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The Tourism Demand of Nonlinear Combination Forecasting based on Time Series Method and WNN

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Abstract

The combination forecasting model IOWGA-EMD-ARMA-WNN is proposed in this paper. The randomness, periodicity and tendency of the original data are showed by EMD decomposition in EMD-ARMA model. WNN combines the advantages of wavelet analysis and BP neural network and improves the learning efficiency and forecasting accuracy. The weight of combination model is decided by forecasting precision of EMD-ARMA model and WNN model based on IOWGA method. At last, the IOWGA-EMD-ARMA-WNN model is used to forecast monthly inboard tourism demand of China and the results show that the proposed combination model has better performance on forecasting accuracy compared with the other models.

Keywords: *Forecast, tourism demand, IOWGA, EMD, ARMA, WNN*

1. Introduction

With the further reform and opening, China has crept into the major tourist country. Healthy and sustainable tourism development can promote adjustment of industrial structure and regional economic growth. It will increase employment opportunities and it is also of great significance to reduce poverty and the gap between rich and poor of China.

International inbound tourism market is an important part of China Tourism Industry. After china entering into WTO, more business people come to China to invest. More international visitors are surprised of the rapid development of China and interested in the exquisite historical culture of china. The number of tourists of business tours, sightseeing tours and family visiting tours increased quickly.

The tourist economy occupies an important position in the national economy. Moreover, it promotes the development of the national economy and the correlative industries. It plays a very important role in the improvement of economic structure. Tourism industry has become the leading sector of economic development of China. It becomes one of the important growth points of national economy. It will become a pillar industry of the Chinese. Inbound tourism as the important aspects of promoting international exchanges and cooperation and increasing foreign exchange earnings, it contributes to the economic development of China.

However, quickly and accurately forecasting the tourism demand and establishing the forecasting model with a clear mechanism has become an important research subject. The tourism demand forecasting start at 1960s. And there are mainly three aspects on studying the tourism demand forecasting. Firstly, methods based on the trend of historical data, including regression analysis method [1-2], time series method [3-9], grey forecasting method [10-13]. Secondly, forecasting the tourism demand based on the tourist market investigation and the analysis of purchasing power [14-15]. This method needs to have a deep understanding of the tourist market. It often set a particular market as the object and lack of awareness of the entire regional tourist market. Thirdly, Gravity models [16-20]. It needs a large number of questionnaire surveys in order to understand the tourist market. Therefore, the forecasting results reflect the characteristics of the regional structure of tourist market, while the total passenger tourism demand is difficult to determine.

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At present, the artificial neural network is used to the tourism demand forecast by many researchers since the ability of parallel processing, self-learning, self-adaptive and better fault tolerance. And lots of studies indicate that ANN is better than traditional prediction methods. For example, the research of Law [21-22] showed that artificial neural network is better than multiple linear regressions. Cho [23] compared ANN with exponential smoothing method and the results show that the forecasting accuracy of ANN is better than exponential smoothing method. The study of Pattie and Snyder [24] showed that ANN is better than Autoregressive Integrated Moving Average Model (ARIMA).

In this paper, the nonlinear combination forecasting based on ARMA and WNN is proposed to forecast inboard tourism demand. The overall structure of the study is as follows: In section 2, we first introduce the EMD-ARMA model, wavelet neural network model and IOWGA operator. Then we proposed the IOWGA-EMD-ARMA-WNN model. In section 3, we use the proposed model for inboard tourism demand forecasting of China. In section 4, the conclusion of this paper is given.

2. The Nonlinear Combination Forecasting Method

In the traditional forecasting process, the single forecasting methods are often adopted based on subjective experience and knowledge of their own. There is no scientific prediction strategy and it mainly depends on the person's own forecasting quality. The single model which is selected may not be optimal. The prediction accuracy also can't be guaranteed.

