Advances in Engineering Research, volume 138
2nd International Conference on Machinery, Electronics and Control Simulation (MECS 2017)

Traffic Flow Prediction Based on Combined Model of ARIMA and RBF Neural Network

Wang Yuqiong*
School of Traffic and Transportation, Beijing Jiaotong University, Beijing100044,China
15120890@bjtu.edu.cn

Abstract: In this paper, a combined model of ARIMA and RBF neural network is proposed by combined the good linear fit ability of ARIMA and the strong dynamic nonlinear mapping ability of RBF neural network. The velocity of microwave is predicted in real time with the consideration of the temporal characteristics of traffic flow by the models.The results indicate that the Mean Absolute Percentage Error of combined model is lower, and the goodness of fit of combined model is higher.

Keywords: traffic engineering, traffic flow prediction, Combined Model, ARIMA model, RBF neural network model

1.Introduction

In order to solve the traffic problems such as traffic congestion and traffic accidents, Intelligent Transportation System (ITS) has been developed and applied to practice. The core research on ITS is traffic control and guidance, and short-term traffic flow prediction is the data foundation and decision support of traffic control and guidance system.

In recent years, domestic and overseas experts and scholars have proposed a variety of combinatorial models or improved models. Xiaomo Jiang et al. [1] proposed a neural network combined with wavelet analysis for traffic flow prediction; Yanru Zhang et al. [2] used a modified gradient boosting regression tree to predict travel time; Yisheng Lv et al. [3] used a deep learning model for traffic flow prediction, which combines BP neural network and stack automatic encoders; Wu Wei [4] proposed a PSO-PLS (particle swarm optimization-partial least squares regression) combination forecasting method. Sun Liguang et al. [5] proposed a double-layer update mechanism which used a recursive regression method to update the sub-model coefficients and weighting coefficient; Zhang Jinglei et al. [6] used a three-tier structure of the RBF neural network for non-linear combination of RBF and ARIMA; Chen Gang [7] used BP neural network to amend error of the gray prediction model. Qian Wei et al [8] combined BP neural network model and GM (1,1) model with a variable weight coefficients form.

In many prediction models, ARIMA model can reflect the trend of traffic flow time series, and it is easy to apply to traffic flow forecasting, while RBF neural network model has strong dynamic non-linear mapping ability, and it has high satisfaction and accuracy to stochastic sample. Based on the good linear fitting ability of ARIMA model and the powerful dynamic nonlinear mapping ability of RBF neural network model, this paper builds models and uses the speed-based traffic flow state identification

Copyright © 2017, the Authors. Published by Atlantis Press.
This is an open access article under the CC BY-NC license (http://creativecommons.org/licenses/by-nc/4.0/).

method to test the forecast results and evaluate the effect of the model.

2.Combined Model of ARIMA and RBF Neural Network

2.1ARIMA model

ARIMA [9] method, also known as B-J method, is a time series prediction method. The ARIMA method is the result of an effective combination and collocation of the Autoregressive model (AR) and the Moving Average model (MA), called the Autoregressive Moving Average model.

The ARIMA (*p, q*) model is a combination of AR (*p*) and MA (*q*), which is a model established by taking the combined effects of previous states and predictive errors into account. The formula of ARIMA (*p, q*) is

$$y_t - \varphi_1 y_{t-1} - \varphi_2 y_{t-2} - \cdots - \varphi_p y_{t-p} = e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \cdots - \theta_p e_{t-p} \quad (1)$$

In practical applications, it should be noted that the selected sample data should be time-stable data. If not, select the appropriate *d*-order for differential processing, then the model is ARIMA (*p, d, q*) model.

2.2RBF neural network

RBF neural network learning algorithm is generally divided into two categories: (1) The number of hidden layer neurons is growing gradually, under the training objectives to achieve the adjustment of weights and thresholds;(2) The number of neurons in the hidden layer is determined (the same as the number of training samples), and the threshold value of the hidden layer is also determined. The weights and thresholds of the output layer are solved by the linear equations. As the second algorithm iterates faster with the higher the accuracy, so this paper uses the second algorithm. The specific learning algorithm steps are:

（1）Determine the center of the radial basis function of the hidden layer neurons.

The input matrix of train set samples is ***P*** (*M* × *Q* matrix), the output matrix is ***T*** (*N* × *Q* matrix), and the radial basis function center ***C*** corresponding to *Q* implicit neurons is

$$C = P' \quad (2)$$

Where *Q* is the number of train set samples, *M* is the input variable dimension, and *N* is the output variable dimension.

（2）Determine the hidden layer neuron thresholds.

