

# FORECASTING MODEL FOR THE INTERNATIONAL TOURISM DEMAND IN TAIWAN

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## ABSTRACT

**Purpose:** Tourism has been considered a complexly integrated and self-contained economic activity but it is one of the biggest industries in many countries. This paper aims at finding an accurate forecasting model in order to make the tourism industry grow stably.

**Design/methodology/approach:** However, the determinants of the international tourism demand are not fully identified; therefore, in this paper, it is strongly suggested to use Grey forecasting model which is widely used 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". In order to improve the accuracy of the model, an improved & accurate forecasting model FGM is created by combining the Fourier residual modification with the traditional Grey model GM(1,1).

**Findings:** FGM(1,1) had a very low mean absolute percentage error (MAPE) of 1.5755% in the case of monthly international tourist arrival in Taiwan. And therefore, it is selected to forecast the inbound tourism demand in Taiwan for the time being.

**Originality/value:** Though many researches have been conducted in employing Grey forecasting model and Fourier residual modification, they are revisited and applied in the case of the international tourism demand in Taiwan.

Keywords: Tourism demand, Grey forecasting, Fourier modification

## INTRODUCTION

Tourism is considered an integrated and self-contained economic activity but it hasn't been supported by a strong economic theory (Lagos, 1999). Tourism is also a complex activity which includes a strong inter-relationship among different dependable sectors in the economy; such as economic, transportation, commerce, social & cultural services, political and technological changes, etc., (Lagos, 1999). It was concluded that understanding of the variables that influence the demand for international tourism could help policy-makers a lot in planning growth strategies for the tourism industry (Habibi et al, 2009).



However, there has been no standard measure to represent "international tourism demand". It was suggested that international tourism demand be measured in terms of the number of tourist arrival, tourist expenditure (tourist receipts) or the number of nights tourists spent (Witt et al, 1995; Ouerfelli, 2008). 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 international tourism demand in many researches (González & Moral, 1995; Morley, 1998; Lim and McAleer, 2001; Kulendran and Witt, 2001; Tan et al. 2002; Song and Witt, 2003; Song et al., 2003; Dritsakis, 2004; Naude & Saayman, 2005; Ouerfelli, 2008; Habibi et al, 2009). Therefore, in this study, the monthly arrival of international tourists to Taiwan is used to denote the international tourism demand in Taiwan.

Moreover, the determinants of the international tourism demand are not fully identified. As per González & Moral (1995), they could be tourism price (including the cost of travel to and the cost of living for the tourist at the destination), the price index, the income index, marketing expenditures, demographic and cultural factors, the quality-price ratio, etc., Whereas, Witt & Witt (1995) listed them as population, origin country income or private consumption, own price (including the cost of travel to and the cost of living for the tourist at the destination- same as González & Moral (1995)), substitute prices, one-off events, trend, etc., But Hsu & Wang (2008) approached with some marketing aspects which were tour prices, distribution channel of the travel agents, traveller's income. Besides, many of the determinants are neither easily measured nor collected due to their availability. This conclusion is found in different papers written by González & Moral (1995), Witt & Witt (1995), Lagos (1999), Habibi et al. (2009).

Due to the above limitations in collecting relevant data of international tourism demand in Taiwan, 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. The residuals from the conventional Grey model are then modified with Fourier series to form a new one. These two models are then compared based on their accuracy indicators and the best one is selected to forecast the international tourism demand in Taiwan.

# LITERATURE REVIEW

# 1. Grey Model

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" (Hsu & Chen, 2003; Liu, 2007). 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 (Wang et al, 2011). 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  $x^{(0)}$ :  $x^{(0)} = \{x^{(0)}(1), x^{(0)}(2), x^{(0)}(3), \dots, x^{(0)}(k), \dots, x^{(0)}(n)\}$ 

where  $x^{(0)}(k)$  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

$$x^{(1)} = \left\{ x^{(1)}(1), x^{(1)}(2), x^{(1)}(3), \dots, x^{(1)}(k), \dots, x^{(1)}(n) \right\}$$
(2)  
$$x^{(1)}(k) = \sum_{j=1}^{k} x^{(0)}(j)$$

where

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

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

(1)

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:

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

where

$$B = \begin{bmatrix} -\left(x^{(1)}(1) + x^{(1)}(2)\right)/2 & 1\\ -\left(x^{(1)}(2) + x^{(1)}(3)\right)/2 & 1\\ \dots & \dots\\ -\left(x^{(1)}(n-1) + x^{(1)}(n)\right)/2 & 1 \end{bmatrix} \qquad Y = \begin{bmatrix} x^{(0)}(2), x^{(0)}(3), \dots, x^{(0)}(n) \end{bmatrix}^T$$