In this paper, the Induced Ordered Weighted Geometric Averaging (IOWGA) operator [25] will be used as the combination forecasting method with EMD-ARMA model and WNN model. The basic idea of IOWGA operator is that the order weights are decided on the basis of the fitting precision of each single prediction method at each time point. It overcomes the shortcomings of traditional weighted geometric average combination forecasting method.

2.1 The EMD-ARMA Forecasting Model

In the nature, all kinds of signals generated by the system are often the random process with non-linear and non-stationary. In 1998, N. E. Huang et al from American NASA studied the concept of instantaneous frequency, proposed a new signal processing method - Hilbert Huang Transform (HHT), namely the time frequency analysis method based on EMD. Empirical Mode Decomposition (EMD) is the form that decomposes a complex nonlinear and non-stationary signal into a finite number of stable signal components and expresses the residual amount of superposition of signal change trend. Each stable signal component is called intrinsic mode function. It reflects characteristics of different scale of the signal.

The purpose of EMD decomposition is to get the components of intrinsic mode functions (IMF). IMF forms a series of signal. It is ready for the transformation of Hilbert. The IMF is the signal which meets single component signals of physical interpretation. An IMF must meet the following two conditions:

a. The number of extreme points and zero crossing points. The number of extreme points and zero crossing points must be equal or differ by at most one point from the data length.

b. Mean value is zero. That is the mean value of the local maximum envelope and the local minimum envelope should be zero.

The steps of EMD algorithm are shown in bellow.

Step 1: Determine all the maximum points sequence and minimum points' sequence of the processing sequence $x(t)$. Three times spline interpolation method is used to fit the maximum and minimum values of the sequence. Then we get the upper envelope $v_{\max(t)}$ and lower envelope $v_{\min(t)}$.

Step 2: Work out the mean envelope of upper envelope and lower envelope. That is $m(t)_1 = \frac{v_{\max(t)} + v_{\min(t)}}{2}$. Calculate the difference between $x(t)$ and $m(t)$. That is

$e(t)_1 = x(t) - m(t)_1$.

Step 3: Determine whether $e(t)_1$ meet the conditions of IMF. If it does, set $e(t)_1$ to be the first IMF. If it doesn't, set $e(t)_1$ to be the new pending sequence. Repeat Step 1 and Step 2 k times. Then we get $e(t)_k = e(t)_{k-1} - m(t)_k$ which meet the conditions of IMF. Set $s(t)_1 = e(t)_k$, and $s(t)_1$ is the first IMF of $x(t)$.

Step 4: Set $r(t)_1 = x(t) - s(t)_1$ to be the new pending sequence. Repeat the above Steps. Then we will get an IMF. When $r(t)$ become the constant or monotone function and it can get the IMF component from $x(t)$, the decomposition process ends. The original sequence $x(t)$ could be indicated as $x(t) = \sum_{i=1}^{n} s(t)_i + r(t)$.

From the above steps, the EMD algorithm has been completed. Then the EMD-ARMA model will use the ARMA model to forecast by using the decomposed signals. At last, each signal prediction results are reconstructed to get the final prediction value.

2.2 The Wavelet Neural Network Model

Wavelet neural network is a typical feed forward neural network based on the theory of wavelet analysis. It takes wavelet space as characteristic space of pattern recognition. The signal features are extracted by weighted sum of inner product of wavelet basis and signal vector. Because of the combination of the good time-frequency localization of wavelet transformation and self-learning ability of traditional neural network, the wavelet neural network has strong approximation ability and fault tolerant ability.

In order to better reflect the monthly tourism demand characteristics, the tourism demand data is decomposed into different frequency components of tourism demand sequence by using the multi resolution analysis of wavelet. The basic steps of WNN model are shown in bellow.

Step 1: The monthly tourism demand data are normalized. The normalized values fall in the interval [0, 1].

Step 2: Select the suitable wavelet function and decomposition scale and decompose the tourism demand data by multi resolution decomposition of wavelet.

