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The Forecasting of Weekly Tourists Visiting a Scenic Area in Off-Season by Using Goodness of Fit Weight

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Abstract

Due to the impact of external objective factors, the weekly number of tourist distribution is imbalance and shows strong nonlinear characteristics, especially more obvious in the off-season. Aiming at this problem, this paper built two different forecasting models by SVR and BP neural network in order to guess about the weekly tourist numbers and then, put forward the Goodness of Fit Weight (GFW) and used it to make three SVR-BP combination models (LCM, GEOM-WTD, and HARM). In order to support the results empirically, Data of the Huangshan Scenic Area has been used and the dynamic virtual variable was adopted to deal with the objective factors that influence the weekly visitor numbers. Finally, we compare the results with the two combination models that based on the VARW and MSEW, it shows that the GFW combination model is helpful for the combination forecasting and can be used as one of selections just like other weights, and the use of dynamic virtual variables can further improve the forecasting precision.

Key words: *Tourist off-season; Weekly tourists forecasting; Goodness of Fit Weight; Combination model*

1. Introduction

In recent years, tourism has become one of the fastest growing and the largest industry due to rapid development in economy. More and more people like to enjoy the higher living standards and spiritual culture. The World Tourism Organization predicted that international tourist arrivals worldwide will reach 1.6 billion and tourism receipts will be over US$2 trillion by the year 2020 [1]. In China, according to the China Statistical Yearbook, the number of domestic and foreign tourist arrivals reached to 828 million and the tourism revenue was 415.8 billion Yuan in 2000, but in 2010, the these numbers reached to 2.24 billion and 1.57 trillion Yuan with an annual growth rate of 10.4% and 14.2% respectively.

The rapid development of tourism industry forced that tourism demand forecasting is becoming more and more important, and promoted the study of forecasting model. From the econometric models of the 1960s to the artificial intelligence model presently, there are so many forecasting methods and models which are found by researchers from different tourism demand dimensions in time, space and background, and the effect is very significant, especially travel demand forecasting method was mainly focused on the comparison of model and method [2]. Such as Yolanda [3]used econometric model to analyze the influence of demand for tourism destination that are overcrowded, and give some policy suggestions. The Bayesian method was used by Wong [4] for revising the unrestricted various vector autoregressive (VAR) model and applied to the Hong Kong tourism demand forecasting, the results showed that the Bayesian VAR can effectively

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improve the forecasting accuracy. In other studies conducted in Taiwan [5], the scholars established the adaptive network-based fuzzy inference system (ANFIS) model with the support of empirical data, they found that the ANFIS model has better forecasting performance than the other three models. Other method models include ARIMA [6], GARCH [7], AIDS [8], Neural Network [9], Rough Sets [10], SVM [11, 12], and Fuzzy time series [13].

Any scenic area has tourist season and off-season, and the off-season shows strong nonlinear characteristics. Therefore, the demand forecasting has become more difficult in off-season. Meanwhile, low resource utilization exists in off-season of scenic area, and the staff and equipment may be excessive, so the scenic area management decision should be different from the tourist season. In the light of above discussion, the current paper has the following objectives, which are:

- To predict the off-season tourist trend of a scenic spot for the coming week through the weekly tourist numbers forecasting model and then to provide the valuable reference for the management decisions, personnel and supplies allocation, emergency security (*etc)*.
- To show the Goodness of Fit Weight (GFW) as well as other weights which can improve the forecasting accuracy and to show the dynamic virtual variables are helpful to tourism demand forecasting.

2. Data

In this paper, the total number of sold tickets is taken as the data to be analyzed. The data has been taken from the electronic entrance ticket checked system of Huangshan Scenic Area, one ticket corresponds to one tourist，so the total numbers of ticket sold represents the total number of tourists in a specific period. Huangshan is the National 5A Scenery Sites of China，and it attracts millions of tourists every year. There is a good reputation for Huangshan, that is: “Trips to China's five great mountains render trips to other mountains unnecessary, and a trip to Huangshan renders trips to the five great mountains unnecessary”. Like other scenic areas, due to the objective factors (such as geography and season), Huangshan Scenic Area also has tourist season and off-season, and the weekly tourist number shows strong nonlinear characteristics, especially more obvious in the off-season because of the snow and freezing weather.