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

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

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

$$\hat{x}^{(0)} = \left\{ \hat{x}^{(0)}(1), \hat{x}^{(0)}(2), \hat{x}^{(0)}(3), \dots, \hat{x}^{(0)}(k), \dots, \hat{x}^{(0)}(n) \right\}$$
(6)
$$\begin{cases} \hat{x}^{(0)}(1) = \hat{x}^{(1)}(1) \\ \hat{x}^{(0)}(k) = \hat{x}^{(1)}(k) - \hat{x}^{(1)}(k-1) \\ \hat{x}^{(0)}(k) = \hat{x}^{(1)}(k) - \hat{x}^{(1)}(k-1) \end{cases}$$
(7)

#### 2. Fourier Residual Modification Grey Forecasting Model

GM(1,1) model can perform better if it is modified with Fourier series (Hsu, 2003; Guo et al, 2005; Kan et al, 2010; Askari & Fetanat, 2011; Huang & Lee, 2011). 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:



$$\varepsilon^{(0)} = \left\{ \varepsilon^{(0)}(2), \varepsilon^{(0)}(3), \varepsilon^{(0)}(4), \dots, \varepsilon^{(0)}(k), \dots, \varepsilon^{(0)}(n) \right\}$$
(7)

where

 $\varepsilon^{(0)}(k) = x^{(0)}(k) - \hat{x}^{(0)}(k) \qquad \left(k = \overline{2, n}\right)$ 

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

$$\varepsilon^{(0)}(k) = \frac{1}{2}a_0 + \sum_{i=1}^{F} \left[ a_i \cos\left(\frac{2\pi i}{n-1}k\right) + b_i \sin\left(\frac{2\pi i}{n-1}k\right) \right] \qquad \left(k = \overline{2,n}\right) \tag{8}$$

where  $F = \left[ (n-1)/2 - 1 \right]$  called the minimum deployment frequency of Fourier series (Huang & Lee, 2011) and only take integer number (Hsu, 2003; Guo et al, 2005; Askari & Fetanat, 2011). And therefore, the residual series is rewritten as:

$$\varepsilon^{(0)} = P.C \tag{9}$$

where

$$P = \begin{bmatrix} \frac{1}{2} & \cos\left(\frac{2\pi\times1}{n-1}\times2\right) & \sin\left(\frac{2\pi\times1}{n-1}\times2\right) & \cdots & \cos\left(\frac{2\pi\times F}{n-1}\times2\right) & \sin\left(\frac{2\pi\times F}{n-1}\times2\right) \\ \frac{1}{2} & \cos\left(\frac{2\pi\times1}{n-1}\times3\right) & \sin\left(\frac{2\pi\times1}{n-1}\times3\right) & \cdots & \cos\left(\frac{2\pi\times F}{n-1}\times3\right) & \sin\left(\frac{2\pi\times F}{n-1}\times3\right) \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ \frac{1}{2} & \cos\left(\frac{2\pi\times1}{n-1}\timesn\right) & \sin\left(\frac{2\pi\times1}{n-1}\timesn\right) & \cdots & \cos\left(\frac{2\pi\times F}{n-1}\timesn\right) & \sin\left(\frac{2\pi\times F}{n-1}\timesn\right) \\ & C = \left[a_0, a_1, b_1, a_2, b_2, \dots, a_F, b_F\right]^T$$

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

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

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

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

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

$$\tilde{x}^{(0)} = \left\{ \tilde{x}^{(0)}(1), \tilde{x}^{(0)}(2), \tilde{x}^{(0)}(3), \dots, \tilde{x}^{(0)}(k), \dots, \tilde{x}^{(0)}(n) \right\}$$

$$\begin{cases} \tilde{x}^{(0)}(1) = \hat{x}^{(0)}(1) \\ \tilde{x}^{(0)}(k) = \hat{x}^{(0)}(k) + \hat{\varepsilon}^{(0)}(k) \qquad \left(k = \overline{2, n}\right) \end{cases}$$
(12)

where

In order to evaluate the accuracy of the forecasting model, the residual error ( $\varepsilon$ ) and its relative error ( $\omega$ ) are used (Guo et al, 2005; Liang et al, 2008).  $\varepsilon$  and  $\omega$  of an entry k are expressed as:

\* Residual error: 
$$\varepsilon(k) = x^{(0)}(k) - \hat{x}^{(0)}(k)$$
  $\left(k = \overline{1, n}\right)$   
\* Relative error:  $\wp_k = \left|\varepsilon(k)\right| / x^{(0)}(k)$   $\left(k = \overline{1, n}\right)$ 



