Forecasting Inbound Tourism Demand in Thailand with Grey model

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Abstract: Tourism has been a “smoke-free” and vital industry in many countries because it not only generates a plenty of quality employments but also offers a significant economic contribution to the country’s GDP. In order to make the tourism industry stably grown, understanding of its key determinants becomes critical. Various studies have argued that certain determinants were either biasedly measured or incompletely collected due to their intrinsically subjectivity and/or availability; up to date, no standard models have been generally applied for accurate forecasting the tourism demand in the industry. In this study, we propose Grey forecasting approaches to tackle forecasting tourist-demand accurate problems under the sparsely available tourism-demand data. In the empirical study of annual inbound-tourism demand in Thailand, the forecasting performance of the traditional Grey model joined with a modified Fourier series has been verified to be satisfactory with a relatively low mean absolute percentage error.

Key–Words: $GM(1,1)$, Fourier modification, $FGM(1,1)$, Tourism demand, Grey forecasting model

1 Introduction

Nowadays, tourism has been a fast-growing industry in numerous countries. In the most recent research by MasterCard to compare the growth inbound tourist arrivals in 132 top cities and their cross-border spending with the world real GDP over a five-year period of 2009-2013, it showed that international visitor arrivals grew almost two times faster and their cross-border spending grew over 2.3 times faster as shown in Fig.1 [1]. So the international tourism and travel demand is growing strongly in spite of the permanent debility of constrained demand in the global economy.

Many evidences have also proven that the tourism not only generates a plenty of quality jobs with a great contribution to the GDP but also provides social diversity with enriched culture harmony. It is well known

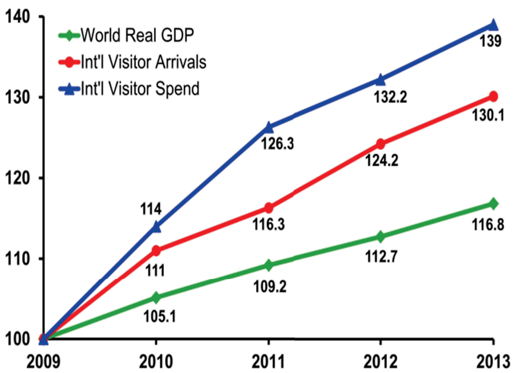

Figure 1: Growth rates of inbound tourist arrivals in 132 top cities and their cross-border spending with the world real GDP (Adapted from [1])

that several direct and supporting industries, such as the hospitality industry, the transport industry, tourist services, food and beverage catering industry, among others, are the primary beneficiaries of the demand created by international visitors.

Employment in these industries also tends to be labor intensive, which makes tourist spending a key driver of employment creation in destination locations. According to the data collected from World Travel & Tourism Council (WTTC) [2], in 2012, tourism directly contributed more than USD2,056 billion to the worldwide GDP, accounting for 2.9% of total GDP. From an general and wider economic impacts, it totally contributed more than USD6,630 billion to the worldwide GDP, accounting 9.3% of total GDP. In term of job generation, tourism directly supported more than 101 million jobs, equally 3.4% of total employment in 2012. If its total contribution is taken into consideration, about 261 million jobs were directly and indirectly supported by the industry, accounting for 8.7% of total employment.

In Thailand, particularly, the number of international tourist arrivals in 2012 was about triple compared to that in 1998. Based on the annual research by the World Travel & Tourism Council [3], in 2012, the total contribution of the tourism industry to Thailand GDP was accounting for 16.7% of GDP (about THB1,896.70 billion); and it supported 12.4% of the total employment with about 4.82 million jobs. In regarding to its direct contribution, the tourism contributed 7.3% of total GDP (about THB825.6 billion) and supported more than 2 million jobs (5.2% of total employment). These figures indicate that tourism is an important industry in Thailand.

