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FORECASTING INTERNATIONAL TOURISM DEMAND- AN EMPIRICAL CASE IN TAIWAN

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ABSTRACT

Tourism, one of the biggest industries in many countries, has been considered a complexly integrated and self-contained economic activity.As key determinants of thetourism demand are not fully identified to some extent different forecasting models vary in thelevel of accuracy. By comparing the performance of diverse forecasting models,including the linear regression, autoregressive integrated moving average (ARIMA), Grey model, and their joint Fourier modified models, this paper aims at obtaining an efficient model to forecast the tourism demand. As a result, the accuracy of the conventional models is found to be significantly boosted with the Fourier modification joined. In the empirical case study of international tourism demand in Taiwan, the Fourier modified seasonal ARIMA model FSARIMA $(2,1,2)(1,1,1)_{12}$ is strongly suggested due to its satisfactorily high forecasting power. We further employ the model to provide the Taiwan's tourism demand in 2013 so as to assist policy-makers and related organizations in establishing their appropriate strategies for sustainable growth of the industry.

Keywords: ARIMA model, Grey model, Tourism demand forecasting, Fourier modification

INTRODUCTION

Nowadays, tourism has been considered as a "smokeless" and important industry in numerous countries in the world because it can not only generate plenty of quality jobs but also offer great contribution to the GDP. According to the data collected from World Travel and Tourism Council

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(WTTC), in 2012, the direct contribution of Tourism to worldwide GDP was USD 2,056.6 billion (2.9% of total GDP); whereas, its total contribution to GDP, including its wider economic impacts, was more than USD6,630 billion (9.3% of GDP). It also directly supported more than 101 million jobs (3.4% of total employment); besides, including jobs indirectly supported by the industry, its total contribution more than 261 million jobs (8.7% of total employment) (WTTC, 2013a). In Taiwan, particularly, the number of international tourist arrivals in 2012 was about triple compared to that in 2001. Based on the published data from WTTC (2013b), in 2012, the total contribution of the tourism industry to Taiwan GDP was about TWD 716 billion; accounting for 5.1% of GDP; and it supported 5.6% of the total employment with 605 thousand jobs. In regarding to its direct contribution, the tourism contributed 1.9% of total GDP, equivalently to about TWD 269 billion and supported 246 thousand jobs, accounting for 2.3% of total employment. Moreover, its total contribution in 2023 has been forecasted to be more than TWD 983 billion to the GDP and about 717 thousand jobs, accounting for about 6.7% of the total employment. These figures indicate that tourism is an important industry in Taiwan. In order to make proper plans for the sustainable development of the national tourism industry, accurately forecasting the tourism demand becomes mandatory.

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. (Lagos, 1999). González and Moral (1995) 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 and Witt (1995) 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 (Hsu and Wang, 2008). However, numerous researchers have concluded that many of the determinants are neither easily measured nor collected due to their availability (González and Moral, 1995; Witt and Witt, 1995; Lagos, 1999; Habibi *et al*., 2009; Nonthapot and Lean, 2013).

Furthermore, 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 and Witt, 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 and 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 and Saayman, 2005; Ouerfelli, 2008; Habibi *et al*., 2009).

Therefore, in this study, the monthly arrival of international tourists to Taiwan from January 2002 to December, 2012 is used to denote the international tourism demand in Taiwan.

Due to the above-mentioned limitations in collecting relevant data and the inherent characteristic of a time series, in this paper, we consider possible forecasting models established under linear regression, autoregressive integrated moving average (ARIMA) which is a well-known forecasting model dealing with time series, and Grey model which has been widely employed in different areas due to its ability to deal with "partial known, partial unknown" information data. The residuals from these models are then modified with Fourier series so as to improve their accuracy. After the possible models are cross-compared based on assigned accuracy indicators, the best one is selected to forecast the international tourism demand in Taiwan. In order to evaluate its forecasting power, we also compare its forecasted values with the actual values from July, 2012 – December, 2012.

STATISTICAL FORECASTING MODELS

Linear regression

Linear regression is widely employed in discovering the underlying relationship between a dependent variable and independent ones. This technique can be found in almost every textbook relating to statistics. In a time series with a key variable of interest *y*, the relationship between *y* and its time period *t* under linear regression comes in the following form:

$$y = \beta_0 + \sum_{i=1}^{n} \beta_i f_i(t) \qquad (1)$$

where $f_i(t)\left(i = \overline{1,n}\right)$ is a function of *t* and the linear parameter $\beta_i\left(i = \overline{0,n}\right)$ is called regression coefficient indicating the estimated change in the dependent variable for a unit change of a relevant independent variable while others are kept unchanged. The regression coefficients can be achieved through least-square methods. The significance of the overall model and of each regression coefficients can be validated by using the significance of F-statistics and t-statistics, respectively.

