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Research Article

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Traffic Flow Forecast Based on Empirical Mode Decomposition and BP Neural Network

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Abstract In order to improve the prediction performance of traffic flow prediction and reduce the impact of noise contained in the original traffic data on the accuracy of prediction, this paper uses a hybrid model of empirical mode decomposition and BP neural network (EMD-BPNN) to predict traffic flow. The original traffic flow data is processed through empirical mode decomposition (EMD). This method can make the data smoother and reduce the noise in the original signal. Then, this thesis uses the bp neural network model (BPNN) to predict traffic flow, which can show the uncertainty and periodicity of traffic flow. In the last step, we compare the prediction results of the EMD-BPNN combined model with the prediction results of the BPNN model without denoising and the support vector machine model (SVM). The final result shows that the EMD-BPNN model can obtain superior prediction results.

Keywords Traffic flow prediction, BP neural network, Empirical mode decomposition, Data denoising

1. Introduction

Traffic flow prediction is an important part of Intelligent Transportation System (ITS). Accurate traffic flow prediction can improve the efficiency of intelligent transportation system in optimizing road capacity. Therefore, a large number of researchers have proposed different traffic flow forecasting methods. At present, traffic flow forecasting methods are mainly divided into two categories. One is traditional mathematical statistical methods, including ARIMA methods [1]. This type of method requires a large amount of historical data and lacks data. The impact on the prediction results is relatively large, so the versatility is relatively low. The other is non-traditional methods, mainly including support vector machine model prediction (SVM) [2], artificial neural network model prediction [3], etc. This type of method uses historical data as input, and then obtains the corresponding relationship between input data and output data, which only requires a large amount of the training can get an excellent predictive model, which is suitable for traffic flow data with non-linear characteristics. BP neural network (BPNN) is a kind of artificial neural network. In 1994, BL. Smith et al [4] used the BP neural network model to predict short-term traffic flow and obtained excellent prediction results. Guo et al [5] used the BP neural network model to predict the traffic flow at the intersection, and proved that the BP neural network model can be applied to different types of road sections. In recent years, Zhang et al [6] used the BP neural network model to predict urban traffic flow in Beijing, indicating that the BP neural network can now also obtain superior results when predicting urban roads with large traffic flows. Because of the excellent performance of the BP neural network model in the field of traffic flow prediction, we have reason to believe that using this model to predict the data in this paper can get accurate prediction results.

On the other hand, due to unexpected circumstances such as special weather, holidays, gatherings, traffic accidents, and the randomness and complexity of the traffic flow itself, the traffic flow data obtained by the detector will be polluted by noise, which will affect the traffic flow. The periodicity and regularity of the data, and the traffic flow data containing noise will affect the results of the traffic flow prediction. Therefore, in order to improve the accuracy of prediction, it is important to denoise the data. In the field of denoising traffic flow data, there have been many studies to eliminate anomalies in the original data. In the prediction model based on phase space reconstruction proposed by Peng et al [7] in the traffic flow prediction, the original traffic flow data was processed by wavelet denoising, and the results showed that the predicted results of the denoised data were significantly better than the original data. The disadvantage of wavelet denoising is that different parameters will affect the denoising results. In order to further improve the denoising effect, Huang et al [8] proposed an empirical mode decomposition method, which can decompose the original data into multiple components according to different frequencies. Then remove the noise by removing high frequency components. This denoising method has been applied to data denoising in different fields until today. In the field of traffic flow prediction, Chen et al [9] decomposed the original data into multiple intrinsic modal functions through the method of empirical mode decomposition, and then imported them as input into the recursive Hermite neural network model. The results show that this method improves the prediction performance. X. Chen et al. used four different types of wavelet denoising methods and empirical mode decomposition methods to denoise the original traffic flow data, and then used the support vector machine model to predict the traffic flow. The results show that the EMD denoising effect is excellent Yu wavelet denoising. In summary, based on the excellent performance of the EMD method in the direction of data denoising, this paper chooses to use the empirical mode decomposition method for denoising.

