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Modeling Average Daily Traffic Volume using Neural Network-Wavelet Hybrid Method

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Abstract

Forecasting traffic volume accurately and in a timely manner plays an important role to providing real-time traffic information, reducing congestion in pathways, and improving traffic safety. A combination of multi-layer back-propagation neural networks (BPNN) and wavelet transform is used for forecasting average daily traffic volume. Real data used in modeling are taken from the Qom-Tehran road during 2006-2008. Given the proposed method (WBPNN), the traffic volume data were initially preprocessed using wavelet transform. The input signal (the daily traffic volume time series) is decomposed into low- and high-frequency components up to 5 levels using the mother wavelet function Haar, so that more complete information would be obtained regarding the problem dynamics. The processed data are then fed to the neural network as training and test data. The trained network is validated considering evaluation functions such as MAE, MAPE, and VAPE. The results indicate that the proposed method predicts daily traffic volume with great precision and puts forward a model using native parameters, in addition to increased prediction accuracy.

Keywords: *Neural network, prediction, wavelet transform, daily traffic volume, modeling.*

1. Introduction

Transportation planning calls for using accurate traffic data to evaluate traffic volume predictions at any given time and place. Constant increase in the traffic volume of rural and urban roads in the recent years has given rise to traffic congestions and jams at certain points of time in the pathways of many traffic systems. Fortunately, intelligent transportation systems (ITS) offer solutions for mitigating such problems. Predicting traffic volume accurately and in a timely manner is among these solutions and plays a vital role in effectively controlling traffic chaos with respect to ITS. In particular, such traffic flow forecasting supports 1. The development of proactive traffic control strategies in advanced traffic management systems (ATMSs), 2. real-time route guidance in advanced traveler information systems (ATISs) and 3. evaluation of these dynamic traffic control and guidance strategies as well [2].

The success of many ATIS and ATMS applications depends largely on the accuracy of the selected traffic flow modeling and forecasting algorithms. Numerous methods have been developed and compared since the 1970s to improve the accuracy of traffic flow forecasting. These methods can generally be categorized into the following groups: autoregressive integrated moving average (ARIMA) models, nonparametric regression, Kalman filtering theory, neural networks, support vector machines (SVMs), and hybrid models.

Of the existing traffic flow forecasting methods, Neural Networks are the most widely used ones. One major reason is that neural networks have a strong function approximation capability and can better model the complicated relationship between historical and future traffic flow data than other methods [3]. On the other traffic flow is a complicated process influenced by many dynamic factors, so it is found that using composite models to describe and forecast the effect of different factors on the traffic flow is appropriate [2].

In this paper, a hybrid method is used for predicting average daily traffic volume. This method is a combination of multi-layer back-propagation neural networks and wavelet transform. At first, real traffic volume data are processed via wavelet transform. Afterward, the processed data are used for training the designed neural network.
Finally, the modeling is validated by means of evaluation functions and the results are investigated. The present modeling is performed according to the native parameters of Iran and may be employed in practical applications.

2. Literature review

Traffic volume is among unstable time series. Predicting traffic volume is in the main complicated with indeterminate conditions along with weakness in database. No single predictor that is known by everyone as the best method has been developed so far.