In spite of its aforementioned importance, tourism has been considered not only as an integrated and self-contained economic activity without a strong support from economic theories but also as a complex system due to a strong inter-relationship existing among different dependable sectors in the economy such as economic, transportation, commerce, social & cultural services, political and technological changes, etc., [4]. While Gonzlez and Moral [5] pointed out that tourism demand is strongly affected by various factors, including tourism price, price index, income index, marketing expenditures, demographic and cultural factors, the quality-price ratio, etc., Witt & Witt [6] considered different determinants such as population, origin country income or private consumption, own price, substitute prices, one-off events, trend, etc. Also, some marketing aspects such as tour prices, distribution channel of the travel agents, traveler's income were also suggested [6]. However, numerous researchers have concluded that many of the determinants are neither easily measured nor collected due to their availability [4, 6-8].

Furthermore, there has been no standard measure to represent "inbound tourism demand". It was suggested that inbound tourism demand be measured in terms of the number of tourist arrival, tourist expenditure (tourist receipts) or the number of nights tourists spent [6, 8]. But, due to the complexity in collecting the data of tourist expenditure and the number of nights tourists spent, tourist arrival has been widely used as an appropriate indicator of inbound tourism demand in many researches [4, 6-15]. Therefore, in this study, the annual arrival of inbound tourists to Thailand from 1997 to 2012 is used to denote the inbound tourism demand in Thailand.

Due to the above limitations in collecting relevant data of inbound tourism demand in Thailand, it is therefore suggested to use Grey forecasting approach which has been widely employed in different areas due to its ability to deal with the problems of uncertainty with few data points and/or "partial known, partial unknown" information, to predict the demand.

Grey theory offers a new approach to deal mainly with the problems of uncertainty with few data points and/or poor information which is said to be "partial known, partial unknown" [17, 18]. Liu [18] made a summary of the advances of Grey theory and its applications. *GM(1,1)* has been successfully applied to many different areas as reviewed by Liu [18], including: geology by Xu and Wu in 1994, oil and natural gas distribution in Talimu Basin in Xinjiang Province of China by Wu and Xu in 2002, medicine by Tan in 1996 and 2004, hydrology by Xia in 1994, agriculture by Guo in 1994, waste flow allocation planning by Zou et al in 2000, image compression by Hsu et al in 2000, shipboard fire-detection system by Kuo in 2003, hazard and alert time determination for an aircraft flying in wind-shear field by Zhou and Liu in 1994, multi-radar low-altitude little target tracking system by Liu and Chen in 2002, processing of measuring data in reverse engineering by Ping and Zhou in 2003. Recently, there have been many other applications of *GM(1,1)* in forecasting power system [17], port throughput [19], global integrated circuit industry [20], logistics demand [21], crude oil production and consumption in China [22], inventory in global supply chain [23], the rigidity change of a linear motion guide [24], and accounting earnings [25]. Especially, in the tourism industry, *GM(1,1)* has been widely used [26-30].

The core of the theory is the grey dynamics model which is usually called Grey model (GM). The Grey model is used to execute the short-term forecasting operation with no strict hypothesis for the distribution of the original data series [29]. The general GM model has the form of *GM(d,v)*, where d is the rank of differential equation and v is the number of variables appeared in the equation. The basic model of Grey model is *GM(1,1)*, a first-order differential model with one input variable which has been successfully applied in many different researches. It is obtained based on the following procedure.

Step 1:
Suppose an original series with n entries is $x^{(0)}$:

$$x^{(0)} = \{x_1^{(0)}, x_2^{(0)}, \ldots, x_k^{(0)}, \ldots, x_n^{(0)}\}, \quad (1)$$

where $x_k^{(0)}$ is the value at time k $\left(k = \overline{1, n}\right)$.

Step 2:
From the original series $x^{(0)}$, a new series $x^{(1)}$ can be generated by one time accumulated generating operation (1-AGO), which is

$$x^{(1)} = \{x_1^{(1)}, x_2^{(1)}, \ldots, x_k^{(1)}, \ldots, x_n^{(1)}\}, \quad (2)$$

where $x_k^{(1)} = \sum_{j=1}^{k} x_j^{(0)}$.