The main purpose of this paper is to obtain accurate traffic flow prediction results through data denoising and neural network model. The academic contributions of this thesis mainly include the following aspects:

(1) Remove high-frequency components through empirical mode decomposition, and denoise the original traffic flow data.

(2) Use an effective neural network model (BP neural network) to predict the denoised traffic flow data.

(3) We apply our proposed hybrid model to the traffic flow data collected by the detector to verify the prediction performance. The prediction performance is quantified by three statistical indicators (RMSE, MAE, MAPE).

(4) Compare the prediction results of the EMD-BPNN model with the prediction results of the BPNN model and the prediction results of the SVM model.

2. Methods

2.1. Empirical Mode Decomposition

Compared with other denoising methods, the EMD method only needs to analyze the data itself and does not need to adjust other parameters. The EMD decomposition will decompose the original signal according to the time scale characteristics of the original signal, and each component has the time scale characteristics of the original signal. It has advantages when dealing with non-linear signals.

In the past, when performing signal processing, Fourier transform was usually used to change the time-frequency signal, so as to study its characteristics in different frequency domains. When performing Fourier transform, each local processing will cause Changes in the global sequence, however, for many time series data, local signal fluctuations do not have the ability to affect the overall situation.

Therefore, when dealing with nonlinear and non-stationary signals, empirical mode decomposition is a suitable method. When using the empirical mode decomposition method to process data, he can decompose non-stationary and nonlinear data into a finite number of stationary sequences with characteristics. The basic idea of empirical mode decomposition is that the signal is composed of a limited number of intrinsic mode functions. According to the time scale characteristics of the data itself, the time series is gradually decomposed, and the eigenmode function (IMF) is extracted with different characteristic scales. Each IMF represents a characteristic vibration form of an inherent signal. The decomposed components should meet two basic conditions.

The number of extreme values and the number of zero-crossing points should be equal or differ by 1.

The average value of the upper envelope formed by the local maximum and the lower envelope formed by the local minimum should be zero.

For time series data, the steps of empirical mode decomposition are as follows

1. Find all the maximum and minimum points of the original data sequence s(t), and fit all the maximum

points with a cubic spline function. This curve is the upper envelope of the data. All the minimum points are also fitted with cubic spline function to fit the lower envelope data. M(t) is the average value of the upper and lower envelopes. The upper and lower envelopes are represented by u(t) and l(t) respectively.

$$h(t) = s(t) - m(t) \tag{1}$$

h(t) as the difference between the two

2. If h1(t) does not meet the above two basic requirements of the IMF, then you need to use h1(t) as the original data and repeat the above steps until hn(t) meets these two requirements. At this time, hn(t) that meets the requirements is IMF1(t).

3. Let the residual be

$$r(1)t = s(t) - IMF(t) \tag{2}$$

4. Repeat steps one to three steps with r(1)t as the new input sequence until the termination condition is met (usually the last residual satisfies monotonicity). Through the above steps, a series of IMF(i) (i =1, 2,..., N) is selected, and the original signal s(t) is reconstructed from these intrinsic modal functions, namely

$$s(t) = \sum_{i=1}^{n} IMF(t) + R(t) \tag{3}$$

Where R(t) is the residual after EMD decomposition

The above is the decomposition process of the target sequence s(t). The frequency of the IMF(k) component gradually decreases with the increase of k, that is to say, the first decomposed component is the high-frequency part of the sequence data, which contains noise Relatively high. The final remaining R(t) is the trend term used to reflect the trend of the original sequence.