Autoregressive integrated moving average (ARIMA) model

ARIMA is a well-known forecasting model for a time series which can be made stationary by differencing or logging. A time series may have non-seasonal or seasonal characteristics. A non-seasonal ARIMA model usually has the form of *ARIMA (p, d, q)*, where the parameters *p, d* and *q* are non-negative integers that respectively denote the order of the autoregressive, integrated, and moving average parts of the model. Seasonality in a time series is referred as a regular pattern of changes that repeats over S time-periods. A seasonal time series can be made stationary by seasonal differencing which is defined as the difference between a value and a value with lag multiplied with S. Seasonal ARIMA model incorporates both non-seasonal and seasonal factors in a multiplicative model with the form of *SARIMA (p, d, q) (P,D,Q)$_S$*, where *p, d,* and *q* are the parameters in non-seasonal ARIMA model as mentioned above; *P, D, Q*, and *S* are respectively the seasonal order of autoregressive, differencing, moving average and the time span of repeating seasonal pattern. The overall procedure to obtain an ARIMA/SARIMA model can be referred to Hanke and Wichern (2008) and Etuk (2012).

Grey model

In dealing with the problems of poor information data set, Grey theory has been frequently used (Hsu and Chen, 2003; Liu, 2007). Grey model (GM), the core of the theory, is used to execute short-term forecasting operation with no strict hypothesis for the distribution of the original data series (Wang *et al*., 2011). A GM model has the form of *GM (rd, nv)*, where *rd* is the rank of differential equation and *nv* is the number of variables appeared in the equation. The fundamental model of Grey model is the first-order differential model with one input variable *GM (1, 1)* which has been successfully used in various applications. Suppose an original series with n entries is $y^{(0)}$:

$$y^{(0)} = \left\{ y_1^{(0)}, y_2^{(0)}, y_3^{(0)}, \ldots, y_k^{(0)}, \ldots y_n^{(0)} \right\} \qquad (2)$$

where $y_k^{(0)}$ is the value at time k $\left(k = \overline{1,n}\right)$. From the original series $y^{(0)}$, a new series $y^{(1)}$ can be generated by one time accumulated generating operation (1-AGO), which is

$$y^{(1)} = \left\{ y_1^{(1)}, y_2^{(1)}, y_3^{(1)}, \ldots, y_k^{(1)}, \ldots y_n^{(1)} \right\} \qquad (3)$$

where $$y_k^{(1)} = \sum_{j=1}^{k} y_j^{(0)}$$

Then the GM (1, 1) model is usually stated in the form of

$$\hat{y}_k^{(1)} = \left[y_1^{(0)} - \frac{b}{a} \right] e^{-a(k-1)} + \frac{b}{a} \qquad \left(k = \overline{1,n}\right) \qquad (4)$$

Where a is called developing coefficient and b is called grey input coefficient. These parameters are obtained by the least square method as the following equation

$$\left[a,b\right]^T = \left(B^T B\right)^{-1} B^T Y. \qquad (5)$$

where

$$B = \begin{bmatrix} -\left(y_1^{(1)} + y_2^{(1)}\right)/2 & 1 \\ -\left(y_2^{(1)} + y_3^{(1)}\right)/2 & 1 \\ \cdots & \cdots \\ -\left(y_{n-1}^{(1)} + y_n^{(1)}\right)/2 & 1 \end{bmatrix} \qquad Y = \left[y_2^{(0)}, y_2^{(0)}, \ldots, y_n^{(0)} \right]^T$$

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

$$\hat{y}^{(0)} = \left\{ \hat{y}_1^{(0)}, \hat{y}_2^{(0)}, \hat{y}_3^{(0)}, \ldots, \hat{y}_k^{(0)}, \ldots, \hat{y}_n^{(0)} \right\} \qquad (6)$$

