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ENHANCED PREDICTION ACCURACY OF GREY FORECASTING MODEL: A CASE BY TOURISM INDUSTRY IN VIETNAM

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Abstract: grey forecasting based on the grey system theory is a diverse forecasting model and has been successfully applied in various fields. In recent years, many scholars have proposed new procedures or new models with different ways to improve the prediction accuracy of grey forecasting for fluctuating data sets. However, the prediction accuracy of the existing grey forecasting models may not be always satisfactory in different scenarios. For example, the data not only consist of trend, seasons but highly fluctuate with lots of noise as well. To overcome this drawback, this paper proposed two effective combined grey models, namely Fourier grey Model (1, 1) (abbreviated as F-GM (1, 1)) and Fourier Nonlinear grey Bernoulli Model (abbreviated as F-NGBM (1, 1). Two proposed models were built by using Fourier series to modify their residual values. To verify their performance and effectiveness, these proposed models were used to forecast the international tourism demand in Vietnam from Jan. 2006 to Mar. 2016. The empirical results demonstrated that the accuracy of both GM (1, 1) and NGBM (1, 1) forecasting models after using Fourier series to revise their residual error provided more accuracy than original ones in terms of in-sample and out-of-sample cases. Further more, this paper also indicated that the F-GM (1, 1) is the better model than other forecasting models in forecasting the international tourist arrival to Vietnam with average MAPE of in-sample and out-of-sample of 0.013% and 5.19 %, respectively.

Keywords: grey system theory, GM (1, 1), NGBM (1, 1), Fourier series, International tourism demand

1 Introduction

Grey system theory established during the 1980s by Deng [12] is a quantitative method dealing with grey systems that are characterized by both partially known and partially unknown information [13-16]. The main purpose of the grey system theory focuses on the relationship between the analysis model constructions, for circumstances such as: uncertainty, multi-data input, discrete data, and insufficient data through prediction and decision- making. Nowadays, the field of grey system can be summarized in six main parts, namely grey generating, grey relational analysis, grey model, grey prediction, grey decision making and grey control. With its advantages and various approaches, grey system theory has been widely used in industry, social systems, ecological systems, economy, geography, traffic, management, agriculture, environment, education, etc.

Grey prediction models are one of most important parts of grey system theory. They have been popularized in the time series prediction due to their simplicity and ability to characterize an unknown system with high accuracy, using as little as four data points [17, 18]. During the past two decades, the grey prediction models have been successfully applied to various fields,

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such as tourism [19], energy [20, 21], financial and economics [22-24], IC industry [25], marine and sea port industry [26-28].

Although grey models have been successfully adopted in various fields and they have provided us with promising results, in some cases, the classical GM (1, 1) model exhibits certain limitations that directly affect the model applicability as well as prediction accuracy. Therefore, it is necessary to improve the prediction performance as well as to overcome the restriction existing in the traditional grey model (abbreviated as GM (1, 1)) and Nonlinear grey Bernoulli Model (abbreviated as NGBM (1, 1). To upgrade the prediction accuracy of GM (1, 1) and NGBM (1, 1), this paper used Fourier series to modify the residual errors in GM (1, 1) and NGBM (1, 1) models, and these models are finally compared based on their accuracy and the better one is selected to forecast the inbound tourism demand in Vietnam. The remaining of this paper was organized as follows. In section 2, the concept of classical GM (1, 1) and NGBM (1, 1), and Fourier Residual Modification of these models were presented. Based on the fundamental functions of these models, the empirical results were shown in section 3. Finally, section 4 summarized the findings.

2 Modeling and Methodology

2.1 Classical GM (1, 1) model

GM (1, 1) is the basic model of grey forecasting modeling, a first order differential model with one input variable which has been successfully applied in many different researches. It is obtained as the following procedure.

Step1: Let raw matrix $X^{(0)}$ stands for the *non-negative* original historical time series data

$$X^{(0)} = \left\{x^{(0)}(t_i)\right\},\ i = 1,2,\ldots,n \tag{1.1}$$

Where $x^{(0)}(t_i)$ is the value at time t_i, and n is the total number of modeling data

Step 2: Construct $X^{(1)}$ by one time accumulated generating operation (1-AGO), which is

$$X^{(1)} = \left\{x^{(1)}(t_i)\right\},\ i = 1,2,\ldots,n \tag{1.2}$$

Where $x^{1}(t_k) = \sum_{i=1}^{k} x^{(0)}(t_i), k = 1,2,\ldots,n$ (1.3)

Step 3: $X^{(1)}$ is a monotonic increasing sequence which is modeled by the first order linear differential equation (1.4)

$$\frac{dX^{(1)}}{dt} + aX^{(1)} = b \tag{1.4}$$

Where the parameter "*a*" is the developing coefficient and "*b*" is the grey input.