2.2. BP neural network

Neural networks are different from traditional computing systems in that their learning ability can solve complex problems such as predicting traffic flow. The feedback neural network (BP) is a multi-layer feed forward neural network that transmits signals forward and errors backward. It has been widely used in traffic prediction. The short-term traffic flow prediction with BP neural network can be roughly divided into two stages: the training stage of the BP neural network and the short-term traffic flow prediction stage. The model framework of BP neural network is shown in the figure 1:

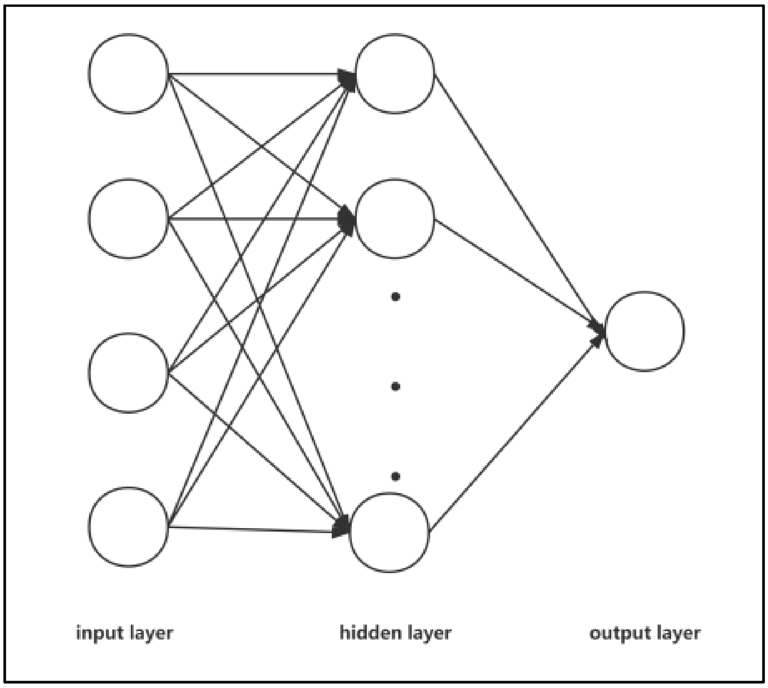

Figure 1: BP neural network model framework

Its steps can be summarized as follows:

(1) Preprocess historical traffic flow data.

(2) Establish a BP neural network and determine the number of nodes in the input layer of the neural network and the number of nodes in the output layer.

(3) Generate a sample database and divide the training set and test set Proportion.

(4) Determine the number of hidden layers of the BP neural network and the number of nodes in each hidden layer.

(5) Input data to predict traffic flow

2.3. EMD-BPNN model

The EMD-BPNN model first decomposes the original traffic flow data into multiple intrinsic modal functions (IMF) through empirical mode decomposition, then removes high-frequency components containing high noise, reintegrates the remaining components, and imports the integrated data The BP neural network model makes predictions and obtains the final prediction results. The workflow of the model is shown in figure 2:

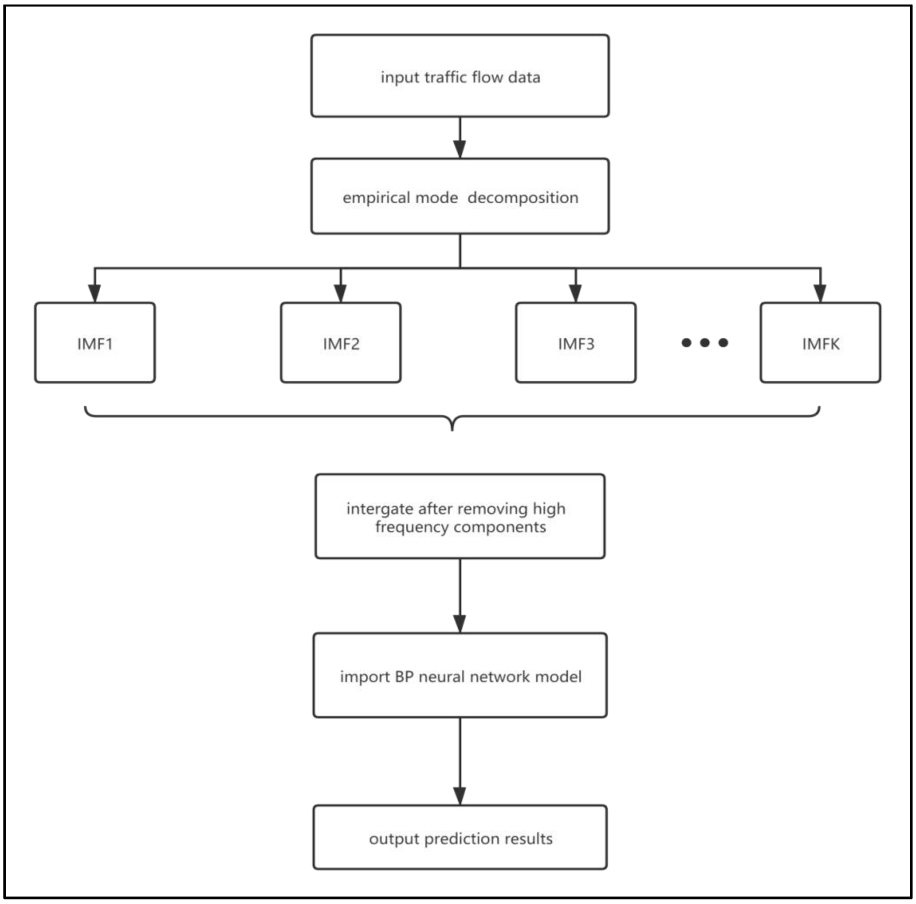

Figure 2: EMD-BPNN model work flow chart

3. Results and Discussion

3.1. Data Description

The data in this paper is obtained from the PEMS database, which collects traffic flow data from more than 39,000 traffic detectors in California. We select data from a detector to predict traffic flow. The data collection time is from 0:00 on March 1, 2021 to 23:55 on March 5, 2021. The time interval for data sampling is 5 minutes (a total of 1,440 traffic flow data were collected in this study). Figure 3 is the position of the detector, and Figure 4 is the image of the traffic flow data.

