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Accurately Forecasting Model for the Stochastic Volatility Data in Tourism Demand

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Abstract

This study attempts to enhance the effectiveness of stochastic volatility data. This work presents an empirical case involving the forecasting of tourism demand to demonstrate the efficacy of the accuracy forecasting model. Work combining the grey forecasting model (GM) and Fourier residual modification model to refine the forecasting effectiveness for the stochastic volatility data, which can estimate fluctuations in historical time series. This study makes the following contributions: 1) combining the grey forecasting and Fourier residual modification models to refine the forecasting effectiveness for the stochastic volatility data, 2) providing an effective method for forecasting the number of international visitors to Taiwan, 3) improving the accuracy of short-term forecasting in cases involving sample data with significant fluctuations.

Keywords: Fourier Residual Modification Grey Forecasting Model (FGM), Grey Forecasting Model (GM), Stochastic Volatility, Tourism Demand

1. Introduction

International tourism has increased rapidly during the past two decades, and has strong implications for decision-makers in government and business. Tourism demand forecasting has been a key issue in national tourism industry development and has attracted increased attention during the past decade. In relation to government agencies, accurate forecasts of tourism flows can assist in forecasting in various areas relevant to policy-making, including price regulation, environmental quality control, and infrastructure provision. For tourism businesses attempting maximizing their profits, accurate forecasts can avoid the financial costs associated with excess capacity and the opportunity costs associated with unfilled demand. Accurate forecasting of tourism demand is important in tourism planning by both the public and business sectors owing to the perishable nature of tourism products. This shows that the forecasting methodology is most relevant and most easily applicable in management, and that demand forecasting is the key objective of management [1-3]. Short-term trends and fluctuating demand can significantly influence decision-making regarding purchasing, inventory and logistics [4]. Accurate forecasting enables companies to control changeable markets, reduce inventory costs, improve customer service and enhance their competitiveness.

Along with the development of forecasting techniques, numerous quantitative methods have been applied to forecast tourism demand. Before the 1990s, traditional regression approaches dominated the tourism forecasting literature, but this situation changed after the mid-1990s as more researchers adopted modern econometric techniques, for example co-integration and error correction models, for modeling and forecasting tourism demand [5-7]. Additionally, previous studies have mainly focused on traditional econometric analysis, with the regression model [8-10], Time-series model [11-13], and an ARIMA model providing one example [11,14,15]. These models are highly effective for forecasting long-term tourism demand, but perform poorly in forecasting short-term and fluctuating data sets [16].

The original Fourier model was developed by Brigham [17] and this work extends the Fourier model developed by Hsu [18] and Lin & Lee [16] using the Fourier series model to enhance the forecasting accuracy. Fourier series can yield accurate estimates when the sample data are significantly fluctuating [19]. Moreover, Lee *et al*., [20] noted that some choice-based diffusion models suffer limitations in forecasting demand for new technologies because such models generally depend on historical sales data or adopter data, and thus it is difficult to explain the diffusion of newly introduced technology based on a limited number of data observations is difficult. Regarding the assessment of forecasts of tourism demand, most studies have focused on forecasting long-term tourism demand, and the problem of accurately estimating demand when the sample data is highly variable has been largely ignored. In practice, changes in tourism demand are especially concerning to tourism businesses, particularly in relation to short-term predictions, because in an environment as competitive as the tourism industry, business strategies must be require frequent adjustment in response to dynamic changes in demand.

The need to accurately forecast international tourist arrivals is an essential strategic requirement in the tourism industry, especially for host countries that invest heavily in promotional strategies and are motivated by the economic benefits brought by inbound visitors. In this work, the forecasting method mainly considers short-term tourism demand. This study applied the Fourier residual modification Grey forecasting model (FGM (1, 1)) to forecast overseas passenger numbers. The grey forecasting theory focuses on the system model under uncertainty and information integrality, and can make forecasts based on small quantities of data. Tourism demand is further estimated using Fourier series. The FGM (1, 1) also provides an effective method of dealing predictably with fluctuating data sets. FGM (1, 1) thus provides a more effective forecasting method for solving the problem, namely the difficulty of estimating seasonal variation in international traveler numbers.