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

+ The mean absolute percentage error (MAPE) (Hsu & Chen, 2003; Guo et al, 2005; Hsu & Wang, 2008; Kan et al, 2010; Chang & Liao, 2010; Askari & Fetanat, 2011; Tsaur & Kuo, 2011; Huang & Lee, 2011; Li et al, 2011) (MAPE is also known as the average relative error  $\delta$  (Hua & Liang, 2009; Ma & Zhang, 2009)):

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

+ The post-error ratio C (Hua & Liang, 2009; Ma & Zhang, 2009):

$$C = \frac{S_2}{S_1}$$
  
where:  $+ S_1 = \sqrt{\frac{1}{n} \sum_{k=1}^n \left[ x^{(0)}(k) - \overline{x} \right]^2}$  where  $\overline{x} = \frac{1}{n} \sum_{k=1}^n x^{(0)}(k)$   
 $+ S_2 = \sqrt{\frac{1}{n} \sum_{k=1}^n \left[ \varepsilon(k) - \overline{\varepsilon} \right]^2}$  where  $\overline{\varepsilon} = \frac{1}{n} \sum_{k=1}^n \varepsilon(k)$   $\varepsilon(k) = \begin{bmatrix} x^{(0)}(k) - \hat{x}^{(0)}(k) \\ x^{(0)}(k) - \tilde{x}^{(0)}(k) \end{bmatrix}$ 

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 is, 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* (Hua & Liang, 2009; Ma & Zhang, 2009):

$$P = p \left\{ \frac{\left| \varepsilon(k) - \overline{\varepsilon} \right|}{S_1} < 0.6745 \right\}$$

The higher the P value is, the higher accuracy the model has since P value indicates the 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 (Ma & Zhang, 2009).

+ The forecasting accuracy  $\rho$  (Ma & Zhang, 2009):  $\rho = 1 - MAPE$ Based on the above indexes, there are four grades of accuracy as stated in Table 1.

Table 1: Four grades of forecasting accuracy						
Grade level	MAPE	С	Р	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)	$\geq 0.10$	≥0.65	$\leq 0.70$	$\leq 0.85$		

Table 1: Four grades of forecasting accuracy



## **EMPIRICAL STUDY**

The historical data of the international tourism demand in Taiwan is obtained from the monthly statistical data published on the website of Ministry of Transportation and Communication R.O.C (MOTC) from January 2001 to September 2011. The tourism demand is referred to the number of monthly arrivals of international tourists to Taiwan. There are totally 129 observations which are used to build GM(1,1) model. The GM(1,1) model is found as

$$\hat{x}^{(1)}(k) = 24073272.64e^{0.0075324(k-1)} - 23873472.64$$
(14)

The predicted series is as in the column GM(1,1) of Table 2. From the residual series of GM(1,1) model, the forecast values under FGM(1,1) is obtained as illustrated in column FGM(1,1) of Table 2.

Table 2: Monthly Forecasted value with GM(1,1) and FGM(1,1)

				· · · · · · · · · · · · · · · · · · ·			
	ARRIVALS				ARRIVALS		FGM(1,1)
Jan-01	199800	199800	199800	Jun-06	305127	294760	300888
Feb-01	234386	182014	230147	Jul-06	270850	296988	275089
Mar-01	251111	183390	255349	Aug-06	292561	299234	288323
Apr-01	235251	184777	231012	Sep-06	274118	301496	278357
May-01	227021	186174	231259	Oct-06	301575	303776	297337
Jun-01	239878	187582	235639	Nov-06	318663	306073	322901
Jul-01	218673	189000	222911	Dec-06	323931	308387	319692
Aug-01	224208	190429	219969	Jan-07	274198	310719	278437
Sep-01	193254	191869	197492	Feb-07	261799	313068	257561
Oct-01	192452	193319	188214	Mar-07	345295	315435	349533
Nov-01	190500	194781	194739	Apr-07	316119	317820	311881
Dec-01	210603	196254	206364	May-07	294021	320223	298260
Jan-02	217600	197738	221838	Jun-07	320676	322644	316438
Feb-02	233896	199233	229657	Jul-07	285075	325084	289314
Mar-02	281522	200739	285760	Aug-07	308481	327541	304243
Apr-02	245759	202257	241520	Sep-07	295594	330018	299833
May-02	243941	203786	248179	Oct-07	314519	332513	310281
Jun-02	241378	205327	237139	Nov-07	336370	335027	340608
Jul-02	234596	206879	238834	Dec-07	363916	337560	359677
Aug-02	246079	208444	241840	Jan-08	297442	340113	301681
Sep-02	233613	210020	237851	Feb-08	315134	342684	310896
Oct-02	258360	211608	254121	Mar-08	342062	345275	346300
Nov-02	255645	213207	259883	Apr-08	302819	347886	298581
Dec-02	285303	214820	281064	May-08	314700	350516	318939
Jan-03	238031	216444	242269	Jun-08	340454	353166	336216
Feb-03	259966	218080	255727	Jul-08	307287	355837	311526
Mar-03	258128	219729	262366	Aug-08	311587	358527	307349
Apr-03	110640	221390	106402	Sep-08	307402	361238	311641
May-03	40256	223064	44495	Oct-08	327038	363969	322800
Jun-03	57131	224751	52893	Nov-08	327224	366721	331463
Jul-03	154174	226450	158413	Dec-08	352038	369494	347800