Figure 1 shows the monthly tourist number of Huangshan Scenic Area from March 2008 to December 2013. It is easy to find that there is high number of tourists from April to October than the other months (black). Especially in October (red), due to the comfortable temperature and weather and the National Day Golden Week, the tourist number lies to the highest level in the whole year. In April and May the tourists number lie to the second highest level because of the comfortable temperature and weather and two holidays (Tomb-sweeping Day and May Day). But in June and September (green), the influence of high temperature make the tourist number is relatively low. The temperature is high in in July and August (blue), but the tourist number at the same level with April and May, that’s because the student group can enjoy summer vocation. Table 1 shows the monthly tourist number of Huangshan more intuitive, through this data, we can find that the monthly average number of January to March, November and December are much less than the other months, and under 1/12 of annual tourist number. The five months (January, February, March, November and December) are called off-season of Huangshan Scenic Area.

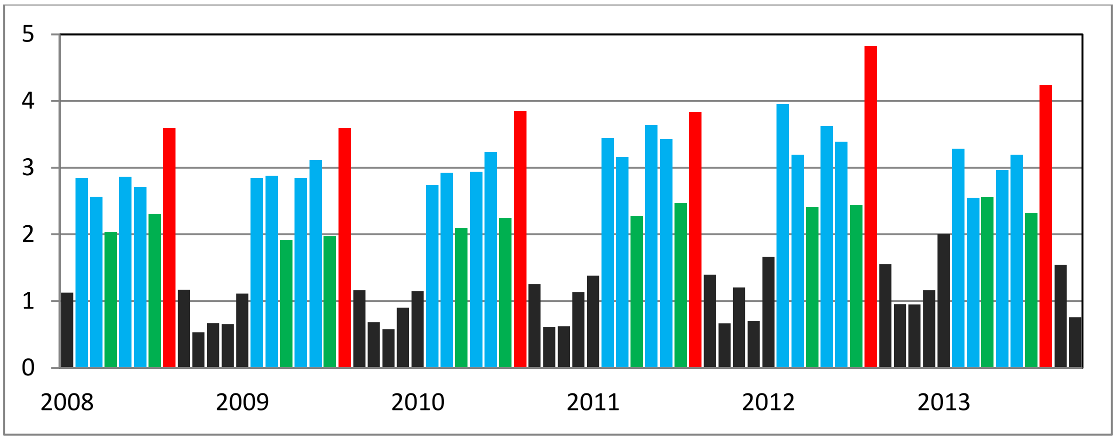

Figure 1. The Monthly Tourist Number of Huangshan Scenic Area (One Hundred Thousand)

Table 1. The Monthly Average Tourist Number and the Average Percentage of the Year from 2008 to 2013

Month	Tourist Number （ten thousand）	Percentage （%）	Month	Tourist Number （ten thousand）	Percentage （%）
January	8.05	3.1	July	31.42	12.09
February	9.13	3.51	August	31.76	12.22
March	13.67	5.26	September	22.9	8.81
April	31.81	12.24	October	39.8	15.33
May	28.76	11.06	November,	13.4	5.16
June	22.14	8.52	December	7.01	2.7

3. Forecasting Methods and Models

3.1. Forecasting Methods

Support Vector Regression (SVR) [12,-15] and Back Propagation Neutral Network (BPNN) [16, 17] were used in weekly tourist number forecasting. Both are already mature artificial intelligence methods and are good to describe nonlinear characteristics data, they have applied to all kinds of forecasting include tourism forecasting. The rules of SVR algorithm is the structural risk minimization, it makes the empirical risk and confidence interval minimum at the same time in order to achieve the expected risk minimization, the solving process which is a convex quadratic programming problem can guarantee the extremal solution is a global optimal solution, and it can overcome dimension disaster and has stronger generalization ability. BPNN can approximate any nonlinear continuous function with arbitrary precision, it owns strong self-learning and adaptive ability, especially its fault tolerance is very high. However, both have their own shortcomings. Such as SVR is easy to fall into local optimum and only suitable for small sample data set, and the BPNN also has a slow convergence speed and strong dependence of the sample and so on. Therefore, we built the SVR-BP combination model that can overcome their disadvantages of single model and expand their advantages at the same time.