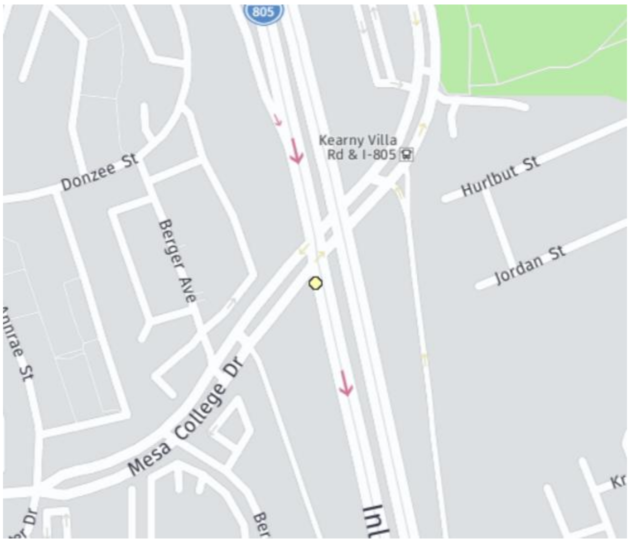

Figure 3: Location distributions for the detector

Table 1: Detector parameters

Freeway	Detector number	Max cap	Lane point
I8	1115938	129.0	4

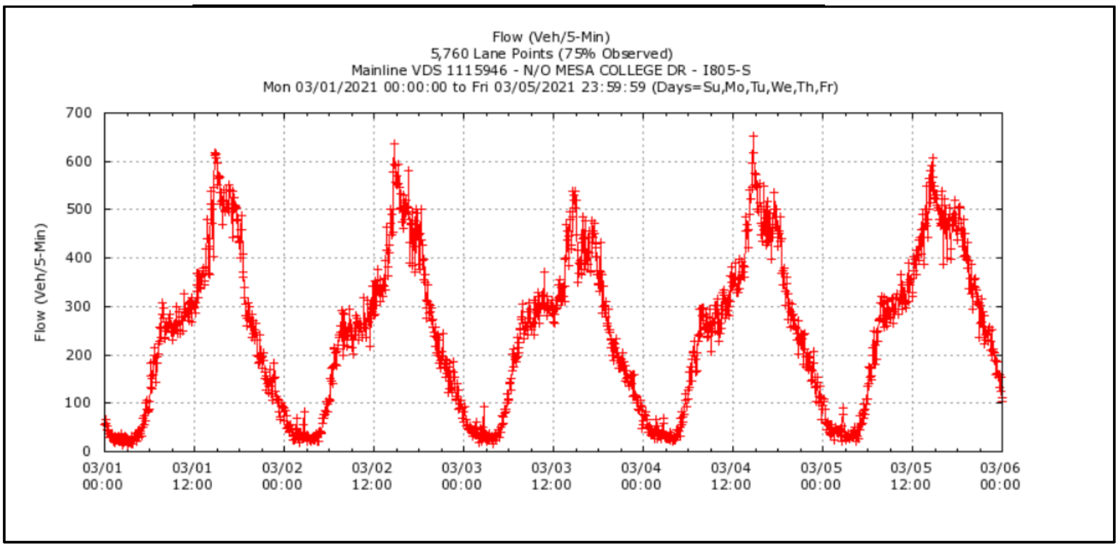

Figure 4: Raw traffic flow data image

3.2. Evaluation standard

The criteria for verifying the prediction performance in this paper are three statistical indicators: RMSE, MAE, and MAPE.

$$\hat{f}_i\ RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(f_i - \hat{f}_i\right)^2} \tag{4}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left(f_i - \hat{f}_i\right) \tag{5}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{f_i - \hat{f}_i}{f_i}\right| \times 100\% \tag{6}$$

Among them is the original traffic flow data of f_i, and $\hat{f}_i$ is the predicted traffic flow data

3.3. Empirical mode decomposition results

The traffic flow data for five consecutive days are decomposed by EMD. From the decomposition result (see Figure 5.), it can be seen that the original traffic flow data is decomposed into 8 IMFs, of which IMF1, IMF2, IMF3, and IMF4 are high-frequency components. After removing the high frequency components, the result after denoising is obtained. It can be seen from Figure 6 that the denoised data is smoother than the original data. This is because EMD denoising reduces the influence of noise on the data. This method can make the traffic flow data show temporal characteristics.