Smith and Demetsky believed that much of the current activity in the area of intelligent vehicle-highway systems (IVHSs) focuses on one simple objective: to collect more data. Clearly, improvements in sensor technology and communication systems will allow transportation agencies to more closely monitor the condition of the surface transportation system. They suggested a new mathematical model, the back-propagation neural network (BPNN), offers an attractive alternative because neural networks can model undefined, complex nonlinear surfaces [4]. Yan et al. studied in forecasting traffic volume, the relationship between data characteristics and the forecasting accuracy of different models, particularly neural network models. To compare and teat the forecasting accuracy of the models, three different data sets of traffic volume were collected from interstate highways, intercity highways, and urban intersections. The data sets show very different characteristics in terms of volatility, period, and fluctuations M measured by the Hurst exponent, the correlation dimension. The datasets were tested using a back-propagation neural network model, a FIR model, and a time-delayed recurrent model. The test results show that the time delayed recurrent model outperforms other models in forecasting very randomly moving data described by a low Hurst exponent. In contrast, the FIR model shows better forecasting accuracy than the time-delayed recurrent network for relatively regular periodic data described by a high Hurst exponent [5]. A radial basis function (RBF) neural network was applied to short-term freeway traffic volumes forecasting. The results indicated. The model offered an appropriate function and it was determined that they need shorter time for calculations [6]. In 2007 a combination approach based on Principal Component Analysis (PCA) and Combined Neural Network (CNN) was presented for short-term traffic flow forecasting. The historical data of the forecasted traffic volume and interrelated volumes have been processed by PCA. The results of PCA form the input data for CNN. It not only reduces the dimension of input variables and the size of CNN, but also reserves the main information of the original variables and eliminates relativity among them. The forecast results show that this approach is better than the typical Error Back-Propagation neural network (BPNN) with the same data [7].

Wavelet networks (WNs) are recently developed neural network models. WN models combine the strengths of discrete wavelet transform and neural network processing to achieve strong nonlinear approximation ability, and thus have been successfully applied to forecasting and function approximations. Xie and Zhang used two WN models based on different mother wavelets for the first time for short-term traffic volume forecasting. The Levenberg-Marquardt algorithm is used to train the WN models because it has better efficiency than the other algorithms based on gradient descent. The WN models are compared with the widely used back-propagation neural network (BPNN) and radial basis function neural network (RBFNN) models. The performance evaluation is based on mean absolute percentage error (MAPE) and variance of absolute percentage error (VAPE). The test and comparison results show that the WN models consistently produce lower average MAPE and VAPE values than the BPNN and RBFNN models [8]. Lin et al. presented a forecasting method called k nearest neighbor based local linear wavelet neural network (KNN-LLWNN) for the on-line, short-term prediction of five-minute traffic volumes at westbound of Interstate 64 in Hampton Road in Virginia. The method is based on combining k nearest neighbor (k-NN), with local linear wavelet neural network (LLWNN). The idea is to apply k-NN method to form the training dataset for LLWNN instead of taking the whole historical dataset for training. For the test dataset, the study's findings appear to confirm the hypothesis that, KNN-LLWNN performs comparable with LLWNN and SVR, and its running time is much lower than LLWNN and SVR because of the introduction of k-NN [14]. In 2013 was introduced a new approach to short-term daily traffic flow prediction based on artificial neural networks. Among the family of neural networks, multi-layer perceptron (MLP), radial basis function (RBF) neural network and wavelets have been selected as the three best candidates for performing traffic flow prediction. Moreover, back-propagation (BP) has been adapted as the most efficient learning scheme in all the cases. It is shown that the coefficients produced by temporal signals improve the performance of the BP learning (BPL) algorithm. Temporal signals provide researchers with a new model of temporal difference BP learning algorithm (TDBPL). The capability and performance of TDBPL algorithm are examined by means of simulation in order to prove that the wavelet theory, with its multi-resolution ability in comparison to RBF neural networks, is a suitable algorithm in traffic flow forecasting [10].

Mao and Shi conducted a research on advancing BP neural network's precision in prediction of traffic flow. The method of prediction of traffic volume was based on the subsection learning of double-layers BP neural network. Using subsection-learning method, the average relative tolerance was decreased by 2.52%. The method need less data, has fast processing speed and high precision, and it can provide availability and exact data for the traffic guidance system [15]. In a study that was Performed by Kang and et al., Standard Neural Networks BPNN that was problems in their training, improved and was used in model of predict the traffic volume. Improved BP neural network avoids the adverse conditions appear in the training of the network effectively, meanwhile, shorten the study times, enable the networks reach the prediction accuracy fast and improve the training speed [16].

