to verify the effectiveness of the proposed algorithm, we establish a short-term traffic flow model with the help of MATLAB. We select the former values x(t-3), x(t-2), x(t-1), x(t) to predict the next value x(t+1). So there are four input layer nodes, and one output layer node. Considering the convergence and training time of the network, the method $2n+1$ [12] is selected to determine the number of hidden layer nodes, where n is the number of input layer nodes. Therefore, we choose the structure 4-9-1. The parameter settings of WNN are shown in Table I.

TABLE I.   SETTINGS OF TRAINING PARAMETERS

Parameters	values
η_1	0.1
η_2	0.01
Max training generation	200

A. Experiment 1

We take the measured traffic data of I80E (Mainline VDS 402814) in San Francisco. The data were detected from 2015.1.8(00:00) to 2015.1.15(23:55) with sampling interval 5 minutes. The testing sample is from 2015.1.15(00:00-

23:55), and the remaining data are taken as the training sample.
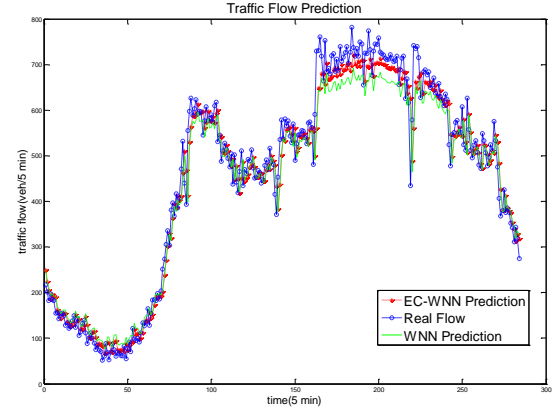

Figure 3. The traffic flow prediction of WNN and EC-WNN

Figure 2 shows the real traffic flow and prediction traffic flow. The blue curve, green curve and red curve represent the real traffic flow, WNN predict traffic flow and EC-WNN predict traffic flow. We can see that EC-WNN traffic flow prediction curve is more approximate to the real traffic flow curve than the WNN.

TABLE II.   THE COMPARISON OF WNN AND EC-WNN

Model	Max MAPE	MAPE	RMSE	EC
WNN	0.18	0.11	44.03	0.95
EC-WNN	0.12	0.09	41.03	0.96

MAPE is a statistical measurement of relative error, reflect the absolute deviation of data. RMSE is a statistical characteristic of error, reflect the discrete degree of samples. The smaller MAPE and RMSE represent the better performance of prediction. EC is used to show the fitting degree between the predicted value and the real traffic flow value, the bigger value, the better prediction. From Table II, we can see that the max MAPE of EC-WNN is 0.12, while the max MAPE of WNN is 0.18, it has been reduced by 33%, it means that the EC-WNN is more stable. The MAPE and RMSE values of EC-WNN are both smaller than the values of WNN. All of the metrics show that the prediction outputs of EC-WNN are more approximate to the measured data, so the established EC-WNN prediction model is superior to traditional WNN model in prediction accuracy.

B. Experiment 2

We take the measured traffic data of I880S (Mainline VDS 400312) in Alameda County. The data were detected from 2015.1.1(00:00) to 2015.1.8(23:55) with sampling interval 5 minutes. The testing sample is from 2015.1.8(00:00-14:00), and the remaining data are taken as the training sample.
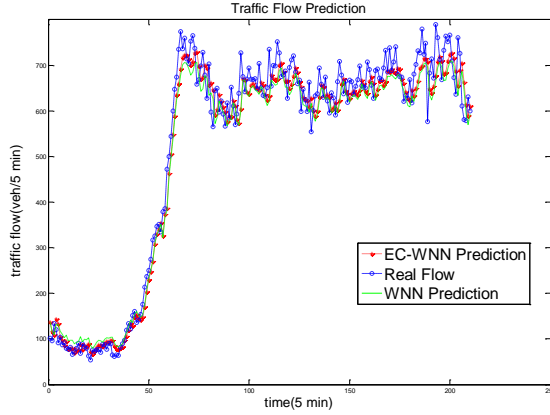
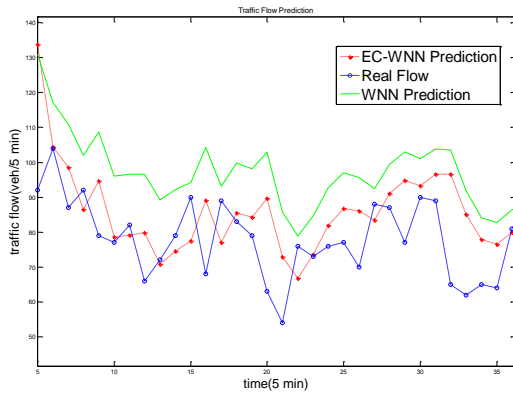Figure 4. The traffic flow prediction of WNN and EC-WNN

Figure 5. Details of Figure 3

Figure 4 shows the detail of Figure 3, we can see it clearly that EC-WNN traffic flow prediction curve is more approximate to the real traffic flow curve than the WNN.

TABLE III. THE COMPARISON OF WNN AND EC-WNN

Model	Max MAPE	MAPE	RMSE	EC
WNN	0.16	0.11	48.54	0.95
EC-WNN	0.1	0.08	41.29	0.96

The data from Table III reflects the same result, EC-WNN prediction model is more stable and it is superior to traditional WNN model in prediction accuracy.

V. CONCLUSIONS

To predict the short-term traffic flow more accurately, this paper has briefly introduced a new approach to the traffic flow prediction. The real detected traffic data are used to test the accuracy of the model. Simulation results have shown that the established EC-WNN prediction model is superior to traditional WNN in qualification-rate of prediction. It could be an efficient method to predict the real-time dynamic traffic flow.

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