Step 3: The wavelet sequence on each scale are taken as input variables, they are used to train BP neural network and forecasting.

Step 4: At last, the forecasting results is got.

The flow chart of WNN is shown in bellow:

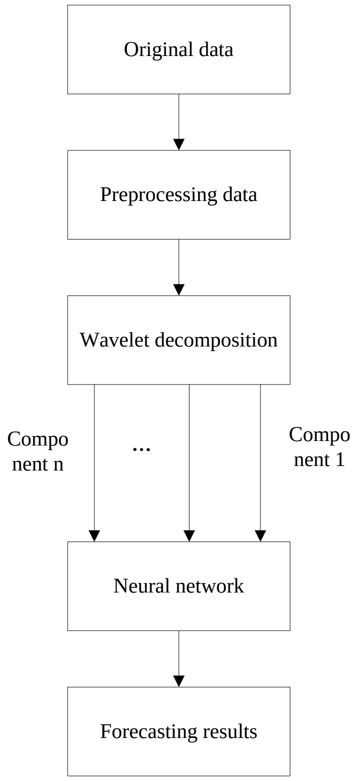

Figure1. The Flow Chart of WNN

2.3 IOWGA Operator

Let $<v_1,a_1>,<v_2,a_2>,\cdots,<v_m,a_m>$ as the m two-dimensional arrays.

$$I_W(<v_1,a_1>,<v_2,a_2>,\cdots,<v_m,a_m>)=\prod_{i=1}^{m}a_{v-index(i)}^{w_i} \tag{1}$$

The function I_W is the m-dimensional IOWGA operator. v_i is called induced value of a_i. $v-index(i)$ Is subscript of ith large number according to the order from big to small in $v_1,v_2,\ldots,v_m$. The IOWGA operator takes the ordered weighted geometric averaging for $a_1,a_2,\ldots,a_m$ which is sorted in descending order according induced value. w_i Has nothing to do with the size and position of a_i. It relates to the position of induced value. The combination forecasting model based on IOWGA operator is

$$p_{it}=\begin{cases}1-\left|(x_t-x_{it})/x_t\right| & \text{when } \left|(x_t-x_{it})/x_t\right|<1\\ 0 & \text{when } \left|(x_t-x_{it})/x_t\right|\geq 1\end{cases} \tag{2}$$

Where p_{it} is the forecasting accuracy of ith forecasting model $p_{it}\in[0,1]$.

We regard p_{it} as the induced value of forecasting value x_{it}. Thus, the forecasting accuracy of the m models at time t and its forecasting values in the related interval make up the number of m two-dimensional arrays $<p_{1t},x_{1t}>,<p_{2t},x_{2t}>,\cdots,<p_{mt},x_{mt}>$. They are the weighted vectors of OWGA for different forecasting models. The forecasting accuracy sequence $p_{1t},p_{2t},\ldots,p_{mt}$ of different models at time t is sorted in descending order. Set $p-index(it)$ is the subscript of ith big forecasting accuracy. The IOWGA combination forecasting value of forecasting accuracy sequence $p_{1t},p_{2t},\ldots,p_{mt}$ at time t is

$$I_W(<p_{1t},x_{1t}>,<p_{2t},x_{2t}>,\cdots,<p_{mt},x_{mt}>)=\prod_{i=1}^{m}{x_{p-index(it)}}^{w_i},t=1,2,\cdots,N \tag{3}$$

The Eq. (3) shows that the weight of IOWGA combination forecasting model has nothing to do with the selection of models. It relates to the forecasting precision of each single prediction method at each time point. The forecasting accuracy becomes the induced value of single model at time t. The higher forecasting accuracy model has the larger weight.