In another Research the method of combining multiple linear regression with back propagation (BP) neural network was proposed, using BP neural network to compensate the model error of multiple linear regression. The combination model and the corresponding algorithm program was made, and used to predict the short-term traffic flow. Two different methods of selecting the input layer parameters were used and compared, while the new method has higher accuracy and stability [9]. Duddu and Pulugurtha focused on the application of the principle of demographic gravitation to estimate link-level annual average daily traffic (AADT) based on land-use characteristics. According to the principle, the effect of a variable on AADT of a link decreases with an increase in distance from the link. The spatial variations in land-use characteristics were captured and integrated for each study link using the principle of demographic gravitation. Negative binomial count statistical models (with log-link) were developed as data were observed to be over-dispersed while neural network models were developed based on a multilayered, feed-forward, back-propagation (BP) design for supervised learning. The results obtained indicate that the neural network model yielded better results in estimating AADT than any other approach considered in this research [11].

In present investigation, a combination of multi-layer back-propagation neural networks (BPNN) and wavelet transform is used for predicting average daily traffic volume. In this method (WBPNN), traffic volume data are initially preprocessed using wavelet transform. The input signal is decomposed into low- and high-frequency components, so that more complete information would be obtained about the problem dynamics. These data are then mapped from the V-T to V-V environment, in view of influential factors. This mapping is based on time delays of the traffic data fed to the model. The resulting data are used for training the neural network. The trained networks are validated using evaluation functions such as MAE, MAPE, and VAPE and the results are examined.

3. Research method

3.1 Neural Networks

Artificial neural networks are information processing patterns modeled after biological neural networks such as the human brain. The key element of this pattern is its new information processing structure consisting of a great number of elements (neurons) with internally coordinated connections. Artificial neural networks transfer the knowledge or the law hidden within data to the network structure by processing empirical data. This is called training. Thanks to their considerable ability in inferring results from complex data, neural networks may be employed for extracting patterns and different features the detection of which is highly difficult for human and computer.

On the other hand, traffic volume is among unstable time series. Predicting traffic volume is in the main complicated with indeterminate conditions along with weakness in database. Hence, neural networks may be used for predicting traffic volume and detecting existing information in traffic data. Upon practically using artificial neural networks, almost 90% of artificial neural network models use the BPNN model or its modified forms. The BPNN is widely used for performance estimation, pattern recognition, information compression, etc.

3. 1. 1. BPNN Neural Networks

The BP neural network is to put Error Back Propagation algorithm of multilayer feed-forward network which have nonlinear continuum transfer functions into application of neural network, than training by this algorithm. BP algorithm characteristic is the signal forward calculation and error back propagation, the signal flow characteristics as shown in Fig. 1.

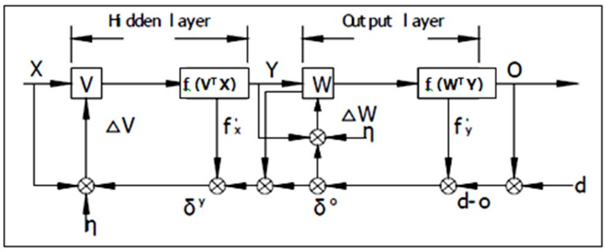

Fig. 1 Signal flow of BP algorithm

Signal transduction forward process: input signals X from the output layer after entering, through the processing of each node weight vector V_j in hidden layer, than get this layer output signal Y. This signal forwards to the input layer, through each node weight vector W_k in input layer and gets output signals O of this layer.

Reverse process: comparing the expected output d in output layer and actual output O, and get the error signal δ^0, than calculates the output layer weights adjustment quantity. Error signal δ^0, through each node of hidden layer reverse get the Error signal δ^y in hidden layer, which can calculate hidden layer weights adjustment quantity. These signal errors are the basis for modifying each unit weights. This adjustment process for weights of each layer by signal positive dissemination and back-propagation is round and round. Weights constantly adjust process, is also the training of network learning process [16].