The number of neurons in the hidden layer is the same as that of the train set, and the threshold column matrix $\boldsymbol{b_1}$ corresponding to the neurons of *Q* hidden layer is determined by

$$\begin{cases} b_1 = \left[b_{11}, \quad b_{12}, \quad \cdots, \quad b_{1Q} \right]' \\ b_{11} = b_{12} = \cdots = b_{1Q} = \dfrac{0.8326}{spread} \end{cases} \quad (3)$$

Where *spread* is the radial basis function expansion speed.

(3) Determine the weights and thresholds between hidden layer and the output layer.

When the center of radial basis function and threshold of the neuron of the hidden layer are determined, the output $\boldsymbol{a_i}$ of the hidden layer neuron is

$$\begin{cases} a_i = \exp(-\|C - p_i\|^2 b_1) \\ p_i = [p_{i1}, \quad p_{i2}, \quad \cdots, \quad p_{iM}]' \end{cases} \tag{4}$$

Assuming that the connection weight matrix of the hidden layer and the output layer is $\boldsymbol{W}$ ($N \times Q$ matrix), the threshold is b_2, and the implied neuron output matrix is $\boldsymbol{A}$, then the linear transformation of the output layer is

$$\begin{cases} [W \quad b_2] \bullet [A; \quad I] = T \\ I = [1, \quad 1, \cdots \quad 1]_{1\times Q} \\ A = [a_1, \quad a_2, \quad \cdots, \quad a_Q] \\ b_2 = [b_{21}, \quad b_{22}, \quad \cdots, \quad b_{2N}]' \end{cases} \tag{5}$$

2.3Combined model

In this paper, we use a nested combination. A time series of data y_t is regarded as a linear autocorrelation structure L_t and non-linear structure N_t. The ARIMA model is used to predict the traffic flow data. The predicted results are denoted by L'_t and the predicted residual errors sequence $\{e_t\}$ is obtained. Using the RBF neural network to predict $\{\boldsymbol{e_t}\}$, the predicted results are denoted by N'_t, and the training set and test set of the data are derived from the $\{\boldsymbol{e_t}\}$ predicted by the first ARIMA model. The formula is expressed as follows

$$\begin{cases} y_t = L_t + N_t \\ e_t = y_t - L'_t \\ \hat{y}_t = L'_t + N'_t \end{cases} \tag{6}$$

3.Performance evaluation method

In this study, Mean Absolute Percentage Error (MAPE) and Determination Coefficient (R^2) are used to evaluate the accuracy of the prediction results and model fits. The smaller Mean Absolute Percentage Error is, the better prediction effect of the corresponding model is. The range of Determination Coefficient is from 0 to 1,the bigger it is, the better the performance of the corresponding model is. However, formulas as follows

$$MAPE = \frac{\sum_{i=1}^{n} \frac{\left|\hat{y}_i - y_i\right|}{y_i}}{n} \tag{7}$$

$$R^2 = \frac{\sum_{i=1}^{n} (\hat{y}_i - \bar{y})}{\sum_{i=1}^{n} (y_i - \bar{y})} \tag{8}$$

Where $\hat{y}_i$ is the ith predicted value, y_i is the ith measured value, $\bar{y}$ is the average of the measured values, and n is the number of predicted samples.

4.Application and Analysis

The sample is taken from April 15, 2013 to April 19 ,2013(Monday to Friday), April 22 to April 24 (Monday to Wednesday) for a total of eight days of early peak (7: 30-9: 30), that is 480 speed value. The range of parameters are: p = 0 to 4, d = 0 to 2, q = 0 to 4. Because the data is non-stationary data, we need to proceed the second-order difference. After mathematical test, we can get q = 1, p = 3, d = 2 while model fits is best. The model is used to predict 60 speed value of the early peak on April 25 (Thursday) with the established ARIMA (3,2,1) model, as shown in Figure 1.

There is a total of six days' early peak (7: 30-9: 30) 360 speed value as a training set which from April 15 - 19 (Monday to Friday) and 22 (Monday), and two days' early peak of 120 speed data from April 23 -24 Day (Tuesday to Wednesday) as a test set to predict the April 25 (Thursday) morning peak speed. RBF neural network has five inputs and one output, with five consecutive times to predict the next moment of speed. We model the neural network with MATLAB software, selecting the Radial basis for the network type, 0.001 for the training target, and 1.0 for the growth speed of radial basis function. The prediction is shown in Fig 2.

Firstly, we use the ARIMA model to predict and get residual data $\{\boldsymbol{e_t}\}$, and then use$\{\boldsymbol{e_t}\}$ as the RBF training set and test set. The parameters of the two sub-models are the same as the previous work. The results of the prediction is shown in Figure 3.