Step 3:
A first-order differential equation with one variable is expressed as:

$$\frac{dx^{(1)}}{dt} + ax^{(1)} = b \quad (3)$$

where a is called developing coefficient and b is called grey input coefficient. These two coefficients can be determined by the least square method as the following:

$$[a, b]^T = \left(B^T B\right)^{-1} B^T Y \quad (4)$$

where

$$B = \begin{bmatrix} -\left(x_1^{(1)} + x_2^{(1)}\right)/2 & 1 \\ -\left(x_2^{(1)} + x_3^{(1)}\right)/2 & 1 \\ \vdots & \vdots \\ -\left(x_{n-1}^{(1)} + x_n^{(1)}\right)/2 & 1 \end{bmatrix}$$

$$Y = \begin{bmatrix} x_2^{(0)} \\ x_3^{(0)} \\ \vdots \\ x_n^{(0)} \end{bmatrix}$$

Therefore, the forecasting equation for $GM(1,1)$ is expressed as:

$$\hat{x}_k^{(1)} = e^{-a(k-1)} \left[x_1^{(0)} - \frac{b}{a}\right] + \frac{b}{a} \quad \left(k = \overline{1, n}\right) \quad (5)$$

Based on the operation of one time inverse accumulated generating operation (1-IAGO), the predicted series $\hat{x}^{(0)}$ can be obtained as following:

$$\hat{x}^{(0)} = \{\hat{x}_1^{(0)}, \hat{x}_2^{(0)}, \cdots, \hat{x}_k^{(0)}, \cdots, \hat{x}_n^{(0)}\}, \quad (6)$$

where

$$\begin{cases} \hat{x}_1^{(0)} = \hat{x}_1^{(1)} \\ \hat{x}_k^{(0)} = \hat{x}_k^{(1)} - \hat{x}_{k-1}^{(1)} \quad \left(k = \overline{2, n}\right) \end{cases}$$

In order to make proper plans for the sustainable development of the tourism industry, it is vital to have accurate forecasts of the tourism demand, which attracts and motivates many scholars in search for a good forecasting model. Thus, in order to improve the accuracy of the model, its residuals series is then modified with Fourier series to form a new one.

$GM(1,1)$ model can perform better if it is modified with Fourier series [19, 20, 26-30, 32]. The procedure to obtain the modified model (hereafter called $FGM(1,1)$) is as the following.

Based on the predicted series $\hat{x}^{(0)}$ obtained from the $GM(1,1)$ model, a residual series named $\varepsilon^{(0)}$ is defined as

$$\varepsilon^{(0)} = \{\varepsilon_2^{(0)}, \varepsilon_3^{(0)}, \cdots, \varepsilon_k^{(0)}, \cdots, \varepsilon_n^{(0)}\} \quad (7)$$

where $\varepsilon_k^{(0)} = x_k^{(0)} - \hat{x}_k^{(0)} \quad \left(k = \overline{2, n}\right)$

Expressed in Fourier series, $\varepsilon_k^{(0)}$ is rewritten as:

$$\varepsilon_k^{(0)} = \frac{a_0}{2} + \sum_{i=1}^{F} \left[a_i \cos\left(\frac{2ik\pi}{n-1}\right) + b_i \sin\left(\frac{2ik\pi}{n-1}\right)\right] \quad (8)$$

where: $F = [(n-1)/2 - 1]$ is called the minimum deployment frequency of Fourier series [28] and only take integer number [19-21,31]. And therefore, the residual series is rewritten as:

$$\varepsilon^{(0)} = P \cdot C \quad (9)$$

where

$$P = \left(\left[\frac{1}{2}\right]_{(n-1)\times 1} \quad P_1 \quad \cdots \quad P_k \quad \cdots \quad P_F\right)$$

$$P_k = \begin{pmatrix} \cos\left(\frac{2\pi\times 2\times k}{n-1}\right) & \sin\left(\frac{2\pi\times 2\times k}{n-1}\right) \\ \cos\left(\frac{2\pi\times 3\times k}{n-1}\right) & \sin\left(\frac{2\pi\times 3\times k}{n-1}\right) \\ \vdots & \vdots \\ \cos\left(\frac{2\pi\times n\times k}{n-1}\right) & \sin\left(\frac{2\pi\times n\times k}{n-1}\right) \end{pmatrix}$$