3.2 Wavelet transform

The main idea behind the one-dimensional wavelet transform of a signal is that it is broken up into two parts: high-frequency and low-frequency parts. The elements of a signal edge are mainly to be found in high-frequency parts. In the next stage, the low-pass part is again divided into two low-frequency and high-frequency parts. This may repeat as many times as needed depending on application [12].
The purpose of wavelet transform (which is a linear transform) is to transfer the signal from time domain to the joint time-frequency domain. The continuous wavelet transform is as Eq. (1) below:

$$W_f(a.b) = \int_{-\infty}^{+\infty} f(t)\,.\frac{1}{\sqrt{a}}\,\Psi^*\left(\frac{t-b}{a}\right) dt \qquad (1)$$

Where $\Psi(t)$ is the mother wavelet and a and b are continuous values. Wavelet transform may be interpreted in this way that the transform value equals the degree to which the function $f(t)$ resembles the function $\frac{1}{\sqrt{a}}.\Psi\left(\frac{t-b}{a}\right)$, because wavelet transform is indeed obtained from the dot product of the $f(t)$ signal and the $\frac{1}{\sqrt{a}}.\Psi\left(\frac{t-b}{a}\right)$ base vector. This represents the projection of $f(t)$ along this base vector. It is obvious that the greater the value of the product, the greater the similarity between these two. Moreover, among the most important features of wavelet transform is that the mother wavelet may be selected from among a large set of functions [13].

3.3 Time series

With regard to time series, what we deal with is a function of time. A time series is a set of statistical observations sorted in terms of time. For instance, the daily traffic volume data are presented here in terms of time. In Fig. 2 we have the annual variation trend of daily traffic volume.

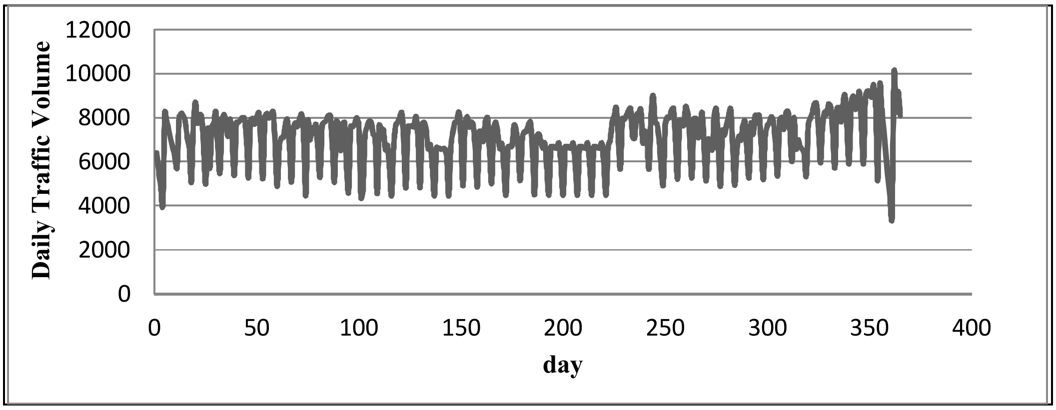

Fig. 2 The annual variation trend of daily traffic volume

Having traffic volumes at specified time intervals, the future traffic volume may be predicted. In this respect, neural networks are used as tools for estimating these data.

3.4 proposed method

A combination of the multi-layer back-propagation neural networks (BPNN) method and wavelet transform is used for predicting average daily traffic volume. In this method (WBPNN), traffic volume data are initially preprocessed using wavelet transform. The input signal is decomposed into low- and high-frequency components, so that more complete information would be obtained about the problem dynamics. Therefore, the input signal is decomposed up to 5 levels using the mother wavelet function Haar and it is then fed to the network as training and experimentation data. Fig. 3 shows the changes made to the main signal after analysis.