Let $e_{p-index(it)} = \ln x_t - \ln x_{p-index(it)}$,then the total sum of square logarithm error is

$$S = \sum_{i=1}^{m}\sum_{j=1}^{m} w_i w_j \left(\sum_{t=1}^{N} e_{a-index(it)} e_{p-index(jt)}\right) \tag{4}$$

The combination forecasting model based on IOWGA is

$$\min S = \sum_{i=1}^{m}\sum_{j=1}^{m} w_i w_j \sum_{t=1}^{N} e_{a-index(it)} e_{p-index(jt)}$$

$$s.t \begin{cases} \sum_{i=1}^{m} w_i = 1, \\ w_i \geq 0, i = 1, 2, \ldots, m \end{cases} \tag{5}$$

The combination forecasting model is a quadratic programming problem. It can be turned to linear programming problem by Kuhn-Tucker condition.

2.3 The IOWGA-EMD-ARMA-WNN models

After the tourism demand forecasting data got by EMD-ARMA model and WNN model, the forecasting accuracy will be calculated and they will be used to calculate the weight of combination model with IOWGA method. Then the combination model of IOWGA-EMD-ARMA-WNN is established to forecast the tourism demand. The flow chart of IOWGA-EMD-ARMA-WNN model is shown in bellow.

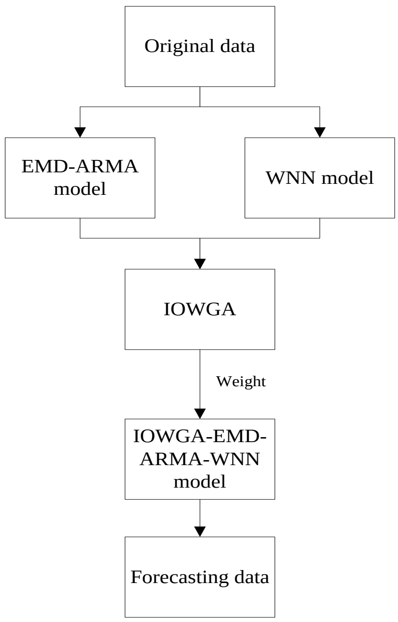

Figure 2. The Flow Chart of IOWGA-EMD-ARMA-WNN Model

3. Experiment and Simulation Analysis

In this paper, the proposed IOWGA-EMD-ARMA-WNN model is used to forecast monthly inboard tourism demand of China. The data is from 1985 to 2011. Firstly, the Chinese inboard tourism demand data is decomposed by EMD method. Then we get eight IMF components. The decomposition results shown in Fig3.