Step 4: In order to estimate the parameter "*a*" and "*b*", Eq. (1.4) is approximated as

$$\frac{\Delta X^{(1)}(t_k)}{dt_k} + aX^{(1)}(t_k) = b \tag{1.5}$$

Where $\Delta X^{(1)}(t_k) = x^{(1)}(t_k) - x^{(1)}(t_{k-1}) = x^{(0)}(t_k)$ (1.6)

$$\Delta t_k = t_k - t_{k-1} \quad (1.7)$$

If the sampling time interval is units, then let $\Delta t_k = 1$, using

$$z^{(1)}(t_k) = px^{(1)}(t_k) + (1-p)x^{(1)}(t_{k-1}),\ k = 2,3,..,n \quad (1.8)$$

to replace $X^{(1)}(t_k)$ in Eq. (1.5), we obtain

$$x^{(0)}(t_k) + az^{(1)}(t_k) = b,\ k = 2,3,\ldots,n \quad (1.9)$$

Where $z^{(1)}(t_k)$ in Eq. (1.8) is termed background value, and *p* is production coefficient of the background value in the range of (0, 1), which is traditionally set to 0.5.

Step 5: From Eq. (1.9), the value of parameter "*a*" and "*b*" can be estimated using least square method. That is $\begin{bmatrix} a \\ b \end{bmatrix} = (B^T B)^{-1} B^T Y_n$ (1.10)

where

$$B = \begin{bmatrix} -z^{(1)}(t_2) & 1 \\ -z^{(1)}(t_3) & 1 \\ \cdots\cdots & \cdots\cdots \\ -z^{(1)}(t_n) & 1 \end{bmatrix} \quad (1.11)$$

and $Y_n = \left[x^{(0)}(t_2), x^{(0)}(t_3), \ldots, x^{(0)}(t_n))\right]^T$ (1.12)

Step 6: The solution of Eq. (1.4) can be obtained after the parameter "*a*" and "*b*" have been estimated. That is

$$\hat{x}^{(1)}(t_k) = \left[\left(x^{(0)}(t_1) - \frac{b}{a}\right)e^{-a(t_k - t_1)} + \frac{b}{a}\right], k = 1,2,3,\ldots \quad (1.13)$$

Step 7: Applying inverse accumulated generating operation (IAGO) to $\hat{x}^{(1)}(t_k)$, the predicted datum of $x^{(0)}(t_k)$ can be estimated as

$$\begin{cases} \hat{x}^{(0)}(t_1) = x^{(0)}(t_1) & (1.14) \\ \hat{x}^{(0)}(t_k) = \hat{x}^{(1)}(t_k) - \hat{x}^{(1)}(t_{k-1}) & (1.15) \end{cases},\ k = 2,3,\ldots$$

2.2 Nonlinear-grey Bernoulli model "NGBM (1, 1)"

The procedures of deriving NGBM are as follows:

Step1: Let raw matrix $X^{(0)}$ stands for the *non-negative* original historical time series data

$$X^{(0)} = \left\{x^{(0)}(t_i)\right\},\ i = 1,2,\ldots,n \quad (2.1)$$

Where $x^{(0)}(t_i)$ corresponds to the system output at time t_i, and n is the total number of modeling data.

Step 2: Construct $X^{(1)}$ by one time accumulated generating operation (1-AGO), which is

$$X^{(1)} = \{x^{(1)}(t_i)\},\ i = 1,2,\ldots,n \tag{2.2}$$

where
$$x^1(t_k) = \sum_{i=1}^{k} x^{(0)}(t_i), k = 1,2,\ldots,n \tag{2.3}$$

Step 3: $X^{(1)}$ is a monotonic increasing sequence which is modeled by the Bernoulli differential equation

$$\frac{dX^{(1)}}{dt} + aX^{(1)} = b\left[X^{(1)}\right]^r \tag{2.4}$$

Where the parameter "*a*" is called the developing coefficient and "*b*" is the named the grey input and "*r*" is any real number excluding *r* = 1.