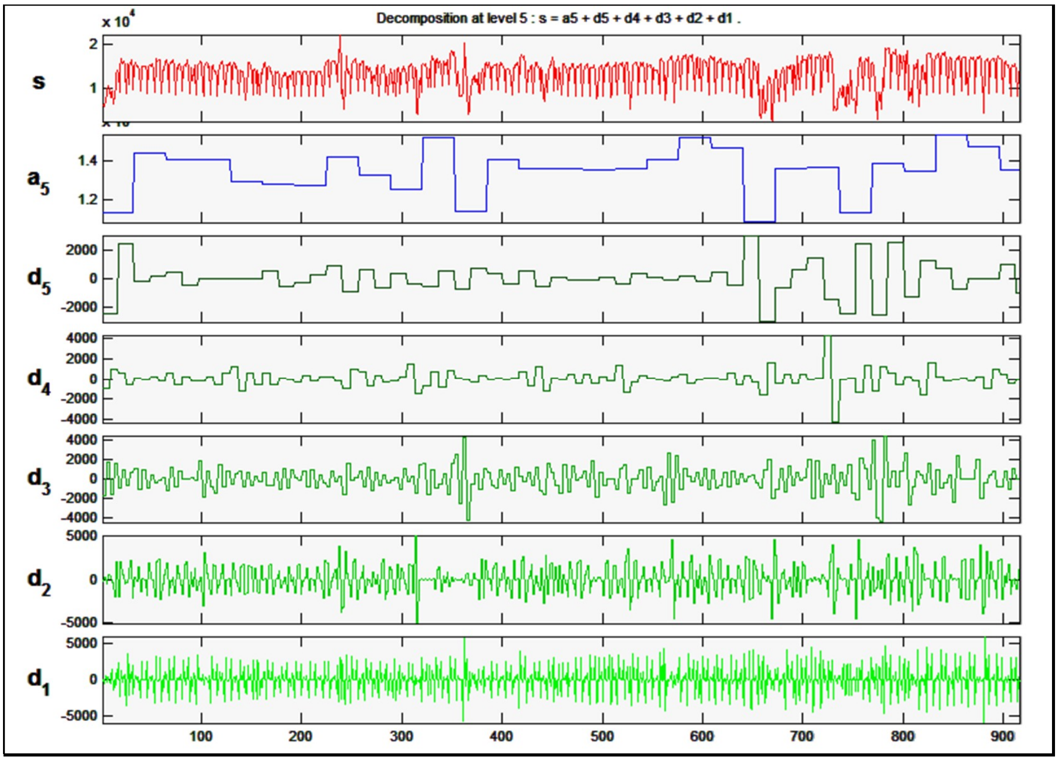

Fig. 3 Analyzing the daily traffic volume frequency using the mother wavelet function Haar

As can be seen in Fig. 3, the S signal is decomposed into its constituent components. Thus, according to Eq. (2), we have:

$$S = a_5 + d_5 + d_4 + d_3 + d_2 + d_1 \qquad (2)$$

Therefore, instead of the S signal, its components are fed to the neural network. In this event, the neural network will have an increased ability in extracting the features existing in traffic data and the network will be able to allow for the dynamics of traffic volume data in modeling.

Generally, in order to be able to predict a time series using neural networks (e.g. the daily traffic volume time series), the necessary time delays should be firstly applied to the data according to the influential factors. Hence, through a change of variables in the traffic volume data, they are mapped to a new domain.

Traffic volume data have a weekly trend. Traffic volume is high in the beginning days of the week and at the end of each week, traffic volume decreases. On the other hand, each weekday is similar to its corresponding weekday in the previous week. Another type of such connection is the dependency of the current day's traffic volume on that of the previous days. In any event, the current day's traffic is related to that of the previous days and the factors causing fluctuations in the previous days' traffic volumes affect current day's traffic. Now, in view of Eq. (3), we have:

$$V\,(t) = f\,(\sum_{i=1} V(t-i))\ , \qquad i = 1-7, 14, 21, 28, 91 \quad (3)$$

In the above relation, t indicates time, which is equal to a day, $V\,(t)$ represents daily traffic volume on the t-th day, and f is a function describing traffic volumes on different days. This relation shows that the current day's traffic volume depends on the traffic volume of the present week, the corresponding day of the previous week, two weeks ago, three weeks ago, four weeks ago, and finally three months ago. Therefore, the mapping of data starts from the beginning of the data and according to the existing returns. If substitution starts from the beginning of the data, a negative index is created. For instance, in Eq. (4), we have:

$$if\ t = 1 \ => V(t-7) = V(-6) \qquad (4)$$

Hence, substitution cannot start from the beginning of the data, moving onward so that the farthest return would be compensated. The farthest return in here is 91. Thus, we should start from 92. So, there will be a loss of data as many as Max returns from the beginning of the data.