3.2. Combination Model

Combination model was firstly introduced by Bates and Granger [18] in the late 1970's, and it attracted the attention of many researchers. It has become mature at present and often used in the tourism demand forecasting. Although many studies have shown that combination model is not always better than the single model [19], but combination model can reduce the risk of forecasting failure [20-21], and in other industries such as economy and finance [22-26], researchers found that combination model has a better and more robust forecasting accuracy than the single model. Hence, it can be argued that the combination model is can be very effective in tourism demand forecasting [27- 28]. The reason is obvious, that each single model has its own advantages and disadvantages, but one important advantage of combination model is that it can synthesize advantages and take out or reduce disadvantages of each single model.

The combination model include linear combination model (LCM) [29], weighted geometric mean (GEOM-WTD) and weighted harmonic mean (HARM-WTD) [30]. The formula as shown below

LCM $z_t = w_1 x_t^1 + w_2 x_t^2$ (1)

GEOM-WTD $z_t = [x_t^1]^{w_1}[x_t^2]^{w_2}$ (2)

HARM $z_t = \frac{x_t^1 x_t^2}{w_1 x_t^1 + w_2 x_t^2}$ (3)

and z_t is the finally predicted value, x_t^1 and x_t^2 are the two predicted value which get by SVR and BPNN respectively, w_1 and w_2 are two weights of two methods and $w_1 + w_2 = 1$.

3.3. Goodness of Fit Weight (GFW)

The Goodness of Fit Weight (GFW) refers to the fitness level of regression line of estimated value to that of actual value, if the actual value is closer to the regression line, the level of fitness is higher, but if the actual value is not closer to the regression line, the level of fitness is lower. The GFW essentially reflects the forecasting model that is good or bad, but the authors found no previous study in which the GFW has been used as a weight of combination model. So in allusion to above weights w_1 and w_2, we propose the GFW and it is defined by

$$w_1 = \frac{1-R_2^2}{(1-R_1^2)+(1-R_2^2)} = \frac{1-R_2^2}{2-R_1^2-R_2^2} \qquad w_2 = 1 - w_1 \tag{4}$$

R_1^2 and R_2^2 are Goodness of Fits of two methods. Maybe there is a question, why can't we define the GFW as follow

$$w_1 = \frac{R_1^2}{R_1^2+R_2^2} \qquad w_2 = \frac{R_2^2}{R_1^2+R_2^2} \tag{5}$$

That's because the most basic requirement of combination model is that the forecasting value of each single model can't be too bad and the Goodness of Fit should be close to 1, if we define the GFW like Eq. (5), both the weights must be near 1/2, the advantages of weight can't better reflect in the combination model. Meanwhile, in order to verify the effectiveness of the GFW, we compare and analyze forecasting result of the GFW to variance weight (VARW) [29] and mean square error weight (MSEW) [31] which are already applied universally and maturely. VARW and MSEW are given by

VARW $w_1 = \frac{\sigma_2^2}{\sigma_1^2+\sigma_2^2} \qquad w_2 = 1 - w_1$ (6)

MSEW $w_1 = \frac{MSE_2}{MSE_1+MSE_2} \qquad w_2 = 1 - w_1$ (7)

4. Empirical Research

4.1. Sample and Data Processing

One of the purposes of this paper is to forecast weekly number of tourist visiting scenic area in off-season, and in order to contain the entire off-season and taking every week is seven days. We put 1 or 2 days of early April and late October in each year as off-season, and got the final 5 sample intervals which included 2008.10.30 ~ 2009.4.1, 2009.10.30 ~ 2010.4.1, 2010.10.30 ~ 2011.4.1, 2011.10.31 ~ 2012.4.1 and 2012.10.30 ~ 2013.4.1 five time periods, every time period contained 22 weeks, so the sample size is 110.

Data processing has a crucial influence on the model robustness; different processing methods may lead to a deviation of the final forecasting result. Our processing method is that we first got logarithmic sequence of the original sequence, and then normalized the logarithmic sequence to [0.15, 0.85] interval, the normalization rule [32] was given by

$$Y_t = \frac{N_t - N_{min}}{N_{max} - N_{min}} * 0.7 + 0.15 \tag{8}$$

and N_t is the logarithmic sequence, $N_{\max}$ and $N_{\min}$ are the maximum and the minimum of logarithmic sequence respectively, Y_t is the simulation sequence.