Step 4: In order to estimate the parameter "*a*" and "*b*", Eq. (2.4) is approximated as

$$\frac{\Delta X^{(1)}(t_k)}{dt_k} + aX^{(1)}(t_k) = b\left[X^{(1)}(t_k)\right]^r \tag{2.5}$$

where
$$\Delta X^{(1)}(t_k) = x^{(1)}(t_k) - x^{(1)}(t_{k-1}) = x^{(0)}(t_k) \tag{2.6}$$

$$\Delta t_k = t_k - t_{k-1} \tag{2.7}$$

If the sampling time interval is units, then let $\Delta t_k = 1$, using

$$z^{(1)}(t_k) = px^{(1)}(t_k) + (1-p)x^{(1)}(t_{k-1}),\ k = 2,3,..,n \tag{2.8}$$

To replace $X^{(1)}(t_k)$ in Eq. (2.5), we obtain

$$x^{(0)}(t_k) + az^{(1)}(t_k) = b\left[z^{(1)}(t_k)\right]^r,\ k = 2,3,\ldots,n \tag{2.9}$$

Where $z^{(1)}(t_k)$ in Eq. (2.8) is termed background value, and p is production coefficient of the background value in the range of (0, 1), which is traditionally set to 0.5.

Step 5: From Eq. (2.9), the value of parameter "*a*" and "*b*" can be estimated using least square method. That is

$$\begin{bmatrix} a \\ b \end{bmatrix} = (B^T B)^{-1} B^T Y_n \tag{2.10}$$

Where
$$B = \begin{bmatrix} -z^{(1)}(t_2) & (z^{(1)}(t_2))^r \\ -z^{(1)}(t_3) & (z^{(1)}(t_3))^r \\ \cdots & \cdots \\ -z^{(1)}(t_n) & (z^{(1)}(t_n))^r \end{bmatrix} \tag{2.11}$$

And
$$Y_n = \left[x^{(0)}(t_2), x^{(0)}(t_3), \ldots, x^{(0)}(t_n))\right]^T \tag{2.12}$$

Step 6: The solution of Eq. (2.4) can be obtained after the parameter "*a*" and "*b*" have been estimated. That is

$$\hat{x}^{(1)}(t_k)=\left[\left(x^{(0)}(t_1)^{(1-r)}-\frac{b}{a}\right)e^{-a(1-r)(t_k-t_1)}+\frac{b}{a}\right]^{\frac{1}{1-r}},\ r\neq 1,\ k=1,2,3,\ldots \tag{2.13}$$

Step 7: Applying inverse accumulated generating operation (IAGO) to $\hat{x}^{(1)}(t_k)$, the predicted datum of $x^{(0)}(t_k)$ can be estimated as

$$\begin{cases}\hat{x}^{(0)}(t_1)=x^{(0)}(t_1) & (2.14)\\ \hat{x}^{(0)}(t_k)=\hat{x}^{(1)}(t_k)-\hat{x}^{(1)}(t_{k-1}) & (2.15)\end{cases},\ k=2,3,\ldots$$

2.3 Fourier Residual Modification

In order to improve the accuracy of forecasting models, the Fourier series has been widely and successfully applied in modifying the residuals in grey forecasting model GM (1,1) which reduces the values of MAPE. So, this good methodology should also be considered in this case. The overall procedure to obtain the modified model is as the followings:

Let x is the original series of *n* entries and v is the predicted series (obtained from GM (1, 1) or NGBM (1, 1). Based on the predicted series v, a residual series named ε is defined as:

$$\varepsilon=\{\varepsilon(k)\},\ k=2,3,..n \tag{2.16}$$

where $\varepsilon(k)=x(k)-v(k)$, $k=2,3,..n$ (2.17)

Expressed in Fourier series, $\varepsilon(k)$ is rewritten as

$$\hat{\varepsilon}(k)=\frac{1}{2}a_{(0)}+\sum_{i=1}^{Z}\left[a_i\cos\left(\frac{2\pi i}{n-1}(k)\right)+b_i\sin\left(\frac{2\pi i}{n-1}(k)\right)\right],k=1,2,3,.,n \tag{2.18}$$

where $Z=(\frac{n-1}{2})-1$ is the minimum deployment frequency of Fourier series [19] and only takes integer number. Therefore, the residual series is rewritten as