Now, the problem is mapped from the T-V to the V-V domain with the change of variables. The delays applied to the network input data are based on an effective connection with the predicted variable. The extent which the selection of these inputs has been strong, accurate, and effective will be finally known once the results are clear. The processed data are divided into training and experimentation data ([11] and [15]). The model is trained using 80% of the data and it is then validated using 20% of the data. Once input data are ready, the respective neural network is prepared for training. The present network is a three-layer network with hyperbolic tangent activation functions and linear transfer function, having 5 neurons in the input layer and 7 neurons in the hidden layer. The output layer also has 1 neuron, according to the predicted value being the daily traffic volume.

There are two groups of fast algorithms for training neural networks. The first group is the heuristic methods and the second group is the numerical optimization methods [1]. Levenberg-Marquardt algorithm (Train lm), one of the numerical optimization methods, is selected and used for training the designed network. Then, the networks trained via the experimentation data are validated using evaluation functions such as mean absolute error (MAE), mean absolute percentage error (MAPE), and variance of absolute percentage error (VAPE). The formula of each of the evaluation functions may be found in Eq. (5), (6) and (7) respectively.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|\hat{y}(i) - y(i)| \quad (5)$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{\hat{y}(i) - y(i)}{y(i)}\right| \times 100\% \quad (6)$$

$$VAPE = Var\left(\sum_{i=1}^{N}\left|\frac{\hat{y}(i) - y(i)}{y(i)}\right|\right) \times 100\% \quad (7)$$

4. Field studies

4.1 Acquiring information

Among the information used for neural network training and predicting average daily traffic volume is the real data of daily traffic volume obtained from the traffic counter on the respective road. These data pertain to the older Qom-Tehran road during 2006-2008 and were taken from the website of the Road Maintenance and Transportation Organization in Iran.

4.2 Categorizing and sorting information

The acquired data are organized in a database in Excel and sorted in terms of time of occurrence. For generating unavailable data, the average of the temporal equivalent of the same data in previous and subsequent years is used. In this case, the data pertaining to the beginning and end of the previous and subsequent month are used, if necessary. For example, in case the data of May 2008 are unavailable, the traffic volume data pertaining to the same month in 2007 and 2009 are used, with weekday priorities. Now, if May 2008 starts on a Tuesday, whereas this month does not start on the same day in the previous and subsequent years, the data are averaged according to the Tuesday closer to the beginning of May in the previous and subsequent years. This Tuesday may be May 2 in the previous year or April 30 in the subsequent year. This causes the sequence of traffic volumes on weekdays and months to be retained and the obtained data to be more similar to real values.

5. Analysis and modeling

5.1 Performing modeling and presenting solutions

In this section of the research, the daily traffic volume data are modeled according to the method presented in the previous section. The model is then calibrated and validated by means of different evaluation functions. Further, the results are presented in various figures and tables. Table 1 is about the prediction error of the proposed method (WBPNN) for the experimental data and the validation of the trained model.

Table 1: Results of the prediction error of the proposed method (WBPNN) for the experimental data

Model / Error	*The Propesed Model WBPNN for 10 Outputs*									
	1	2	3	4	5	6	7	8	9	10
MAE	0.01802	0.01348	0.01061	0.01088	0.00998	0.00998	0.01074	0.00841	0.00692	0.01204
MAPE (%)	6.6476	5.0765	4.5142	4.9643	4.4633	4.223	4.5112	4.3666	3.6922	4.9687
VAPE (%)	0.7554	0.4881	0.6262	1.0189	0.8787	0.8656	0.4312	0.9666	0.6894	0.8689
R test	0.99968	0.99867	0.999	0.99897	0.99945	0.99914	0.99899	0.99986	0.9998	0.99833

Fig. 4 and 5 demonstrate the prediction errors of the data experimented by the WPBNN model.