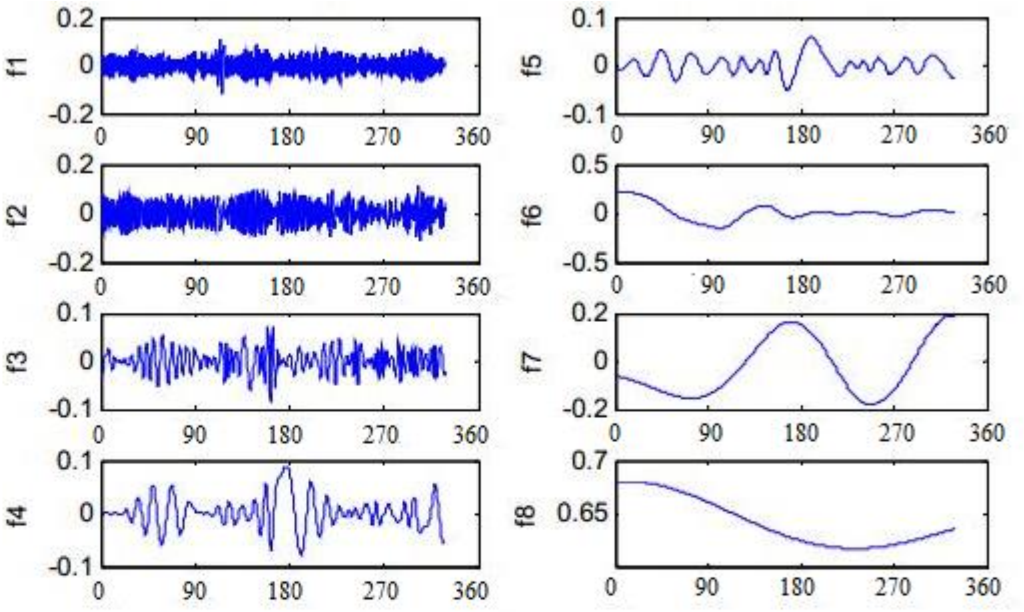

Figure 3. Components of IMF of OriginalData

From Fig. 3, we find that f1, f2, f3 show the randomness of monthly tourism demand data. F4 and f5 show the periodicity of the data and f6, f7 and f8 show the tendency of the original data. F8 Plays an important role to the tourism demand variation since its amplitude seems consistent with the amplitude of original tourism demand while the other components only influence on the fluctuation of tourism demand curve.

Then, we calculate the autocorrelation coefficient and partial autocorrelation coefficient with 95% confidence interval for each IMF component in order to make the preliminary judgment to the model. The following figures show the autocorrelation and partial autocorrelation of different components.