To summarize, this work develops a model that can improve the accuracy of forecasts of fluctuating tourism demand. This study applied the FGM (1, 1) approach to enhance the ability to forecast international tourist numbers to Taiwan. For this study, the rest of the paper is organized as follows. Section 2 introduces methodology. Section 3 describes data source and analyzes the empirical findings. Finally, the conclusions are presented in Section 4.

2. Methodology

2.1. Grey Forecasting Model (GM)

Grey system theory was developed by Deng [21]. The Grey forecasting model (GM) represents the core of Grey system theory which treats all variables as Grey quantities within a certain range. GM then gathers available data to determine the internal regularity. In managing the disorganized primitive data the model then examines the nature of the internal regularity. The model was devised by transforming the arranged sequence into a differential equation. The algorithm of GM (1, 1) is described as follows [22,23].

Assuming the raw data series to be $x_0 = \left(x_0(1),\ x_0(2),\ \cdots, x_0(n)\right)$ and GM involves the following steps:

Step 1. Creating a sequence of first-order accumulated generating operation (AGO)

x_1 is defined as x_0's first-order AGO sequence. That is,

$$x_1 = \left(x_1(1), x_1(2), \cdots, x_1(n)\right) = \left(\sum_{k=1}^{1} x_0(k), \sum_{k=1}^{2} x_0(k), \cdots, \sum_{k=1}^{n} x_0(k)\right) \tag{1}$$

Step 2. Defining parameters *a* and *b*

The first-order differential equation of GM (1, 1) model is

$$\frac{\mathrm{d}x_1(t)}{\mathrm{d}t} + ax_1(t) = b \tag{2}$$

where t denotes the independent variables in the system, a represents the developed coefficient, b is the Grey controlled variable, and a and b denote the model parameters requiring determination.

Step 3. Calculating the values of *a* and *b*

The values of a and b becomes by the ordinal least-square method (OLS) as

$$\begin{bmatrix} a \\ b \end{bmatrix} = \left(B^T B\right)^{-1} B^T Y_N \tag{3}$$

Furthermore, accumulated matrix B is

$$B = \begin{bmatrix} -0.5\left(x_1(1) + x_1(2)\right) & 1 \\ -0.5\left(x_1(2) + x_1(3)\right) & 1 \\ \cdots & \cdots \\ -0.5\left(x_1(n-1) + x_1(n)\right) & 1 \end{bmatrix} \tag{4}$$

Meanwhile, the constant vector YN is

$$Y_N = \left[x_0(2), x_0(3), \cdots, x_0(n)\right]^T \tag{5}$$

Step 4. Defining the prediction model

The approximate relationship can be obtained as follows by substituting a obtained in the differential equation, and solving raw data series.

$$\hat{x}_1(k+1) = \left(x_0(1) - \frac{a}{b}\right)e^{-ak} + \frac{b}{a} \tag{6}$$

Step 5. Obtaining the forecasting values based on IAGO

When $\hat{x}_1(1) = \hat{x}_0(1)$, the sequence one-order inverse-accumulated generating operation (IAGO) of reduction is obtained as $\hat{x}_0(k+1) = \hat{x}_1(k+1) - \hat{x}_1(k)$. Given $k = 1, 2, \cdots, n$ the sequence of reduction is obtained as follows:

$$\hat{x}_0 = \left[\hat{x}_0(2), \hat{x}_0(3), \cdots, \hat{x}_0(n)\right] \quad (7)$$

2.2. Fourier Residual Modification Grey Forecasting Model (FGM)

The application of physical system is subject to influence by causes its stability in the real world is not examined [24]. The grey model exhibited variable speed. The grey model develops with corresponding regular exponents during different periods and the forecasting accuracy is low. Therefore, GM may be unable to forecasting the instable variance. The Fourier residual modification Grey forecasting model (FGM (1, 1)) was proposed by Tan & Chang [24]. The method of GM residual correction adopted by AGO and the regularity of the origin series reduces the forecasting accuracy.