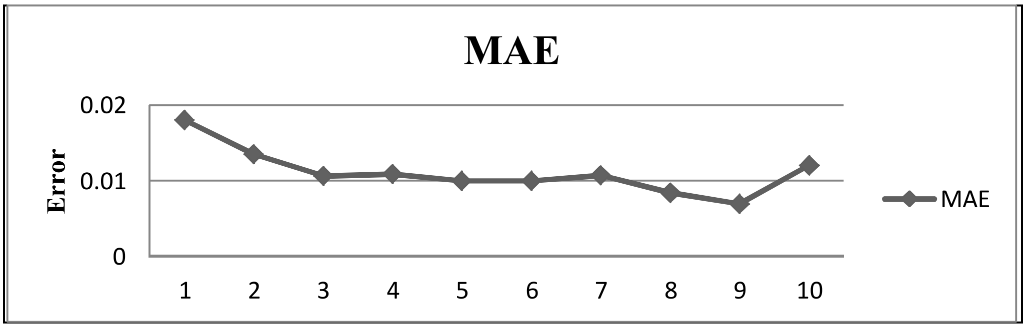

Fig. 4 Prediction error of the experimental data using MAE evaluation function in 10output

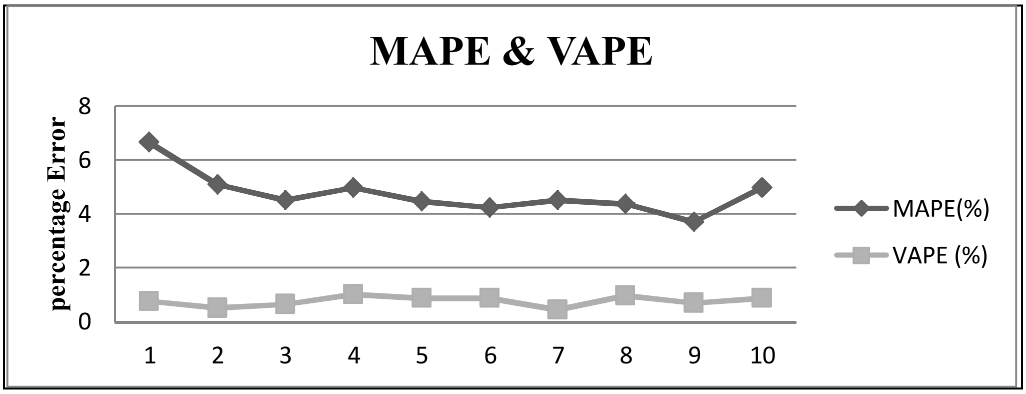

Fig. 5 Prediction error of the experimental data using MAPE and VAPE evaluation functions in 10 output

Fig. 6 and 7 show the diagrams of real values and values predicted by the proposed method together with regression coefficient and the diagram of the conformity of the model output with real traffic flow data.

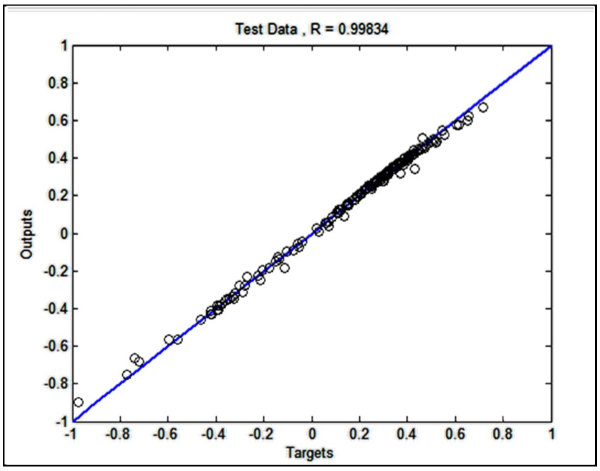

Fig. 6 Real values and those predicted by the proposed method for experimental data