$$\varepsilon=PC \tag{2.19}$$

where

$$P=\begin{bmatrix}\frac{1}{2} & \cos\left(\frac{2\pi\times 1}{n-1}\times 2\right)\sin\left(\frac{2\pi\times 1}{n-1}\times 2\right) & \ldots & \cos\left(\frac{2\pi\times Z}{n-1}\times 2\right)\sin\left(\frac{2\pi\times Z}{n-1}\times 2\right)\\ \frac{1}{2} & \cos\left(\frac{2\pi\times 1}{n-1}\times 3\right)\sin\left(\frac{2\pi\times 1}{n-1}\times 3\right) & \ldots & \cos\left(\frac{2\pi\times Z}{n-1}\times 3\right)\sin\left(\frac{2\pi\times Z}{n-1}\times 3\right)\\ \ldots & \ldots & \ldots & \ldots\\ \frac{1}{2} & \cos\left(\frac{2\pi\times 1}{n-1}\times n\right)\sin\left(\frac{2\pi\times 1}{n-1}\times n\right) & \ldots. & \cos\left(\frac{2\pi\times Z}{n-1}\times n\right)\sin\left(\frac{2\pi\times Z}{n-1}\times n\right)\end{bmatrix} \tag{2.20}$$

and $C=[a_0,a_1,b_1,a_2,b_2,\ldots,a_Z,b_Z]$ (2.21)

The parameter a_0, a_1, b_1, a_2, b_2… a_Z, b_Z are obtained by using the ordinary least squares method (OLS) which results in the equation of

$$C = \left(P^T P\right)^{-1} P^T \varepsilon^T \tag{2.22}$$

Once the parameters are calculated, the modified residual series is then achieved based on the following expression

$$\hat{\varepsilon}(k) = \frac{1}{2} a_{(0)} + \sum_{i=1}^{Z} \left[a_i \cos\left(\frac{2\pi i}{n-1}(k) \right) + b_i \sin\left(\frac{2\pi i}{n-1}(k) \right) \right] \tag{2.23}$$

From the predicted series V and $\hat{\varepsilon}$, the Fourier modified series $\hat{v}$ of series v is determined by

$$\hat{v} = \left\{ \hat{v}_1, \hat{v}_2, \hat{v}_3, \ldots, \hat{v}_k, \ldots, \hat{v}_n \right\} \tag{2.24}$$

where

$$\hat{v} = \begin{cases} \hat{v}_1 = v_1 \\ \hat{v}_k = v_k + \hat{\varepsilon}_k \quad (k = 2,3,\ldots,n) \end{cases} \tag{2.25}$$

2.4 Evaluative precision of forecasting models

In order to evaluate the forecast capability of the model, Means Absolute Percentage Error (MAPE) index was used to evaluate the performance and reliability of forecasting technique [29]. It is expressed as follows:

$$MAPE = \frac{1}{n} \sum_{k=2}^{n} \left| \frac{x^{(0)}(k) - \hat{x}^{(0)}(k)}{x^{(0)}(k)} \right| \times 100\% \tag{2.26}$$

where $x^{(0)}(k)$ and $\hat{x}^{(0)}(k)$ are actual and forecasting values in time period *k*, respectively, and n is the total number of predictions. Lewis [30] interprets the MAPE results as a method to judge the accuracy of forecasts, where more than 50% is an inaccurate forecast, 20%-50% is a reasonable forecast, 10%-20% is a good forecast, and less than 10% is an excellent forecast.

3 Data and Empirical Results

Tourism is one of the world's most important and fastest growing economic sectors, generating quality jobs and substantial wealth for economies around the globe. According to the data collected from World Travel & Tourism Council (WTTC) [1], tourism directly and indirectly contributes US $7 trillion to the global economy (9.5 percent of global GDP), not only outpacing the wider economy, but also growing faster than other significant sectors such as financial and business services, transport and manufacturing. It also supports directly nearly 266 million jobs - 1 in 11 of all jobs in the world. The sustained demand for tourism, together with its ability to generate high levels of employment continues to prove the importance and value of the sector as a tool for economic development and job creation.

In Vietnam, tourism industry has witnessed significant development in the last 20 years. According to Vietnam National Administration of Tourism (VNAT) [2], there were only about 25,000 inbound arrivals in 1990, but in 2013, more than 7 million arrivals were recorded in total.

The contribution of tourism industry to GDP was VND 311,117 billion (9.6% of total GDP) in 2013, along with more than 4,071,500 directly and indirectly jobs created, equivalent to 7.9 of total employment [1]. These figures indicate that tourism is an important industry in Vietnam. In order for the authorities to make proper plans for the development of the tourism industry, it is critical to forecast the tourism demand accurately.