The accuracy of predictions made using GM (1, 1), this study applied the FGM (1, 1) approach to increase its prediction capabilities. **Figure 1** shows the process of FGM (1, 1), while the following illustration details the method used to establish the steps of FGM for the residual correction, which are detailed as follows [16,19,24].

Step 1. Obtain the residual series from operating GM (1, 1)

When, the sequence one-order inverse-accumulated generating operation (IAGO) of reduction is obtained in the form of Equation (7) and the residual series is defined as:

$$\varepsilon_0 = \left[\varepsilon_0(2), \varepsilon_0(3), \cdots, \varepsilon_0(n)\right]^T \quad (8)$$

where

$$\varepsilon_0(k) = x_0(k) - \hat{x}_0(k), \quad k = 2, \cdots, n. \quad (9)$$

Step 2. Define FGM (1, 1)

The continuous residual series can be modeled using Fourier series as:

$$\hat{\varepsilon}_0(k) = \frac{1}{2}a_0 + \sum_{i=1}^{k_a}\left(a_i \cos\left(\frac{i2\pi}{T_a}k\right) + b_i \sin\left(\frac{i2\pi}{T_a}k\right)\right) \quad (10)$$

In Equation (10), $k > 0$ a and T_a indicates the period of the residual series, $T_a = n - 1$. And the continuous residual series can be modeled by Fourier series as:

$$\hat{\varepsilon}_0(k) = \frac{1}{2}a_0 + \sum_{i=1}^{k_a}\left(a_i \cos\left(\frac{i2\pi}{T_a}k\right) + b_i \sin\left(\frac{i2\pi}{T_a}k\right)\right), \quad (11)$$

$$\text{for } k = 2, 3, \cdots, n.$$

Equation (11) can be estimated as:

$$P \cdot C = \varepsilon_0 \quad (12)$$

where

$$C = \left(P^T P\right)^{-1} P^T \varepsilon_0 \quad (13)$$

$$C = \left[a_0, a_1, b_1, a_2, b_2, \cdots, a_{ka}, b_{ka}\right]^T \quad (14)$$

in Equation (15), $k_a = \left[(n-1)/2\right] - 1$ and means the minimoum deployment frequency of Fourier series.

Step 3. Correct original prediction series

The modeled residual series can be modeled as:

$$\varepsilon_0 = \left[\varepsilon_0(2), \varepsilon_0(3), \cdots, \varepsilon_0(n)\right]^T \quad (16)$$

Finally, the original prediction series of FGM (x_a) can be corrected as:

$$\hat{x}_{a0}(k) = \hat{x}_0(k) + \hat{\varepsilon}_0(k), \quad k = 2, 3, \cdots, n. \quad (17)$$

2.3. Evaluate Accuracy of Prediction

Following generating and developing the above model, further tests are necessary to clarify the forecast and actual values. To demonstrate the efficiency of the proposed forecasting model, this study adopts the residual error test method to compare the actual and forecast values. Herein, Equations (18) and (19) are used to calculate the residual and average residual error of Grey forecasting.

$$\text{Error} = \left|\left[x_0(k) - \hat{x}_0(k)\right] / x_0(k)\right|, \quad k \geq 2 \quad (18)$$

$$\text{Average error} = \sum_{k=1}^{n}\left|\left[x_0(k) - \hat{x}_0(k)\right] / x_0(k)\right| \Big/ n \quad (19)$$

$$p = \begin{bmatrix} \frac{1}{2} & \cos\left(\frac{2\pi\cdot 1}{T_a}2\right) & \sin\left(\frac{2\pi\cdot 1}{T_a}2\right) & \cdots & \sin\left(\frac{2\pi\cdot k_a}{T_a}2\right) \\ \frac{1}{2} & \cos\left(\frac{2\pi\cdot 1}{T_a}3\right) & \sin\left(\frac{2\pi\cdot 1}{T_a}3\right) & \cdots & \sin\left(\frac{2\pi\cdot k_a}{T_a}3\right) \\ & & & \cdots & \\ \frac{1}{2} & \cos\left(\frac{2\pi\cdot 1}{T_a}n\right) & \sin\left(\frac{2\pi\cdot 1}{T_a}n\right) & \cdots & \sin\left(\frac{2\pi\cdot k_a}{T_a}n\right) \end{bmatrix} \quad (15)$$