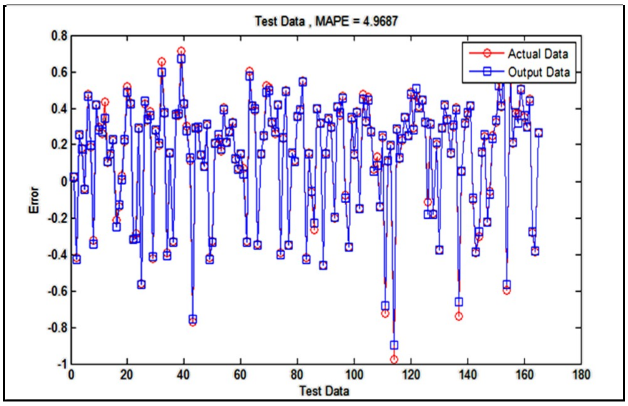

Fig. 7 Diagram of the conformity of model output with real traffic flow data

5.2 Discussion

The performance of the proposed method (WBPNN) for predicting daily traffic volumes was presented in various tables and diagrams. The present model has a mean absolute error (MAE) of 0.01110, mean absolute percentage error (MAPE) of 4.7427, and variance of

absolute percentage error (VAPE) of 0.7589. The regression coefficient is also equal to 0.99918 on average.
In the research conducted in [8], the MAPE value for the experimental data is 8.3 in the best case and the VAPE value is 0.7. In [14], the best-case value for MAPE is reported to be 10.51. Therefore, it is clear that the proposed method predicts daily volumes of traffic flow more accurately and presents a model using native parameters, in addition to increased accuracy in prediction. The value presented for the variance of absolute percentage error is an average of 10 successive favorable takes. This value has more fluctuations compared with the values offered in [8]. Among the reasons behind this fact is the number of annual holidays. As we know, one of the factors affecting traffic flow including traffic volume is holidays. Since the number of holidays in Iran is far more than that in other countries and these days are scattered all through the year, the traffic volume fluctuates more. For instance, the daily traffic volume for the respective route in the present research is less on holidays compared with non-holidays and ordinary traffic flow. On the other hand, the holidays of the lunar calendar move as much as 10 days compared with the previous year, because the lunar calendar year is shorter than the solar calendar year. Thus, the time these holidays occur varies annually. This itself accounts for the fluctuations of the variance of absolute percentage error in the modeling.

6. Conclusion

Forecasting traffic volume accurately is vital for properly designing the geometrical parameters of roads and traffic control devices, so that the designs would meet the demands of present and future traffic in a logical period of time. As traffic flow itself is a complicated process influenced by many dynamic factors, it is found that using composite models to describe and forecast the effect of different factors on the traffic flow is appropriate [2]. Therefore, a hybrid method consisting of back-propagation neural networks and wavelet transform for predicting daily traffic volume. In the proposed method (WBPNN), the traffic volume data are initially preprocessed via wavelet transform. The neural network is then trained using these data and it is evaluated. The results indicate that the proposed method (WBPNN) has an MAE value of 0.01110, MAPE value of 4.7427, and VAPE value of 0.7589. The regression coefficient is also equal to 0.99918 on average. In [8] and [14], 8.3 and 10.51 are respectively presented as the values for the evaluation function MAPE. Hence, the proposed method (WBPNN) predicts the daily traffic volume more accurately and puts forward a model with native parameters, in addition to increased accuracy in prediction. The present method may be employed with favorable reliability for practical applications in Iran.

7. Offering propositions

1. Using other hybrid methods for prediction
2. Conducting research on different types of data sets, such as highway, freeway, road, and urban data sets
3. Examining and modeling hourly traffic volumes and shorter
4. Evaluating different prediction methods of traffic flow parameters

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