However, "tourism demand" is a vague concept which is not easily measured by a certain standard. It was suggested that inbound tourism demand be measured in terms of the number of tourist arrivals, tourist expenditure (tourist receipts) or the number of nights tourists spent [3, 4]. However, due to their complexities in collecting the data of tourist expenditure as well as the number of nights tourists spent, the number of tourist arrivals has been widely used as an appropriate indicator of inbound tourism demand in many researches [5-11]. Therefore, in this study, the monthly arrivals of international tourists to Vietnam are used to denote the inbound tourism demand in Vietnam.

3.1 Data collection

The historical data of the inbound tourism demand in Vietnam are obtained from the monthly statistical data published on the website of Vietnam National Administration of Tourism from January 2006 to March 2015. The inbound tourism demand is referred to the number of monthly arrivals of international tourists to Vietnam. There are totally 122 observations available as stated in Table 1 [2]. Because we want to know where the in-sample fit predicts the out-of-sample forecasting performance of the model, we separate our data into two parts: the in-sample data set (Jan. 2006 - Dec. 2015) and out-of-data set (Jan., Feb., and Mar. of 2016).

Table 1. Monthly arrivals of international tourists to Vietnam

(Unit: Tourist arrivals)

Month	**Year**										
	2006	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**
Jan	349000	369017	420000	370000	416249	506424	630000	651812	776174	700692	**805072**
Feb	336000	380000	441000	342913	446323	542671	681849	570476	842026	756000	**833098**
Mar	307081	362336	424954	303489	473509	475733	561877	587366	709725	617895	**820480**
Apr	309000	350878	411000	305430	432608	460000	620000	613919	745980	690440	
May	282500	304848	382000	292842	350982	480886	456749	558751	674204	576868	
Jun	274070	335000	210333	279150	375707	446966	417429	567291	539776	529445	
Jul	303000	343000	330000	277998	410000	460000	466000	658325	564736	593566	
Aug	288148	356000	339000	314915	427935	490000	525292	676719	618588	664985	
Sep	277000	358000	315000	294000	383463	286618	460238	614827	590881	626324	
Oct	276000	332762	296742	227859	440071	518477	495576	628695	559002	649099	
Nov	305577	340000	279904	387871	428295	611864	655701	731034	608617	732740	
Dec	324625	354000	375995	376400	449570	593408	614673	722349	657304	760798	

Source: Website of Vietnam National Administration of Tourism [2]

To solve the GM (1, 1) and NGBM (1, 1) model, and modified model with Fourier residual modification, Microsoft Excel is used in this study. Excel offers two useful functions, namely Mmult (array 1, array 2) to return the matrix product of two relevant arrays and Minverse (array) to return the inverse matrix. These two functions are of great help to find out the values of parameters in GM (1, 1), NGBM (1, 1) and Fourier residual modification.

To find out the parameters in GM (1, 1) and NGBM (1, 1) model as well as modified model of their models, Microsoft Excel is used. Besides a basic function in excel, Excel software also offers two useful functions named Mmult (array 1, array 2) to return the matrix product of two relevant arrays and Minverse (array) to return the inverse matrix. These two functions are of great help to find out the values of parameters in GM (1, 1), NGBM (1, 1) and Fourier residual modification.

3.2 GM (1, 1) model for the international tourist arrivals to Vietnam

From historical data in Table 1 and based on the algorithm expressed in section 2.1, the coefficient parameters *a* and *b* in GM (1, 1) for the inbound tourism in Vietnam are calculated as $a = -0.00805$, $b = 279746.5047$, and the GM (1, 1) model for inbound tourism in Vietnam is then

$$\hat{x}^{(1)}(k) = 35097803.31 \times e^{0.00805(k-1)} - 34748803.31$$

The evaluation indexes of GM (1, 1) model are also listed in Table 2. The residual series of GM (1, 1) is modified with Fourier series as illustrated in section 3.3

3.3 Modified GM (1, 1) model by Fourier series "F-GM (1, 1) model"

The residual series of GM (1, 1) obtained in section 3.2 is now modified with Fourier series as per the algorithm stated in section 2.3. With this modified series, the forecasted values of the international arrivals to Vietnam based on Fourier residual modified GM (1, 1) model F-GM (1, 1) are calculated based on the equations (2.23) and (2.24). The evaluation index of F-GM (1, 1) is summarized in Table 2.