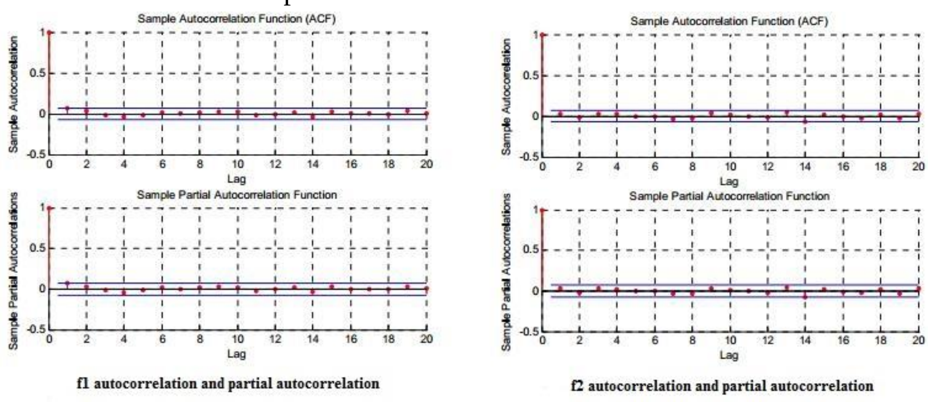

Figure 4.The Autocorrelation and Partial Autocorrelation of *f1* and *f2*

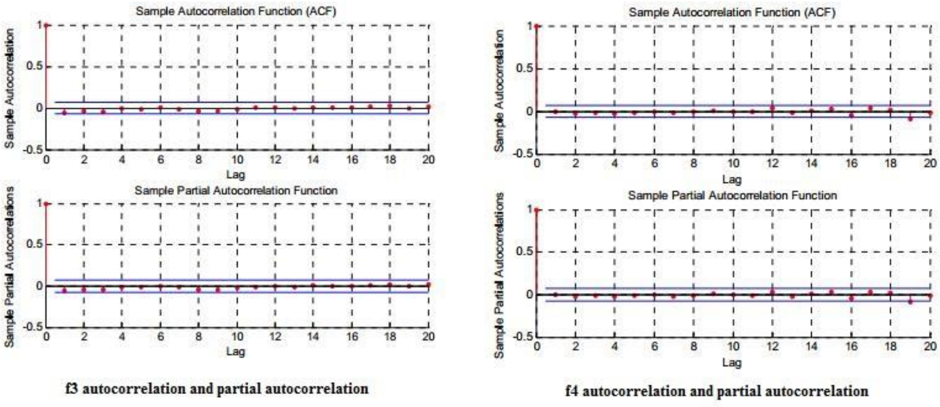

Figure5. The Autocorrelation and Partial Autocorrelation of *f3* and *f4*

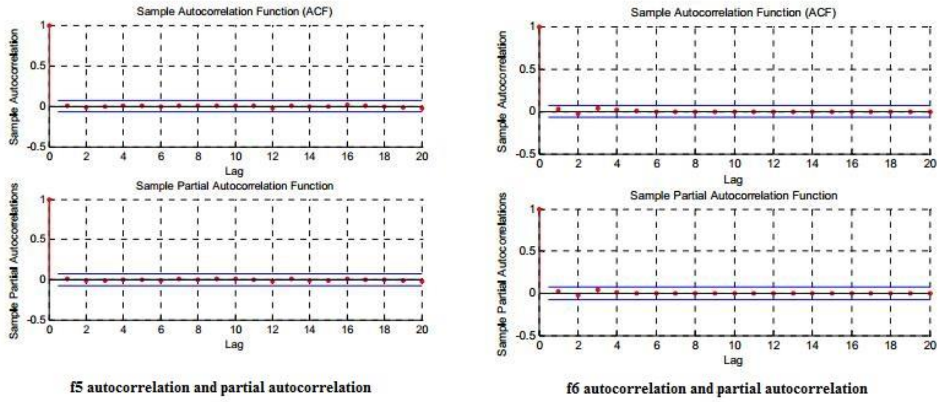

Figure 6. The Autocorrelation and Partial Autocorrelation of *f5* and *f6*

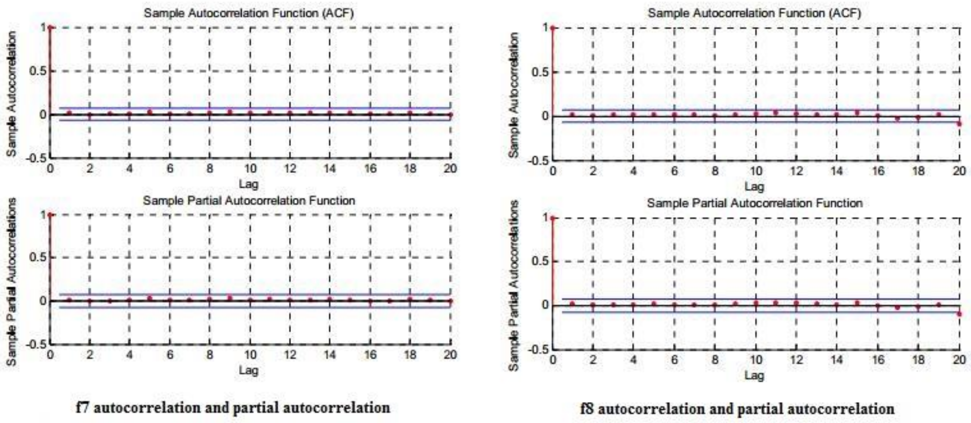

Figure 7.The Autocorrelation and Partial Autocorrelation of *f7* and *f8*

The AIC function in MATLAB toolbox is used for fitting each component. The best model which making the AIC reach the minimum value is selected. And the value of p and q of current ARMA model is the final model order. The ARMA model is shown in Table 1.

Table1. The ARMA Model of Each Component

f1	*f2*	*f3*	*f4*
ARMA(5,14)	*ARMA(13,10)*	*MA(16)*	*ARMA(2,19)*
f5	*f6*	*f7*	*f8*
ARMA(2,11)	*ARMA(4,14)*	*ARMA(2,20)*	*AR(5)*

The eight ARMA models are used to forecast. Then the forecasting results are restructured and the final prediction value will be got. The WNN model is established by MATLAB toolbox. Then we used the forecasting results of the two models and IOWGA method to calculate the weight of IOWGA-EMD-ARMA-WNN model. After the weight of combination model got, the final combination forecasting results will be solved.