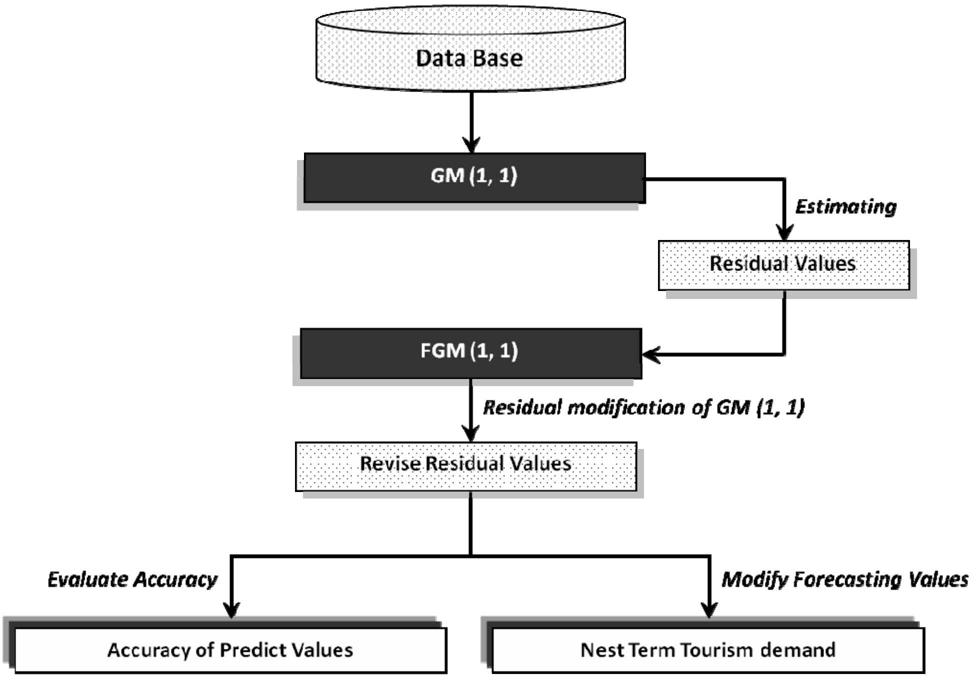

Figure 1. FGM (1, 1) procedure for forecasting tourist demand.

Table 1. The number of tourist visit to Taiwan from 2006 to 2007.

Year	Month	Asia	America	Europe	Oceania	Africa
2006	Sep.	164,980	33,479	16,911	4915	700
	Oct.	181,050	43,770	21,610	5500	880
	Nov.	193,510	44,260	22,450	5890	710
	Dec.	190,390	47,950	17,170	6670	670
2007	Jan.	173,730	36,280	17,370	5970	590
	Feb.	147,280	37,920	16,090	4750	760
	Mar.	210,610	45,880	23,910	6130	880
	Apr.	175,030	42,610	21,200	6070	940
	May.	171,540	39,770	17,820	5200	570
	Jun.	175,540	48,200	21,290	6370	830
	Jul.	148,140	46,350	20,650	6380	670
	Aug.	171,200	40,850	19,870	5900	820
	Sep.	177,530	35,334	18,166	6353	923
	Oct.	181,170	46,233	23,920	6751	706

3. Applying FGM (1, 1) to Undulated Data

This research adopts data provided by the Taiwan Tourism Bureau on the number of tourist visits to Taiwan. The data include number of tourist visits to Taiwan from Asia, America (include North and South America), Europe, Oceania and Africa. The data period lasts from August 1, 2006 to July 31, 2007. **Table 1** lists the number of tourist visits to Taiwan from Asia, America, Europe, Oceania and Africa from 2006 to 2007.