$$C = [a_0, a_1, b_1, a_2, b_2, \ldots, a_F, b_F]^T$$

The parameters $a_0, a_1, b_1, a_2, b_2, \ldots, a_F, b_F$ are obtained by using the ordinary least squares method (OLS) which results in the equation of:

$$C = (P^T P)^{-1} P^T \left[\varepsilon^{(0)}\right]^T \tag{10}$$

Once the parameters are calculated, the predicted series residual $\hat{\varepsilon}^{(0)}$ is then easily achieved based on the following expression:

$$\hat{\varepsilon}_k^{(0)} = \frac{a_0}{2} + \sum_{i=1}^{F} \left[a_i \cos\left(\frac{2ik\pi}{n-1}\right) + b_i \sin\left(\frac{2ik\pi}{n-1}\right) \right] \tag{11}$$

Therefore, based the predicted series $\hat{x}^{(0)}$ obtained from $GM(1,1)$ model, the predicted series $\tilde{x}^{(0)}$ of the $FGM(1,1)$ is determined by:

$$\tilde{x}^{(0)} = \{\tilde{x}_1^{(0)}, \tilde{x}_2^{(0)}, \ldots, \tilde{x}_k^{(0)}, \ldots, \tilde{x}_n^{(0)}\} \tag{12}$$

where

$$\begin{cases} \tilde{x}_1^{(0)} = \hat{x}_1^{(0)} \\ \tilde{x}_k^{(0)} = \hat{x}_k^{(0)} + \hat{\varepsilon}_k^{(0)} \qquad (k = \overline{2, n}) \end{cases}$$

Forecasting result of the same period is then used to compare the accuracy of this modified model and *ARFIMA-FIGARCH* proposed by Chokethaworn et al. [16] who claimed that the models named autoregressive fractionally integrated moving-average (*ARFIMA*) and *FIGRACH* are firstly used in their study to forecast the international tourist arrivals in Thailand. We will compare the performance of our proposed forecasting model with their models to illustrate the forecasting power of our models suggested in this study. A brief review of the two models *ARFIMA* and *FIGRACH* is presented as the following.

1.1 ARFIMA Model

An autoregressive fractionally integrated moving-average model is an extension of the original autoregressive integrated moving average (*ARIMA*) models which are widely used to forecast a time series which can be made stationary by differencing or logging. For an arbitrary time series, it may have either non-seasonal or seasonal characteristics. A time series with a regular pattern of changes that repeats over S time-periods is called a seasonal series. With a seasonal time series, the average values at some particular times within the seasonal intervals are frequently different from those at other times; therefore, a seasonal time series is usually a non-stationary series.

A general multiplicative model seasonal *ARIMA* model for a time series x_t has the form of $SARIMA(p,d,q)(P,D,Q)_S$ which is defined by:

$$\Phi_P(B^S)\phi_p(B)(1-B)^d(1-B^S)^D x_t = \theta_q(B)\Gamma_Q(B^S)\varepsilon_t \tag{13}$$

The functions in equation 13 are defined as:

- $\phi_p(B) = (1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p)$ is a non-seasonal auto-regressive operator;
- $\theta_p(B) = (1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q)$ is a non-seasonal moving average operator;
- $\Phi_P(B^S) = (1 - \Phi_1 B - \Phi_2 B^2 - \cdots - \Phi_p B^p)$ is a seasonal auto-regressive operator;
- $\Gamma_Q(B^S) = (1 - \Gamma_1 B^1 - \Gamma_2 B^2 - \cdots - \Gamma_Q B^Q)$ is a seasonal moving average operator;
- $(1-B)^d(1-B^S)^D$ is a difference filter including non-seasonal differencing order d and seasonal differencing order D.