The performance of model is judged by root mean square error (RMSE) and mean absolute error (MAE). The equation is as follows.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2} \tag{6}$$

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

Table 2. The Forecasting Performance of Different Models

	IOWGA-EMD-ARMA-WNN	ARMA	BP-NN
MAE	0.020076792	0.02730171	0.029233016
RMSE	0.005098882	0.005758805	0.00896548

From table 2, we find that the MAE and RMSE of IOWGA-EMD-ARMA-WNN is the smallest of these three models. This means that the total forecasting accuracy of the combination model is more effective and precise compared with ARMA and BP-NN.

Table 3. The Forecasting Results of IOWGA-EMD-ARMA-WNN

	True value	IOWGA-EMD-ARMA-WNN
2010.07	1150.13	1134.34
2010.08	1171.41	1140.58
2010.09	1103.69	1131.13
2010.10	1163.64	1139.72
2010.11	1089.34	1115.65
2010.12	1146.02	1128.08

Note: The tourism demand unit is ten thousands person-times

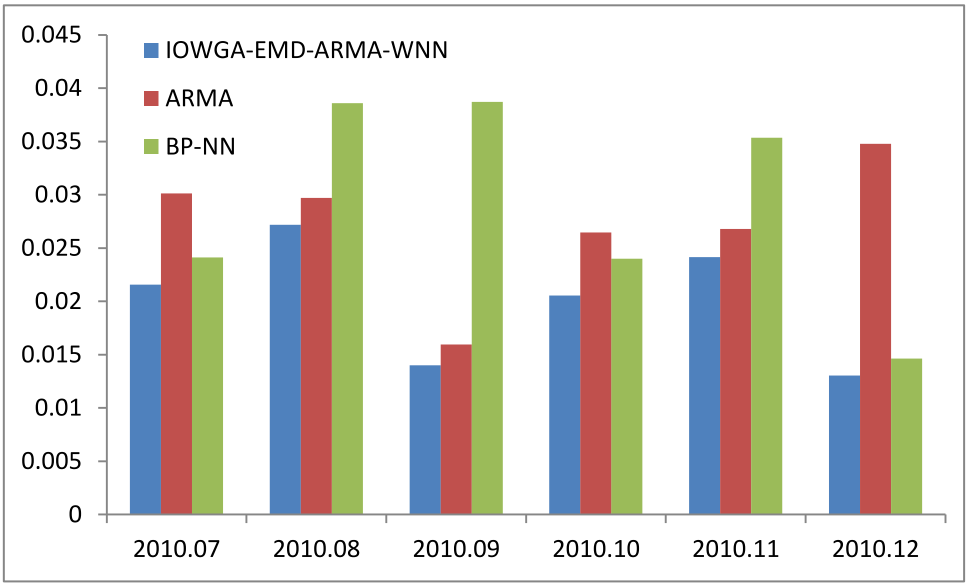

Figure 8. The Absolute Error of Different Models from July 2010 to December 2010

Table 3 shows the forecasting values of IOWGA-EMD-ARMA-WNN model. And the forecasting values are near to true values. The Fig.8 shows the absolute error of IOWGA-EMD-ARMA-WNN model, ARMA model and BP-NN model. From Fig. 8, it can be seen clearly that the absolute error of IOWGA-EMD-ARMA-WNN model is smaller than the other models in each month.

4. Conclusion

In this paper, the combination forecasting model IOWGA-EMD-ARMA-WNN is proposed based on IOWGA method. The EMD decomposition is used to reflect the randomness, periodicity and tendency of the original data in EMD-ARMA model. Compared with BP-NN, the wavelet neural network has strong approximation ability and fault tolerant ability. After getting the forecasting accuracy of EMD-ARMA and WNN models, the weight of combination model with IOWGA method will be calculated. At last, the IOWGA-EMD-ARMA-WNN model is adopted to forecast inboard tourism demand of China. The experiment shows the proposed combination model is better than the other models in this paper.

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