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

Fourier residual modification

Using Fourier series to modify the residuals of *GM (1, 1)* can signifincantly improve the accuracy of the model by reducing the values of RMSE, MAE, MAPE, etc. (Hsu, 2003; Guo *et al*., 2005; Kan *et al*., 2010; Askari and Fetanat, 2011; Huang and Lee, 2011). Hence, the good methodology is also suggested to enhance the performance of the forecasting models considered in this paper. A Fourier residual modified model is obtained as the following. Based on the predicted series $\hat{y}^{(0)}$ obtained from a specific model, a residual series named $\varepsilon^{(0)}$ is defined as:

$$\varepsilon^{(0)} = \left\{ \varepsilon_2^{(0)}, \varepsilon_3^{(0)}, \varepsilon_4^{(0)}, \ldots, \varepsilon_k^{(0)}, \ldots, \varepsilon_n^{(0)} \right\} \qquad (7)$$

where $\qquad \varepsilon_k^{(0)} = y_k^{(0)} - \hat{y}_k^{(0)} \qquad \left(k = \overline{2,n}\right)$

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

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

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

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

where

$$P = \begin{bmatrix} \frac{1}{2} & \cos\left(\frac{2\pi\times 1}{n-1}\times 2\right) & \sin\left(\frac{2\pi\times 1}{n-1}\times 2\right) & \cdots & \cos\left(\frac{2\pi\times F}{n-1}\times 2\right) & \sin\left(\frac{2\pi\times F}{n-1}\times 2\right) \\ \frac{1}{2} & \cos\left(\frac{2\pi\times 1}{n-1}\times 3\right) & \sin\left(\frac{2\pi\times 1}{n-1}\times 3\right) & \cdots & \cos\left(\frac{2\pi\times F}{n-1}\times 3\right) & \sin\left(\frac{2\pi\times F}{n-1}\times 3\right) \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ \frac{1}{2} & \cos\left(\frac{2\pi\times 1}{n-1}\times n\right) & \sin\left(\frac{2\pi\times 1}{n-1}\times n\right) & \cdots & \cos\left(\frac{2\pi\times F}{n-1}\times n\right) & \sin\left(\frac{2\pi\times F}{n-1}\times n\right) \end{bmatrix}$$

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

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:

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

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

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

Therefore, based on the predicted series $\hat{y}^{(0)}$, the predicted series $\tilde{y}^{(0)}$ of Fourier residual modified model is determined by:

$$\tilde{y}^{(0)} = \left\{\tilde{y}_1^{(0)}, \tilde{y}_2^{(0)}, \tilde{y}_3^{(0)}, \ldots, \tilde{y}_k^{(0)}, \ldots, \tilde{y}_n^{(0)}\right\} \qquad (12)$$

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

Let $\widehat{y}_k^{(0)}$ denote the forecasted value at entry k of a specific model. The residual error at the entry is obtained by

$$\varepsilon_k = y_k^{(0)} - \widehat{y}_k^{(0)} \qquad \left(k = \overline{1,n}\right) \qquad (13)$$

In evaluating the model accuracy, the following indexes are often taken into consideration. The mean absolute percentage error (MAPE) (Hsu and Chen, 2003; Guo *et al*., 2005; Hsu and Wang, 2008; Hua and Liang, 2009; Ma and Zhang, 2009; Kan *et al*., 2010; Chang and Liao, 2010; Askari and Fetanat, 2011; Tsaur and Kuo, 2011; Huang and Lee, 2011; Li *et al*., 2011):

$$MAPE = \frac{1}{n}\sum_{k=1}^{n}\left(\left|\varepsilon_k\right| / y_k^{(0)}\right)$$

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

$$C = \frac{S_2}{S_1}$$

where: $S_1 = \sqrt{\frac{1}{n}\sum_{k=1}^{n}\left[y_k^{(0)} - \frac{1}{n}\sum_{k=1}^{n} y_k^{(0)}\right]^2}$ and $S_2 = \sqrt{\frac{1}{n}\sum_{k=1}^{n}\left[\varepsilon_k - \frac{1}{n}\sum_{k=1}^{n}\varepsilon_k\right]^2}$

The smaller the C value, the better the accuracy of the model. The small error probability P (Hua and Liang, 2009; Ma and Zhang, 2009):

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

The higher the P value is, the higher the accuracy of the model. The forecasting accuracy ρ(Ma and Zhang, 2009): $\rho = 1 - MAPE$

As a rule of thumb, certain combination of the above indexes results in four grades of evaluating model accuracy as stated in Table 1.