Table 2. Residual value of tourist visit to Taiwan from 2006 to 2007 by GM.

Year	Month	Asia	America	Europe	Oceania	Africa
2006	Oct.	–2917	594	2080	–154	138
	Nov.	10,790	1160	2824	181	–36
	Dec.	8908	4926	–2552	906	–80
2007	Jan.	–6522	–6669	–2449	150	–164
	Feb.	–31,750	–4953	–3827	–1127	2
	Mar.	32,794	3082	3895	197	119
	Apr.	–1581	–113	1087	79	175
	May.	–3874	–2878	–2392	–849	–199
	Jun.	1315	5627	979	263	57
	Jul.	–24,904	3852	239	214	–107
	Aug.	–671	–1573	–642	–326	39
	Sep.	6823	–7015	–2446	67	138
	Oct.	11,620	3959	3206	404	–83

3.1. Estimate Residual Series of Tourists from Five Continents

This study applies a novel method, namely the Fourier residual modification Grey forecasting model (FGM (1, 1)), to forecast tourism demand in Taiwan. **Table 2** lists residual value for international tourist arrivals from five continents to Taiwan from 2006 to 2007 by GM.

Table 3. Forecasting Asian tourism demand to Taiwan using GM and FGM.

Year	Month	t	Actual numbers	GM (1, 1)			FGM (1, 1)		
				Forecasted numbers	Residual value	Residual Error (%)	Forecasted numbers	Forecasted numbers	Residual Error (%)
2006	Nov.	1	193,510	182,720	10,790	5.58	8,518	191,238	1.17
	Dec.	2	190,390	181,482	8908	4.68	11,180	192,662	1.19
2007	Jan.	3	173,730	180,252	–6522	3.75	–8794	171,458	1.31
	Feb.	4	147,280	179,030	–31,750	*21.56	–29,478	149,552	1.54
	Mar.	5	210,610	177,816	32,794	*15.57	30,522	208,338	1.08
	Apr.	6	175,030	176,611	–1581	0.90	691	177,302	1.30
	May.	7	171,540	175,414	–3874	2.26	–6146	169,268	1.32
	Jun.	8	175,540	174,225	1315	0.75	3587	177,812	1.29
	Jul.	9	148,140	173,044	–24,904	*16.81	–27,176	145,868	1.53
	Aug.	10	171,200	171,871	–671	0.39	1601	173,472	1.33
	Sep.	11	177,530	170,707	6823	3.84	4551	175,258	1.28
	Oct.	12	181,170	169,550	11,620	6.41	13,892	183,442	1.25
Average residual error (%)						6.47			1.30
Accuracy (%)						93.53			98.70

Note: 1. the numbers means tourist numbers from Asia. 2. * maximal residual error.

3.2. Empirical Analysis—FGM of Tourists from Asia for Forecasting Tourism Demand in Taiwan

This study uses the example of tourist visits to Taiwan from Asia. Monthly visitor numbers to Taiwan during the on- and off- seasons are displayed or each continent. Past information shows that February and July fall in the off-season while March is the on-season for international tourist visitors to Taiwan from Asia. **Table 3** shows the actual number, forecast number, residual error and average accuracy rates for tourists from Asia by GM (1, 1) and FGM (1, 1).

Numbers of tourist visits to Taiwan from Asia predicted with GM. The average residual error is 6.47%, there are several maximal residual errors are 21.56% (Feb.), 15.57% (Mar.) and 16.81% (Jul.) and the minimal residual error is 0.39%. Though the accuracy rate is 93.53%, GM (1, 1) is unsuitable for predicting stochastic volatility data.

The number of tourist visit to Taiwan from Asia predicted using FGM. The average residual error is 1.3%, the maximal residual error is 1.54% and the minimal residual error is 1.08%. Although the minimal residual error of FGM exceeds the minimal residual of GM, the accuracy rate is 98.7%.