4.2. Input Variables Determining

The tourist number of Huangshan Scenic Area is mainly affected by the official holidays and bad weather. There are two official holidays in off-season, they are New Year's Day which include 3 days and Spring Festival which include 7 days. Through data observing we found that there is no difference between weekday and the first and last day of official holidays i.e. the tourist number of 1 day of New Year's Day and 5 days of Spring Festival is obviously higher than weekdays. So every week has 0 to 5 holidays, we put forward the dynamic virtual variable which is defined by $H_i = i/5$ (i= 0, 1, 2, 3, 4, 5) H_i means one week had (i) holidays. Bad weather in off-season tourist mainly included blizzard, heavy snow, moderate snow, sleet and rain. The tourist number in these days is lesser than the weekdays like official holidays. We also put forward the dynamic virtual variable to describe the bad weather that is defined by $W_i = i/7$ (i= 0, 1, 2, 3, 4, 5, 6, 7) W_i means one week contained (i) days which are bad weather.

We know that weekly number of tourists is also a kind of time series data, and it has a continuity trend，which means that the tourist number of adjacent weeks have some correlation. So the inputs of the model should also include several weeks that before the predicted week, they are Y_{t-1}, Y_{t-2} *etc*. On the other hand, Y_t is not a complete and continuous time series and consist of five time periods, every time period is continuous. We let the front four parts as the training set, the fifth part, the 2012~2013 as the test set. So we need to analysis separately the correlation of front four time series. The results are that front three parts of sequence data exist two order partial autocorrelation and the fourth part exist three order partial autocorrelation, which means the inputs of the model of front three time series are Y_{t-1}, Y_{t-2}, and the fourth part are Y_{t-1}, Y_{t-2}, Y_{t-3}. But the whole model needs the same lagged variable inputs, so we built the two order (P2) and three order (P3) partial autocorrelation lagged variable inputs two models. Therefore, the inputs of P2 model is a matrix which has 100 lines and 4 columns, and P3 model inputs has 95 lines and 5 columns, the function of two models are

P2 $Y_t = F(Y_{t-1}, Y_{t-2}, H_i, W_i)$ P3 $Y_t = F(Y_{t-1}, Y_{t-2}, Y_{t-3}, H_i, W_i)$

Finally, we used model with better results to build the combination model.

4.3. P2 and P3 Model Comparison Analysis

Through simulation we obtained the compared results and forecasting value of P2 and P3 model of two methods SVR and BPNN, as shown in Table 2 and Figure 2. Overall it can be seen that the SVR method is slightly better than BPNN, this may be because of SVR is more suitable for small sample data, and P2 model is also outperform P3 model a little. The goodness-of-fit (R2) of four models training set are all over 0.8, it shows that the input variables can explain weekly tourist number in a better way. The Mean Absolute Error (MAE) and Maximum Absolute error (MaxAE) of four models are not much different, and Mean Absolute Percentage Error (MAPE) of P2 model is slightly overmatch P3 model. However, we found that all the Maximum Absolute Percentage Error (MaxPE) are over 40% and locate this week (2013.1.8 ~2013.1.14) which at 9 point of Figure 2, and further found the reason is that although the biggest forecasting errors of four model in this week was 7217 persons (BP-P3 model), it is not the maximum error of each single model, and the actual tourist number in this week was so low that had only 9310 persons because of the worse weather, the error rate reach 77.52%. On the contrary, the maximum forecasting error of BP-P3 model is 9377 persons and it locate 19 point of Figure 2 (2013.3.19~2013.3.25), but the error rate is just 16.3%.