Table 1: Four grades of forecasting accuracy

Grade level	***MAPE***	***C***	***P***	$\boldsymbol{\rho}$
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

EMPIRICAL STUDY

The international tourism demand in Taiwan is referred to the number of monthly arrivals of international tourists to Taiwan, obtained from the statistical data published on the website of Ministry of Transportation and Communication R.O.C (MOTC). The data used in this paper include 132 observations, correspondingly from January 2002 to December 2012 as shown in Table

2. Data from January 2002 to June 2012 are used to establish forecasting models; whereas, data from July – December 2012 are used to test the forecasting power of selected model.

Linear regression model

Data from January 2002 – June 2012 are plotted as in Figure 1 which makes us consider the possible relationship between the monthly arrivals (y) and the time periods (t) in either first-order or second-order linear equation, respectively named as LR1 and LR2.

- LR1: $y = \beta_0 + \beta_1 t$
- LR2: $y = \beta_0 + \beta_1 t + \beta_2 t^2$

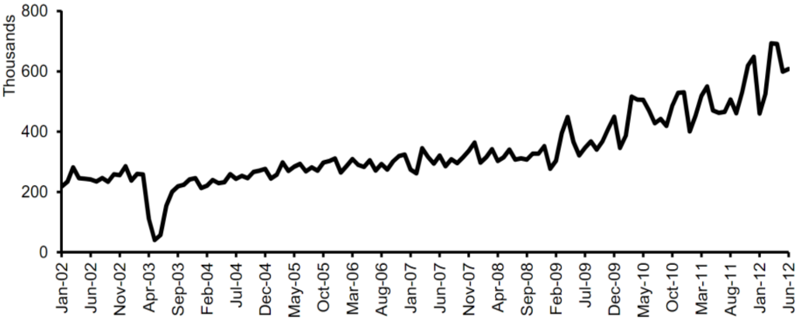

Figure 1: Monthly arrivals of international tourists to Taiwan

Table 2: The number of monthly arrivals of international tourists to Taiwan

Month	Arrivals	Month	Arrivals	Month	Arrivals	Month	Arrivals
Jan-02	217,600	Oct-04	266,590	Jul-07	285,075	Apr-10	506,400
Feb-02	233,896	Nov-04	270,553	Aug-07	308,481	May-10	505,856
Mar-02	281,522	Dec-04	276,680	Sep-07	295,594	Jun-10	470,447
Apr-02	245,759	Jan-05	244,252	Oct-07	314,519	Jul-10	427,763
May-02	243,941	Feb-05	257,340	Nov-07	336,370	Aug-10	442,235
Jun-02	241,378	Mar-05	298,282	Dec-07	363,916	Sep-10	419,389
Jul-02	234,596	Apr-05	269,513	Jan-08	297,442	Oct-10	485,959
Aug-02	246,079	May-05	284,049	Feb-08	315,134	Nov-10	528,998
Sep-02	233,613	Jun-05	293,044	Mar-08	342,062	Dec-10	530,594
Oct-02	258,360	Jul-05	268,269	Apr-08	302,819	Jan-11	400,617
Nov-02	255,645	Aug-05	281,693	May-08	314,700	Feb-11	453,468
Dec-02	285,303	Sep-05	270,700	Jun-08	340,454	Mar-11	518,215
Jan-03	238,031	Oct-05	297,454	Jul-08	307,287	Apr-11	550,158
Feb-03	259,966	Nov-05	302,277	Aug-08	311,587	May-11	470,471
Mar-03	258,128	Dec-05	311,245	Sep-08	307,402	Jun-11	462,640
Apr-03	110,640	Jan-06	264,347	Oct-08	327,038	Jul-11	465,656
May-03	40,256	Feb-06	286,156	Nov-08	327,224	Aug-11	506,898
Jun-03	57,131	Mar-06	309,381	Dec-08	352,038	Sep-11	460,994
Jul-03	154,174	Apr-06	290,043	Jan-09	276,896	Oct-11	530,430
Aug-03	200,614	May-06	283,075	Feb-09	303,302	Nov-11	619,343
Sep-03	218,594	Jun-06	305,127	Mar-09	395,201	Dec-11	648,594
Oct-03	223,552	Jul-06	270,850	Apr-09	448,486	Jan-12	460,064