The ARFIMA model, introduced by Granger and Joyeux [32], Granger [33, 34] and Hosking [35], is usually in the form of $ARFIMA(p,d,q)$ which is obtained from

$$\phi_p(B)(1-B)^d x_t = \delta + \theta_q(B)\varepsilon_t,$$

where

$$\phi_p(B) = (1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p),$$

$$\theta_q(B) = (1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q),$$

δ is a constant, and $(1-B)^d x_t$ is the differencing operator at the order d of the time series x_t.

Certain $ARFIMA$ models with a varied parameter $d \in (-0.5, 1)$ inherit disparate forecasting properties. For instance,

- $ARFIMA$ is said to exhibit intermediate memory or long range negative dependence if $d \in (-0.5, 0)$.
- $ARFIMA$ is said to exhibit short memory if $d = 0$.
- $ARFIMA$ is said to exhibit long memory or long range positive dependence if $d \in (0, 0.5)$.
- $ARFIMA$ is mean reverting and there is no long-term impact to the future values if $d \in [0.5, 1)$.

1.2 $FIGARCH$ Model

Fractionally Integrated Generalized Autoregressive Conditional Heteroscedastic ($FIGARCH$) was first introduced by Baillie et al. [36]. The detailed procedure to obtain $FIGARCH(p, d, q)$ is referred to Tayefi and Ramanathan [37].

In order to evaluate the accuracy of the forecasting model, the residual error (ε) and its relative error ($\wp$) are used [19, 38]. ε and $\wp$ of the k^{th} entry are expressed as:

- Residual error: $\varepsilon_k = x_k^{(0)} - f_k^{(0)} \quad (k = \overline{1, n})$ where $f_k^{(0)}$ is the forecasted value at the k^{th} entry.
- Relative error: $\wp_k = |\varepsilon_k|/x_k^{(0)} \quad (k = \overline{1, n})$

However, there have been some other important indexes to be considered in evaluating the model accuracy. They are:

- The mean absolute percentage error (MAPE) [5,17,19,26-29,31,39-42]:

$$\text{MAPE} = \frac{1}{n}\sum_{k=1}^{n} \wp_k.$$

- The post-error ratio C [21, 26, 27, 43]:

$$C = S_2/S_1$$

where:

$$S_1 = \sqrt{\frac{1}{n}\sum_{k=1}^{n}\left[x_k^{(0)} - \frac{1}{n}\sum_{k=1}^{n} x_k^{(0)}\right]^2}$$

$$S_2 = \sqrt{\frac{1}{n}\sum_{k=1}^{n}\left[\varepsilon_k - \frac{1}{n}\sum_{k=1}^{n} \varepsilon_k\right]^2}$$

The ratio C, in fact, is the ratio between the standard deviation of the original series and the standard deviation of the forecasting error. The smaller the C value, the higher accuracy the model has since smaller C value results from a larger S_1 and/or a smaller S_2.

- The small error probability P [21, 26, 27, 43]:

$$P = p\left\{\left(|\varepsilon_k - \frac{1}{n}\sum_{k=1}^{n}\varepsilon_k|/S_1\right) < 0.6745\right\}.$$

The P value indicates a probability of the ratio of the difference between the residual values of data points and the average residual value with the standard deviation of the original series smaller than 0.6745 [21, 26, 27]. Thus, the higher the P value, the higher accuracy the model has.

Table 1: Four grades of forecasting accuracy

Grade level	$MAPE$	C	P	ρ
I (Very good)	< 0.01	< 0.35	> 0.95	> 0.95
II (Good)	< 0.05	< 0.50	> 0.80	> 0.90
III (Qualified)	< 0.10	< 0.65	> 0.70	> 0.85
IV (Unqualified)	≥ 0.10	≥ 0.65	≤ 0.70	≤ 0.85

- The forecasting accuracy ρ[21, 26, 27]:

$$\rho = 1 - \text{MAPE}.$$

Based on the above indexes, there are four grades of accuracy stated in Table 1.