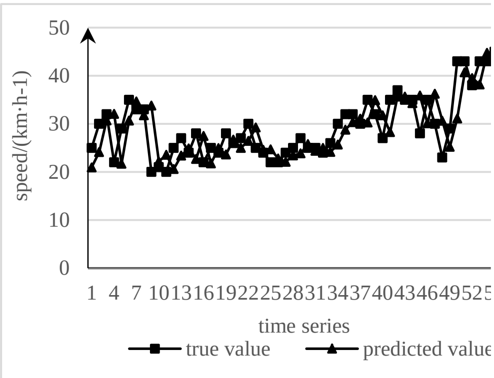

Fig.1 Prediction results of vehicle speed based on ARIMA model

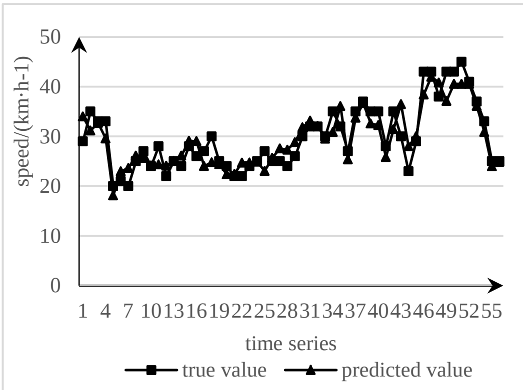

Fig.2. Prediction results of vehicle speed based on RBF neural network

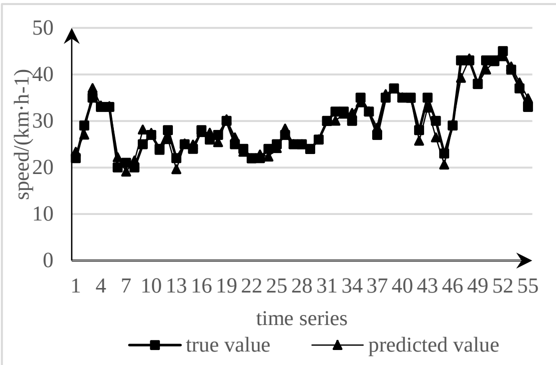

Fig.3 Prediction results of vehicle speed based on Combined model

When using the combined model to predict, the ARIMA model is used to describe the linear structure of velocity and RBF neural network is used to fit the nonlinear structure, which effectively reduces the prediction error. The evaluation index is shown in Table 1.

Tab.1 Evaluation index of models

model	ARIMA	RBF	Combined
MAPE	12.9%	7.7%	4.0%
R^2	0.96	0.87	0.98

5. Conclusions

Based on the practical application, this paper presents a combinatorial model for short-term traffic flow velocity prediction, and it includes two sub-models of autoregressive moving average model (ARIMA) and radial basis function neural network (RBF). The article introduces the principle of sub-models, combination principle and selection principle of data. By using this model to predict the microwave velocity data of the early peak of Beijing expressway, it can be concluded that the ARIMA model is combined with the RBF neural network to eliminate the defects of the single model and has the advantages of the fusion sub-model. The Mean Absolute Percentage Error the predicted result is reduced.

6.References

[1] Xiaomo Jiang and Hojjat Adeli,Hon. M.ASCE, “Dynamic Wavelet Neural Network Model for Traffic Flow Forecasting”, Journal of Transportation Engineering,2005, vol.131, no.10,pp: 771-779

[2] Yanru Zhang, Ali Haghani, “A gradient boosting method to improve travel time prediction”, Transportation Research Part C 58 ,2015,pp: 308–324

[3] Yisheng Lv, Yanjie Duan, Wenwen Kang, et al, “Traffic Flow Prediction With Big Data:A Deep Learning Approach”, IEEE Transactions On Intelligent Transportation Systems, Apr 2015, vol. 16, no. 2,pp:865-872

[4] WU Wei. “Study on PSO-PLS Combined Forecasting model for Short-term Traffic Flow Forecasting”. Chongqing:Chongqing University,2009

[5] SUN Liguang,LI Ruimin,DONG Shan, et al “Research on Short -Term Traffic Flow Prediction Model”, Jounal of Wuhan University of Technology(Transportation Science＆Engineering),2010, vol.34,no.5,pp:874-876

[6] ZHANG Jing-lei, WANG Xiao-yuan, “Traffic Flow Prediction Method Based on Non-linear Hybrid Mode”. Computer Engineering，2010, vol.36,no.5,pp:202-204

[7] Chen Gang. “PREDICTION OF TRAFFIC FLOW BASED ON GREY THEORY AND BP NEURAL NETWORKS”, Harbin：Harbin Institute of Technology,2006

[8] QIAN Wei，YANG Kuang li，YANG Huihui，et al. “Short -Term Traffic Flow Prediction Based on Combined Models”, Computer Simulation,2015, vol.32,no.02,pp:175-178

[9] ZHANG Li. “Study of the Time Series Forecasting Algorithm and System Realization Based on the ARIMA Model”, Zhenjiang:Jiangsu University,2008