3.4 NGBM (1, 1) model for the international tourism arrivals to Vietnam

Using the data in Table 1 and based on the mathematical algorithm expressed in section 2.2, the coefficient parameters *a*, *b* and the power of *r* in NGBM (1, 1) for the international arrivals to Vietnam are calculated as $a = -0.0086$, $b = 524990.85934$, and $r = -0.041$, and the NGBM (1, 1) model for the international visitors to Vietnam is then

$$\hat{x}^{(1)}(k) = \left[(61206321.11)e^{0.0086(1+0.041)(k-1)} - 60616388.23\right]^{\frac{1}{1+0.041}}$$

The evaluation index of NGBM (1, 1) model is also listed in Table 2. The residual series of NGBM (1, 1) is modified with Fourier series as illustrated in section 3.5

3.5 Modified NGBM (1, 1) model by Fourier series "F-NGBM (1, 1) model"

The residual series of NGBM (1, 1) obtained in section 3.4 is now modified with Fourier series as per the algorithm stated in section 2.3. With this modified series, the forecasted values of the international arrivals to Vietnam based on Fourier residual modified NGBM (1, 1) model are calculated based on the equations (2.23) and (2.24). The evaluation index of F-NGBM (1, 1) is summarized in Table 2.

Table 2. Summary of evaluation indexes of model accuracy

Models	**MAPE (%)**			
	In sample	**Performance**	**Out -of -sample**	**Performance**
GM (1,1)	12.84	Good	9.04	Excellent
NGBM(1, 1)	12.68	Good	8.09	Excellent
FGM (1, 1)	**0.013**	**Excellent**	**5.19**	**Excellent**
FNGBM (1 ,1)	**0.014**	**Excellent**	**6.90**	**Excellent**

Table 2 shows the evaluation indexes of each model of GM (1, 1), F-GM (1, 1), NGBM (1, 1) and F-NGBM (1, 1) with its performance in forecasting the international tourist arrivals to Vietnam. Both GM (1, 1) and NGBM (1, 1) forecasting models after using Fourier series revised their residual error provided more accuracy than original ones in terms of in-sample and out-of-sample cases. Furthermore, the results also indicate that the forecast performance of F-GM (1, 1) is the better model compared with to other models with the average MAPE for in-sample and out-of-sample of 0.013 and 5.19 %, respectively. Therefore, F-GM (1, 1) is strongly suggested in this situation. The forecasted values of the international tourism demand from Apr. of 2016 to Jun. 2016 in Vietnam are illustrated in Table 3.

Table 3. Forecasted value of international visitors from Apr. 2016 –Jun. 2016 by F-GM (1, 1)

Time	**Number of international tourist arrival**
Apr. 2016	749,404
May. 2016	744,748
Jun. 2016	777,483

Source: Author's estimate

Table 3 shows that the demand of international visitors in Jun. 2016 will be 777,483 arrivals increasing 30.9% compared with Jun. 2015. With the rapid growth of the demand, providing enough facilities (accommodations, transportations), having different well-organized events, providing enough skillful human resources and upgrading the local services are of extreme importance. Social evils, poor behaviours and corrupt customs need to be removed totally and replaced by the warm, kindhearted, helpful and constructive actions which will gradually build up a good image of Vietnam worldwide. In recent years, people more and more concern about the living environment (climate change, air/water pollution, etc.) and eco-tourism is of the trend. Therefore, the authorities of Vietnam tourism industry should make good plans in protecting the natural forests, waterfalls, rivers, beaches, etc. to turn these into green regions for the sake of stable development of Vietnam tourism industry.

4 Conclusions

The prediction performances in Table 2 clearly show that the modified GM (1, 1) and NGBM (1, 1) models by Fourier series gain much higher accuracy than traditional models. Both F-GM (1, 1) and F-NGBM (1, 1) are good models, but F-GM (1, 1) is the better model with lowest MAPE. Therefore, F-GM (1, 1) is strongly suggested to forecast the inbound tourism demand in Vietnam. Highly precise forecasting result will help the policy makers and related organizations in the tourism industry of Vietnam to arrange enough facilities and human resources for high seasons and also make regular maintenance and training in low seasons just for a stable growth of the industry.

Fourier residual modification has been successfully applied to the fundamental form of GM (1, 1) and the NGBM (1, 1) models to enhance their accuracy; therefore, it is thought to work well with other forecasting models as well. Further researches on this application should be conducted before the suggestion is firmly verified.

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