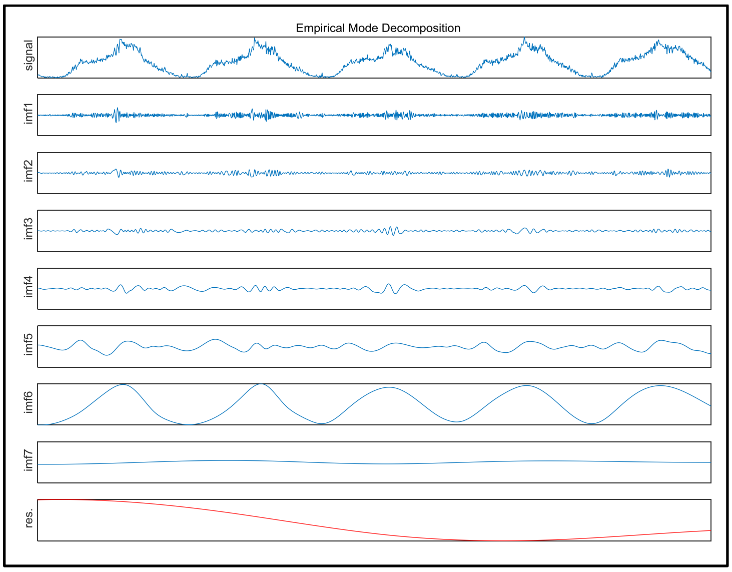

Figure 5: EMD decomposition result of traffic flow data

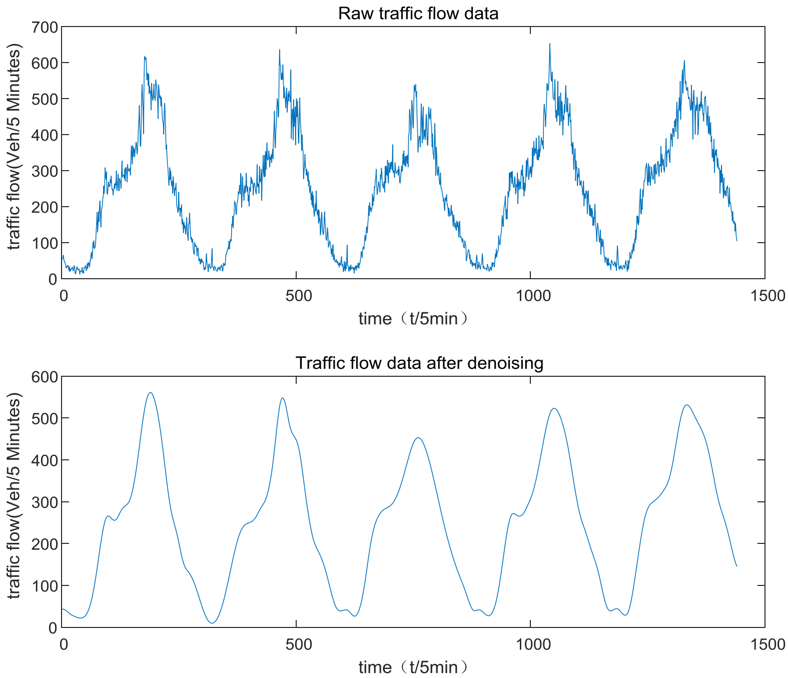

Figure 6: Compare the image between the denoised data and the original data

3.4. BP neural network prediction

Import the denoised data into the BP neural network model to get the final prediction results. It can be seen from Figure 7 that the traffic flow data predicted by the BP neural network shows the change trend and periodic characteristics of the original traffic flow data.

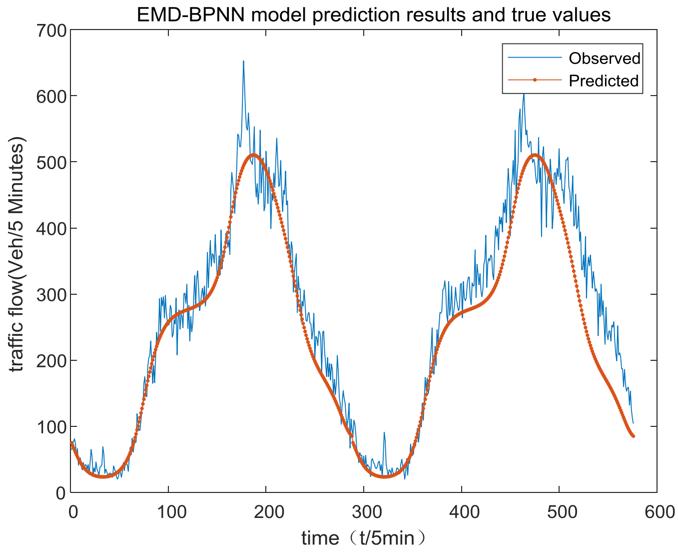

Figure 7: EMD-BPNN model prediction results and true values

3.5. Analysis and Compare

In order to verify the superiority of the prediction results, we compare the prediction results of the EMD-BPNN model proposed in this paper with the BPNN model and the SVM model. The three methods use the same data set. The evaluation indicators of predictive performance are quantified by RMSE, MAE, and MAPE. The comparison images of the prediction results of the three models and the test set data are shown in Figure 8. It can be seen from the image that the traffic flow prediction result of the EMD-BPNN model has the best performance.