In order to find the best model to forecast the international tourism demand in Thailand, this paper follows the below steps:

- After collecting the relevant data of international tourism demand in Thailand, we first use a large portion of them to establish Grey model based on the equations (1) - (6).
- With the Grey model obtained, its residual series is calculated based on the equation (7).
- The original residual series is then modified with Fourier series as shown in equations (8) - (11).
- The forecasted values based on our new proposed model called Fourier Residual Modified Grey Model (FGM) are obtained by equation (12).
- In order to compare the performance of traditional Grey model (GM) and the modified model (FGM) forecasting models, we consider some evaluation indexes as shown in Table 1 to find a better model.
- The selected model is then used to create the forecasts of the international tourism demand in 2012 which are then compared with the actual observations to certify its forecasting power before being used in practice.
- For further emphasis of our proposed model, we compare the performance of ours with the ones proposed by Chokethaworn et al. [16].

2 Empirical Study

The country's capital, Bangkok, is ranked the most visited city in the world [1]. Bangkok overwhelms London, No. 1 tourist destination ranked in 2012, by less than 1%. One of the reasons for the tremendous success of Thailand in the increase in international visitors is that tourism in Southeast Asia has recently been speedily developed in the region's upper-middle class. Particularly, there are several cities in Asia having the fastest increase in air-travel connectivity which is measured in terms of the scope of the city's connections with other cities by air travel and the number of flights for each connection. The increase in the air-travel connectivity in Asia reflects the growing of its wealth and its importance as a business destination.

Thailand has a great potential for the development of national tourism with several attracting conditions in not only the nature with a warm climate, wonderful beaches, and beautiful scenery but also a culture rich in variety which incorporates cultural beliefs and characteristics indigenous to the area with much influence from ancient India, China, Cambodia, along with the neighboring pre-historic cultures of Southeast Asia. Besides, it can offer a high standard of services and low costs compared to other tourist destinations.

However, Thailand's tourist industry are currently facing several challenges in the fluctuation in the security situation, the changes in the world economy, the tourism demand trend and price competitiveness among several countries. Long-term challenges also naturally exist in the development of Thailand's tourist industry. For instance, the infrastructure and traffic safety is currently a big issue to be solved in Thailand; in particular. In developing the tourism industry, conserving nature must be carefully taken into consideration. Tourism will seriously suffer if an excessive number of tourists without a proper management and considerateness are placed on the natural environment. The desires of tourists are becoming more diversified and various types of activities as well as authentic nature and cultural experiences should be well developed. Although there is always a strong tourism demand in the world, a tougher competition in the industry is obviously in existence. Therefore, Thailand's tourism industry should be renovated to maintain its attractions for sustainable development. To achieve this, an accurate forecast accompanied with a good forecasting model is mandatory.

Historical data of the inbound tourism demand in Thailand from 1997 - 2012 (totally 16 observations) are obtained from the annual statistical data published by The Office of Tourism Development [44] as in the "Actual" column of Table 2. Fig. 2 shows a growth trend in the inbound tourism demand in Thailand during the investigated period.

Data from 1997-2011 are used to build $GM(1,1)$ model which is then modified with Fourier series to improve its accuracy level; whereas, the number of

Table 2: Inbound tourism demand *(Unit: 10^6 arrivals)*

Year	Arrivals	Year	Arrivals
1997	7.22	2005	11.52
1998	7.76	2006	13.82
1999	8.58	2007	14.46
2000	9.51	2008	14.20
2001	10.06	2009	14.15
2002	10.80	2010	15.90
2003	10.00	2011	19.23
2004	11.65	2012	22.30

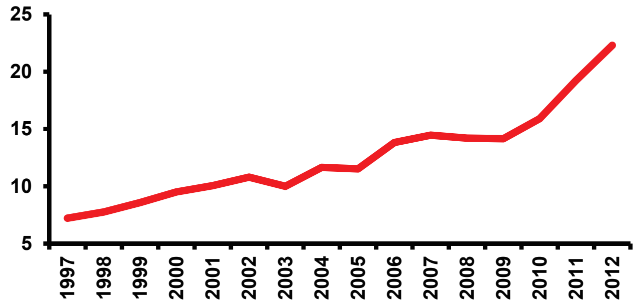

Figure 2: Annual inbound tourist arrivals

inbound tourist arrivals in 2012 is used to check the forecasting power of the selected model.