Nov-03	241,349	Aug-06	292,561	May-09	366,375	Feb-12	525,240
Dec-03	245,682	Sep-06	274,118	Jun-09	321,383	Mar-12	693,185
Jan-04	212,854	Oct-06	301,575	Jul-09	346,718	Apr-12	691,086
Feb-04	221,020	Nov-06	318,663	Aug-09	367,491	May-12	599,098
Mar-04	239,575	Dec-06	323,931	Sep-09	340,645	Jun-12	607,778
Apr-04	229,061	Jan-07	274,198	Oct-09	368,212	Jul-12	592,449
May-04	232,293	Feb-07	261,799	Nov-09	410,489	Aug-12	607,122
Jun-04	258,861	Mar-07	345,295	Dec-09	449,806	Sep-12	550,901
Jul-04	243,396	Apr-07	316,119	Jan-10	345,981	Oct-12	610,342
Aug-04	253,544	May-07	294,021	Feb-10	387,143	Nov-12	671,617
Sep-04	245,915	Jun-07	320,676	Mar-10	516,512	Dec-12	702,588

Relevant statistical analyses of the two linear models are shown in Table 3, 4 and 5. Table 3 indicates that the parameters in LR1 and LR2 are all statistically significant at the level of 5%. The validity of these two models is further confirmed with the results shown in Table-4. Based on the adjusted R-Square in Table-5, it is clearly that LR2 outperforms LR1. Hence, LR2 is used as one forecasting model.

Table 3: Linear regression coefficients

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
LR1	(Constant)	157517.51	10769.25		14.627	0.00
	T	2801.44	147.16	0.863	19.036	0.00
LR2	(Constant)	239493.25	13098.50		18.284	0.00
	T	-1041.17	476.14	-0.321	-2.187	0.03
	t^2	30.26	3.63	1.222	8.331	0.00

Table 4: ANOVA analysis

Model		Sum of Squares	df	Mean Square	F	Sig.
LR1	Regression	1308178542117	1	1308178542117	362.38	0.00
	Residual	447633491948	124	3609947515		
	Total	1755812034065	125			
LR2	Regression	1469647573757	2	734823786878	315.84	0.00
	Residual	286164460308	123	2326540327		
	Total	1755812034065	125			

Table 5: Model summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
LR1	0.863	0.745	0.743	60082.84
LR2	0.915	0.837	0.834	48234.22

ARIMA model

From Figure 1, it can also be concluded that seasonality exists in the series of tourism demand. Therefore, only seasonal ARIMA model is considered in this section. At one degree of both non-seasonal and seasonal difference, the series becomes stationary. Figure 2 shows that $SARIMA(2,1,2)(1,1,1)_{12}$ is appropriate for the time series. Further support can be found in Table-6,

Figure 3 and Figure 4.

Table 6: Summary statistics of *SARIMA (2, 1, 2) (1, 1, 1)$_{12}$*

	Model Fit statistics				Ljung-Box Q(18)		
	R-squared	RMSE	MAPE	MAE	Statistics	DF	Sig.
SARIMA(2,1,2)(1,1,1)$_{12}$	0.931	32546.38	9.53	24116.08	6.34	12	0.898