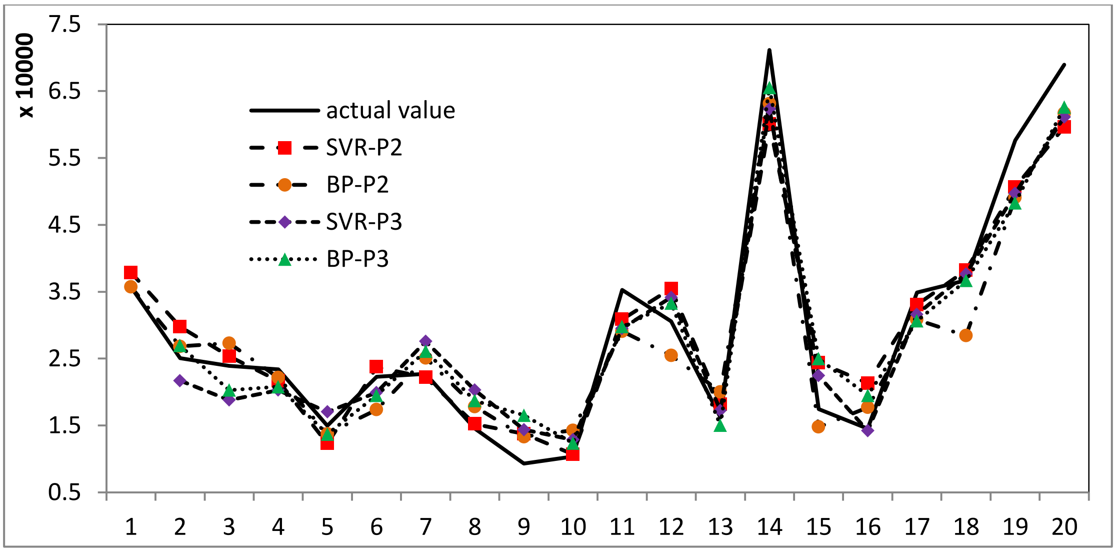

Figure 2. The Forecasting Value of Four Models

Table 2. P2 and P3 Model Results Comparison

Model	Goodness of Fit	MAE	MaxAE	MAPE（%）	MaxPE（%）
SVR-P2	0.888	3788	11067	14.88	47.73
SVR-P3	0.867	4143	8828	17.21	54.29
BP- P2	0.845	4165	8576	16.83	43.22
BP- P3	0.816	4018	9377	18.39	77.52

4.4. Comparative Analysis of Combination Model

According to the comparative analysis of four single models above, we built the SVR-BP combination model by two P2 models, and by using the formula (4), we got the weights of SVR-P2 $w_1 = 0.58$ and BP-P2 $w_2 = 0.42$, so the three combination models are

LCM $z_t = 0.58x_t^1 + 0.42x_t^2$

GEOM-WTD $z_t = [x_t^1]^{0.58}[x_t^2]^{0.42}$

HARM $z_t = \frac{x_t^1 x_t^2}{0.58x_t^1+0.42x_t^2}$

Here, z_t is the final forecasting value, x_t^1 and x_t^2 are the forecasting values of SVR-P2 and BP-P2 respectively.

Table 3 shows the comparison of single and combination model, and Figure 3 is the absolute forecasting error rate of SVR - P2, BP - P2 and three kinds of combination models. Firstly, by combining the MaxPE of Table 3, we can find that some error rates of the combination model are between two single models (such as point 1 of Figure 3). To wit, if the error rate of combination model is less than one single model and it must be greater than the other single model, we can also find it from the MaxPE of Table 3, that's because both the forecasting numbers of two single models in these weeks is less than or more than the actual tourist number. Secondly, in other weeks, the reason of the error rate of combination model is less than the two single models of weeks (point 12 of Figure 3) is the actual value between the two single model forecasting values. Finally, there is an exception week is the 15 point of LCM, the error rate is slightly greater than the BP-P2, this is because the forecasting value of BP-P2 in this week is close to the actual value and the forecasting value of SVP-P2 deviate from the actual value to a great extent. On the other hand, From MAE and MAPE of Table 3, we can make out three combination models' forecasting effects are similar, especially the MAPE is almost the same, and both MAE and MAPE of all the combination models are obviously better than any single model. In short, through Figure 3 and Table 3, it can be seen that forecasting accuracy and robustness of combination model is much better than the single model, so the GFW used in combination model, helps to improve forecasting accuracy.

Table 3. The Comparison of Single and Combination Model

Model	MAE	MaxAE	MAPE（%）	MaxPE（%）
SVR-P2	3788	11067	14.88	47.73
BP-P2	4165	8576	16.83	43.22
LCM	3415	9788	13.60	45.83
GEOM-WTD	3379	9806	13.34	45.82
HARM	3508	9337	13.66	45.08