The fundamental $GM(1,1)$ model for the annual inbound tourism demand in Thailand from 1997 - 2011 is found as:

$$\hat{x}_k^{(1)} = 132.63804e^{0.05941(k-1)} - 125.4180$$

From $GM(1,1)$ model, its residual series can be easily obtained, which is then modified with Fourier series to become a new model named $FGM(1,1)$. The forecasted series with these two models are shown in the last two columns of Table 3.

The forecasts obtained from $GM(1,1)$ and $FGM(1,1)$ are plotted in Fig. 3 which indicates that the forecasts obtained from $FGM(1,1)$ follow closely to the actual number of the inbound tourist arrivals. The relevant indexes to evaluate the accuracy of the $GM(1,1)$ and $FGM(1,1)$ are shown in Table 4.

From Table 4, with the MAPE value of less than 1%, $FGM(1,1)$ outperforms $GM(1,1)$. Hence, it is suggested to forecast the inbound tourism demand in Thailand. Using $FGM(1,1)$, the forecast value of the inbound tourism demand in Thailand in 2009 is 14.21 million arrivals. In comparison to the actual arrival of 2009, our forecast model results in an absolute percentage error of 0.424% which is much lower than that of the model proposed by Chokethaworn et al. [16].

Table 3: Actual versus Forecasts by $GM(1,1)$ and $FGM(1,1)$ *(million arrivals)*

No.	Year	Actual	$GM(1,1)$	$FGM(1,1)$
1	1997	7.22	7.22	7.22
2	1998	7.76	8.03	7.70
3	1999	8.58	8.53	8.64
4	2000	9.51	9.06	9.45
5	2001	10.06	9.62	10.12
6	2002	10.80	10.22	10.74
7	2003	10.00	10.86	10.06
8	2004	11.65	11.53	11.59
9	2005	11.52	12.25	11.58
10	2006	13.82	13.02	13.77
11	2007	14.46	13.83	14.52
12	2008	14.20	14.69	14.14
13	2009	14.15	15.6	14.21
14	2010	15.90	16.57	15.84
15	2011	19.23	17.61	19.29
16	2012	22.30	18.7	20.70

Table 4: Evaluation indexes of model accuracy

Index	$GM(1,1)$	$FGM(1,1)$
$MAPE$	0.0545	0.0099
S_1	15.9646	15.9646
S_2	1.2872	0.2192
C	0.0806	0.0137
P	1.0000	1.0000
ρ	0.9455	0.9901
Forecasting power	Qualified	Very good

In order to further evaluate the accuracy of our proposed model, we now compare the forecast value in 2012 with the actual observation in the same year. It is found that our model suggests 20.70 million which is 7.17% lower than the actual. The tolerance of 7.17% is acceptable in a forecasting model. So, the inbound tourism demand in Thailand in 2013 is forecasted to be 23.87 million arrivals.

With the forecasted values obtained from FGM(1,1), related industries and organizations should have proper policies in attracting international tourists to Thailand and protecting the nature environment to make the national tourism industry grow sustainably.

The benefits of international tourism frequently exceed what can be computed in dollar and cents, but affect the very quality and dynamism of urban culture itself. Due to the need of seeking new and rewarding experiences, especially in the arts, popular culture

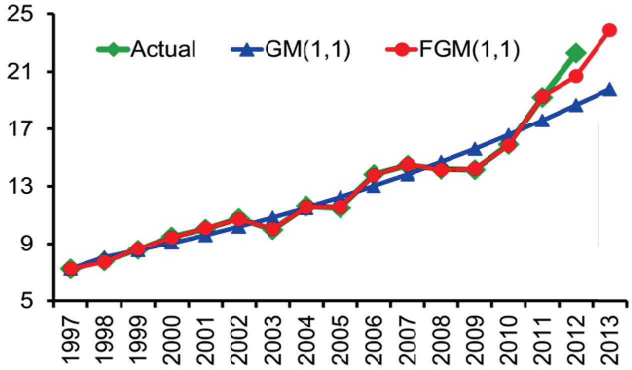

Figure 3: Actual observations versus forecasts

and entertainment, as well as historical and heritage unique sites, in order to attract international visitors, Thailand must preserve the past and the current advantages in ways that uniquely contribute to the attractiveness of the country. Since tourist spending is a powerful catalyst for nurturing urban cultures and driving the growth of creative industries, attracting increasing inbound tourists is the ultimate concern for numerous countries around the world.