<b>Table 2:</b> Monthly Forecasted value with GM(1,1) and FGM(1,1) (continued)							
MONTH	ARRIVALS	GM(1,1)	FGM(1,1)	MONTH	ARRIVALS	GM(1,1)	FGM(1,1)
Aug-03	200614	228162	196376	Jan-09	276896	372287	281135
Sep-03	218594	229888	222833	Feb-09	303302	375102	299064
Oct-03	223552	231626	219314	Mar-09	395201	377938	399439
Nov-03	241349	233377	245587	Apr-09	448486	380796	444247
Dec-03	245682	235142	241443	May-09	366375	383675	370614
Jan-04	212854	236919	217093	Jun-09	321383	386576	317145
Feb-04	221020	238711	216782	Jul-09	346718	389499	350957
Mar-04	239575	240516	243813	Aug-09	367491	392444	363253
Apr-04	229061	242334	224823	Sep-09	340645	395411	344884
May-04	232293	244166	236532	Oct-09	368212	398401	363974
Jun-04	258861	246012	254622	Nov-09	410489	401413	414727
Jul-04	243396	247873	247635	Dec-09	449806	404448	445567
Aug-04	253544	249747	249306	Jan-10	345981	407506	350220
Sep-04	245915	251635	250154	Feb-10	387143	410587	382905
Oct-04	266590	253538	262351	Mar-10	516512	413691	520750
Nov-04	270553	255454	274791	Apr-10	506400	416819	502161
Dec-04	276680	257386	272441	May-10	505856	419971	510094
Jan-05	244252	259332	248491	Jun-10	470447	423146	466208
Feb-05	257340	261293	253102	Jul-10	427763	426345	432001
Mar-05	298282	263268	302520	Aug-10	442235	429569	437996
Apr-05	269513	265259	265274	Sep-10	419389	432817	423628
May-05	284049	267265	288287	Oct-10	485959	436089	481720
Jun-05	293044	269285	288805	Nov-10	528998	439387	533236
Jul-05	268269	271321	272507	Dec-10	530594	442709	526355
Aug-05	281693	273373	277454	Jan-11	400617	446056	404856
Sep-05	270700	275440	274939	Feb-11	453468	449428	449230
Oct-05	297454	277522	293215	Mar-11	518215	452827	522453
Nov-05	302277	279621	306515	Apr-11	550158	456250	545919
Dec-05	311245	281735	307006	May-11	470471	459700	474709
Jan-06	264347	283865	268586	Jun-11	462640	463176	458402
Feb-06	286156	286011	281918	Jul-11	465656	466678	469894
Mar-06	309381	288174	313619	Aug-11	506898	470206	502659
Apr-06	290043	290353	285805	Sep-11	460994	473761	465233
May-06	283075	292548	287314				

**Table 2:** Monthly Forecasted value with GM(1,1) and FGM(1,1) (continued)



Table 3 briefly demonstrates the evaluation indexes of each model with its power in forecasting the international tourism demand in Taiwan.

**Table 3:** Summary of evaluation indexes of model accuracy

Index Model	MAPE	<b>S1</b>	S2	С	Р	ρ	Forecasting power
GM(1,1)	0.160251	94388.05	44932.53	0.47604	0.87	0.839749	Unqualified
FGM(1,1)	0.015755	94388.05	4222.04	0.04473	1.00	0.984245	Excellent

From Table 3, with the low MAPE value of 1.5755%, it can be concluded that the FGM(1,1) outperforms GM(1,1). Therefore, it is strongly suggested to forecast the international tourism demand in Taiwan.

## CONCLUSION

Combining the Fourier residual modification to the traditional Grey forecasting model GM(1,1) results in a highly accurate forecasting model named FGM(1,1). Particularly, in the case of the international tourism demand in Taiwan, despite of the hard assessment of relevant data about its determinants, FGM(1,1) has proved to follow closely and well fit the actual figures with the very low value of MAPE. Highly precise forecasting result will help the policy-makers and related organizations in the tourism industry 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.

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