The above statistics indicate the short-term efficiency of FGM. **Figure 2** compares actual value, GM forecast- ing value and FGM forecasting value. The results show that the curve of GM appears flat and curve of FGM fol- lows undulated curve of actual data and has an undulat- ing appearance. FGM is more effective in predicting stochastic volatility data. From the results, this study develops an accuracy forecasting model for improving the effectiveness of tourism demand in making short-term and stochastic volatility predictions. FGM is estimated for tourist arrivals to Taiwan and obtains an accurate estimate when the sample data exhibit significant fluctuation.

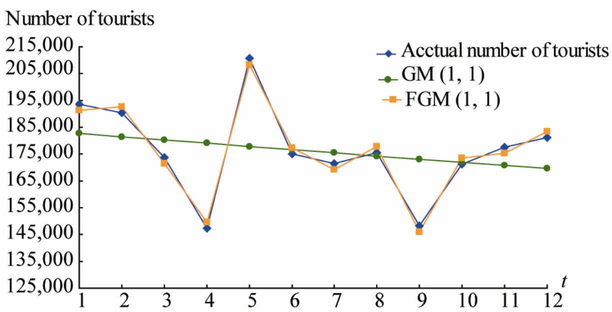

Figure 2. Tourist demand forecasting using GM and FGM for comparison.

4. Conclusions and Discussions

This study makes the following contributions: 1) combining the grey forecasting and Fourier series models to refine the forecasting effectiveness for the stochastic volatility data, 2) providing an effective method for forecasting the number of international visitors to Taiwan, 3) improving the accuracy of short-term forecasting in cases involving sample data with significant fluctuations. Demand forecasting using the proposed model, thus is expected to reduce uncertainty regarding future markets and justify investment in new technology development.

This study applied FGM (1, 1) to tourism demand estimation and empirically tested and using raw data from Taiwan. FGM (1, 1) applies the Fourier series model to revise the residual values of GM (1, 1) and then to accurately forecast short-term f tourism demand, thus drawing up decision problems in the government and business sectors.

Year-round, international tourist arrivals to Taiwan have fluctuated between the on and off seasons. FGM (1, 1) can deal with the rising and falling tendency of data. Generally, consistent with recent research identify which model generates the best forecasts based on the value of calculated mean absolute percentage errors (MAPE) or root mean square errors (RMSE) (Gil-Alana, 2005; Chu, 2004). However, ARIMA is superior to other models for forecasting tourism demand [5,12,25,] and infers that ARIMA receives a coefficient of MAPE less than 10% [26,27]. Nevertheless, this work devises a FGM (1, 1) procedure for forecasting tourist arrivals in Taiwan. The analytical results indicated that using this FGM (1, 1) for forecasting achieves accuracy exceeding 98% and displays good fit performance. The test results reveal that the proposed method can accurately evaluate international traveler numbers when the sample data exhibit significant fluctuations using FGM (1, 1). The FGM (1, 1) is demonstrated to be more reliable via posterior checks and to yield more accurate prediction results than the ARIMA and multiple regression models.

Results of this study are important for tourism industry operators and government agencies interested in forecasting tourism demand. Where possible and appropriate, the use of indirect methods is recommended. Forecasting based on indirect methods with a manageable number of components and FGM (1, 1) can provide more accurate forecasts of numbers of international tourists. Additionally, FGM (1, 1) can provide much more diverse and detailed information than the direct method. This work reaffirms that accurate forecasting of tourism demand is important in tourism planning by both public and business sectors due to the highly perishable nature of tourism products. Especially, short-term trends and floating demand can seriously influence decision-making regarding purchasing, inventory and logistics.

The study results suggest that applying FGM (1, 1) to forecast short term tourism demands can achieve excellent predictions. GM (1, 1) can to estimate the residual values from international tourists numbers base on 12 term, and then FGM (1, 1) to revise the predict values of international tourists arrive in Taiwan in next 12 term. Finally, FGM (1, 1) is applied to forecast international tourist numbers, and then accuracy values for predicting tourism demand are obtained, with residual values first being obtained and then these values being revised as necessary. However, further research on this issue is warranted for further generalizing the study results.

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