Along with the attracting more international visitors, improving public infrastructure and facilities to satisfy their diversified needs become a permanent issue. If this problem can be efficiently managed and arranged with the right policy systems, a virtuous circle can be set in motion; that is, more inbound tourists coming will lead to more and better investment to facilitate the improvement of the infrastructures and the overall urban environment, which in turn makes the destination more attractive to more international visitors. Businesses are then encouraged to set-up in the tourism locations, further improving employment and income. Thus, the tourism cities in Thailand, in one hand, play an important role in sustaining the global service trade of Thailand, and support their respective national economies through stronger growth in employment and income in their urban economies.

In order to make the aforementioned forecasts feasible, several issues must be settled. For example, deterioration in the security situation is perceived as a risk to tourists, which negatively affects the tourism demand. The unstable political situation in Thailand is considered as a serious issue because tourists always concern safety as the top priority in their trips and usually keep away from politicking. In a general speaking, any public unrest and conflict spreads and escalates in a destination will tremendously reduce the tourism demand to it. However, because of the impact of news reporting and widespread multimedia communication, when evaluating the security of a tourist destination, the significance of its unrest may be over-emphasized to attract the attention of the public, which is a key factor affecting the travel plans. While incidents of unrest such as terrorist strikes and political strife generally receive more prominent attention in society, many tourists usually don't pay much attention to smaller issues, such as traffic accidents at the destination. As tourists are out and about in traffic daily, the traffic should be fully monitored and controlled. Though the road traffic in Thailand is not mentioned as much as the public instability, it presents a much greater security risk which must be eliminated for the development of the tourism industry.

Furthermore, in assessing the impact of inflation on the tourism industry, it is important to take comparative price levels and exchange rates into consideration. The Bank of Thailand (BOT), mainly to secure price competitiveness of exports, has not allowed the value of the Baht to rise freely against the Dollar. The Baht is under upward pressure, and a rise in the Baht would have a negative impact on the national tourism industry, especially when the reasonable price level is one of the main reasons for many international tourists to choose Thailand as their travel destination. The low price level in Thailand offsets the costs of long-haul flights, which means that overall costs can be kept in control, even when travelling long distances. Low price level is also a prominent factor to motivate tourists travelling in groups, such as families, special interest tourists and for people intending to spend a longer time in the country. The low price is found as one of the determinants encouraging many people who travel abroad for the first time to choose Thailand as their favorite destination for the oversea experience. This special advantage should still be kept as the key driver for attracting inbound tourism demand in Thailand.

3 Conclusion

Combining the Fourier residual modification to the traditional Grey forecasting model (GM) results in a highly accurate forecasting model named the Fourier-modified Grey forecasting model (FGM). With the $FGM(1,1)$ model, the forecasting Thailand's inbound-tourism demands, modeled by its key determinants, have been effectively and accurately forecasted. Notably, the $FGM(1,1)$ model, compared to the models of $ARFIMA(1,-0.45,1)$ and $FIGARCH(1,-0.07,1)$, possesses less than 1% of mean absolute percentage error (MAPE). Due to its excellent performance under the sparsely available tourism-demand data, we highly recommend this Fourier-modified Grey forecasting model being employed in practice to overcome the forecasting tourist-demand accurate problems. Finally, this precise forecasting result is not only beneficial for the related organizations in planning ahead to prepare sufficient facilities and attainable human resources but also useful for the government's decision-makers over macro and micro levels in laying out strategic policies to promote the smokeless industry. More importantly, it provides insightful initiatives for Thailand's government to enhance the political and social stability for attracting international tourists.

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