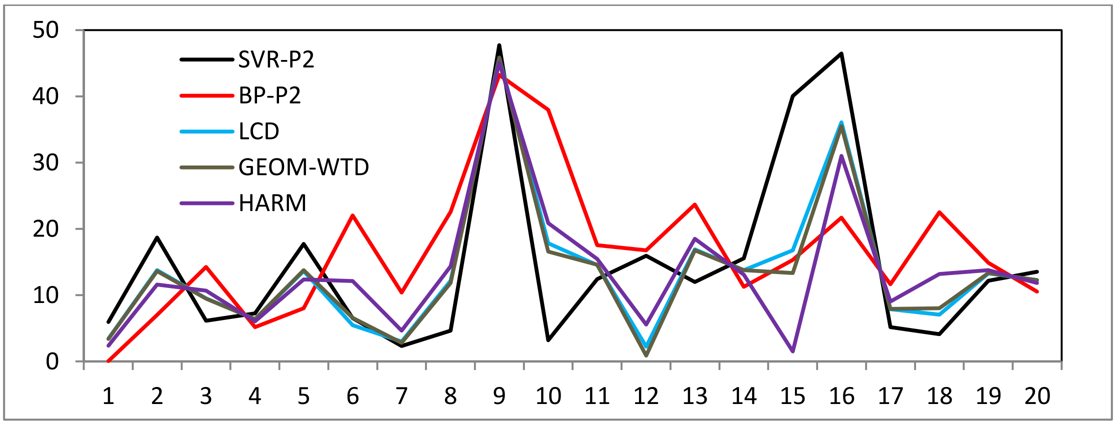

Figure 3. The Absolute Forecasting Error Rate of Five Kinds of Model (%)

4.5. Comparative Analysis of Three Kinds of Weight

As well as GFW, we use the formulas of VARW and MSEW to get the weights of SVR-P2 and BP-P2 respectively,

$$\text{VARW} \quad w_1 = 0.46,\ w_2 = 0.54$$
$$\text{MSEW} \quad w_1 = 0.47,\ w_2 = 0.53$$

it is easy to find both the weights of SVR-P2 are small, but GFW on the contrary, indicates the forecasting error of SVR-P2 has a large fluctuation, from its maximum absolute error and maximum error rate is larger than the BP - P2. It also can be proved by that the MaxAE and MaxPE of SVR-P2 are greater than BP-P2. We got the forecasting results according to two weights and three kinds of combination models, they are shown as Table 4, 5, 6. There is almost no difference between three combination models which use three weights GFW, VARW and MSEW, the MAE and MAPE of the two combination models LCM and GEOM-WTD which use GFW are a little small than VARW and MSEW, but the result of HARM is opposite. Through these comparison results, it is shown that GFW can be used in combination model as well as VARW and MSEW, GFW is another choice of combination model weight.

Table 4. The LCM Forecasting Results of Three Weights

Weight	MAE	MaxAE	MAPE（%）	MaxPE（%）
GFW	3415	9788	13.60	45.83
VARW	3460	9423	13.78	45.29
MSEW	3432	9514	13.67	45.43

Table 5. The GEOM-WTD Forecasting Results of Three Weights

Weight	MAE	MaxAE	MAPE（%）	MaxPE（%）
GFW	3379	9806	13.34	45.82
VARW	3465	9441	13.65	45.28
MSEW	3437	9533	13.55	45.41

Table 6. The HARM Forecasting Results of Three Weights

Weight	MAE	MaxAE	MAPE（%）	MaxPE（%）
GFW	3508	9337	13.66	45.08
VARW	3395	9703	13.26	45.62
MSEW	3424	9613	13.36	45.48

5. Conclusion

Global tourism wave makes tourism demand forecasting is very important. Based on Huangshan Scenic Area as the background in this paper, we analyzed the monthly statistics data of tourists in the past few years and found that every November to March of next year is the tourism off-season. Tourist number in off-season has strong nonlinear characteristic, a single model is difficult to achieve accurate prediction. So several kinds of single model is established by us, in this process, we used the dynamic virtual variables to describe the objective factors which influence weekly tourist number, and then put forward and used the GFW to build three combination models, The simulation results indicated that the GFW combination model is more effective and more robust than any single model. The simulation results also found that GFW is suitable combination model according to compared GFW with other combination weights. In short, the GFW not only provides a new perspective for the tourism demand forecasting but also for other fields demand forecasting in the choice of combination model weight. The other goal of this paper has been achieved, that is the accurate prediction of weekly tourist number can provide scientific and effective reference for decision management of scenic area tourism off-season.

Follow-up research focus on two aspects, one is to further improve the forecasting accuracy, especially some large forecasting error weeks, such as the week of 9 point in Figure 2, the ways we think that include fully using and gaining more scenic area data, finding more influence factors which relate the weekly tourist number, and modifying algorithm of SVR and BP is also important. The other aspect is that this paper was mainly focused on weekly tourist number forecasting, but more shorter-term forecasting as the daily forecasting is also important to the scenic area, the next step is primarily seek for this topic.

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