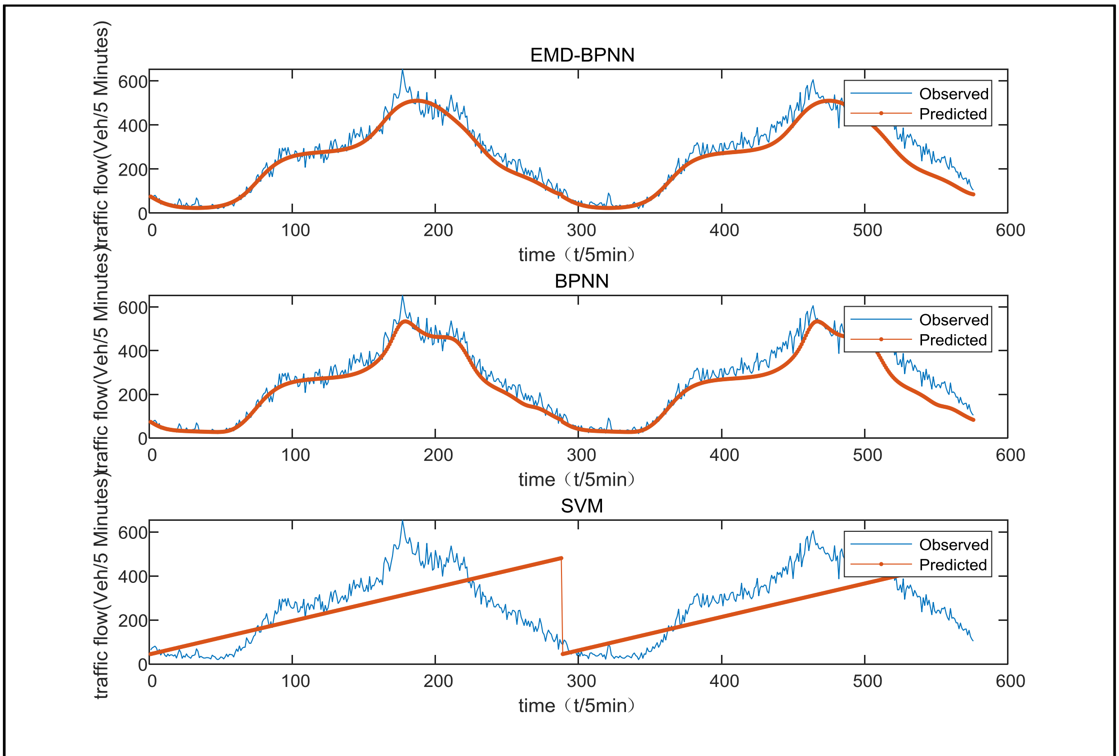

Figure 8: Comparison of the prediction results of the three models and the original data

From the perspective of evaluation indicators, the RMSE, MAE, and MAPE of the EMD-BPNN model are 39.3475, 29.1672, and 13.75, respectively. Compared with the BPNN model, the EMD-BPNN model has higher prediction performance, indicating the effectiveness of EMD denoising, and data denoising can improve the prediction accuracy. The EMD-BPNN model has higher prediction accuracy than the SVM model, indicating that the BP neural network model is more suitable for traffic flow prediction than the traditional machine learning model. In summary, the EMD-BPNN model has excellent performance in the field of traffic flow forecasting and can be used in traffic flow forecasting on different road sections.

Table 2: Comparison of performance indicators of the three models

	RMSE	MAE	MAPE
EMD-BPNN	39.3745	29.1672	13.75
BPNN	49.2422	36.0887	15.42
SVM	139.4549	111.1607	73.53

4. Conclusion

This paper proposes an EMD-BPNN model to predict traffic flow. First, the original traffic flow data is de-noised by EMD decomposition, and then the de-noised data is imported into the BP neural network model to obtain the prediction result. The comparison experiment shows that the EMD-BPNN model can get accurate prediction results. On one hand, the future development direction of this research can add speed, weather factors and other variables to predict traffic flow. On the other hand, this study can use traffic flow data collected from different types of roads to make predictions. In short, the EMD-BPNN model can be used as a new method for traffic flow prediction.

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