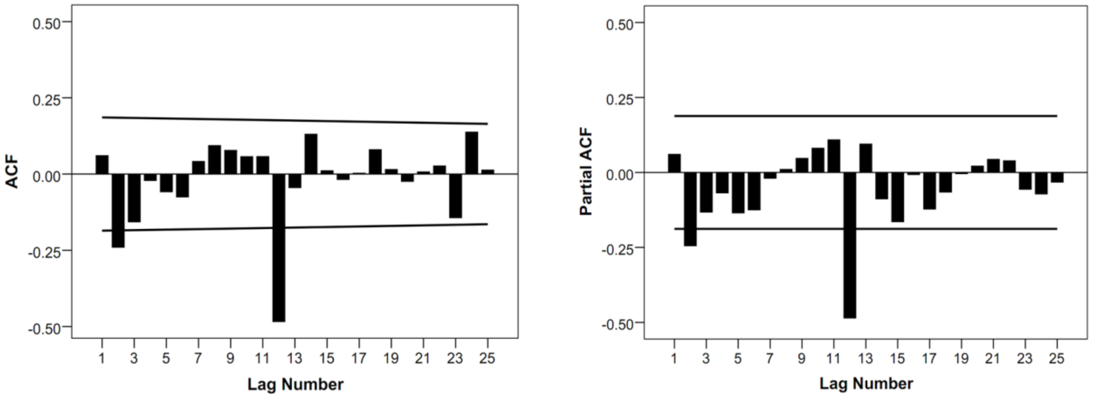

Figure 2: Monthly arrivals of international tourists to Taiwan

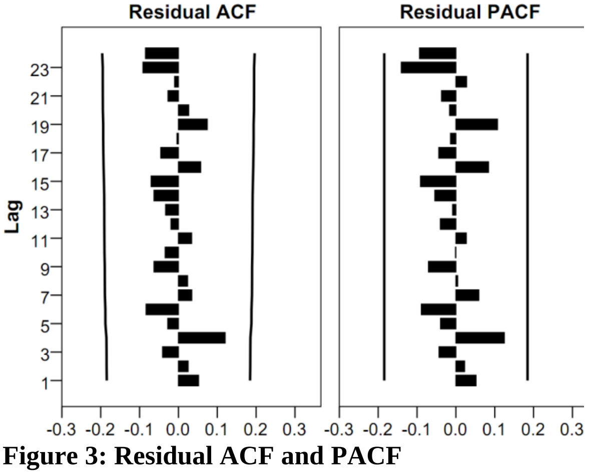

Figure 3: Residual ACF and PACF

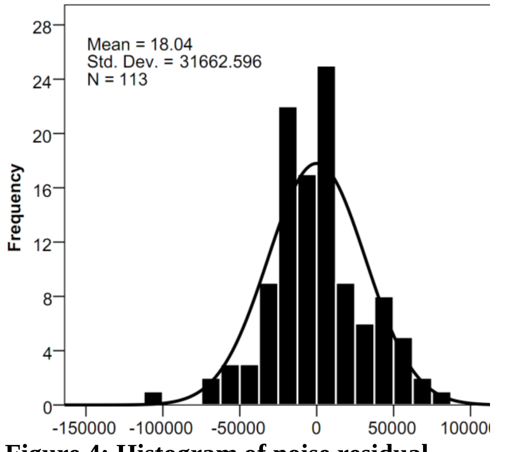

Figure 4: Histogram of noise residual

Grey Forecasting Model GM (1, 1)

In this study, the traditional Grey Model *GM (1, 1)* is established as

$$\hat{y}_k^{(1)} = 19691938.32e^{0.009081305(k-1)} - 19474338.32$$

Fourier residual modified models

Residual series obtained from the above forecasting models are now modified with Fourier series in order to improve their accuracies. Table-7 briefly demonstrates the evaluation indexes of all possible models with their power in forecasting the international tourism demand in Taiwan.

Table 7: Summary of evaluation indexes

Model	MAPE	S_1	S_2	C	P	ρ	Grade
LR2	0.159995	118046.67	47656.55	0.40371	0.921	0.840005	*Unqualified*
SARIMA	0.095303	118046.67	31522.18	0.26703	0.982	0.904697	*Qualified*
GM(1,1)	0.167738	118046.67	51595.93	0.43708	0.897	0.832262	*Unqualified*
FLR2(*)	0.011397	118046.67	4215.26	0.03571	1.000	0.988603	*Good*
FSARIMA(*)	0.008520	118046.67	3342.74	0.02832	1.000	0.991480	*Very good*
FGM(1,1) (*)	0.010630	118046.67	4213.48	0.03569	1.000	0.989370	*Good*

(*): The letter "F" in these models stands for "Fourier modified model".

Table 8: Forecasting power of *FSARIMA(2,1,2)(1,1,1)$_{12}$* Model

Month	Actual *(Arrivals)*	Forecasted *(Arrivals)*	Absolute percentage error
Jul-12	592,449	611,905	0.033
Aug-12	607,122	621,904	0.024
Sep-12	550,901	587,619	0.067
Oct-12	610,342	649,432	0.064
Nov-12	671,617	706,094	0.051
Dec-12	702,588	723,916	0.030

From Table-7, it is clearly proved that if residual series of a specific forecasting model is modified with Fourier series, the model accuracy is significantly improved. Among the mentioned models, *FSARIMA (2, 1, 2) (1, 1, 1)$_{12}$* is selected because it outperforms others in term of low MAPE, low C and high ρ. In order to test its actual forecasting power, the selected model is used to forecast the monthly tourism demand from July – December 2012. The forecasted values are then compared with the actual demand of the same period as illustrated in Table-8. With the low values of absolute percentage errors in Table-8, equivalently MAPE about 4.45%, *FSARIMA(2,1,2)(1,1,1)$_{12}$* is obviously considered as an excellent forecasting model and therefore, strongly suggested to forecast the international tourism demand in Taiwan. The demand in 2013 is forecasted as shown in Table-9.

Table 9: Forecasted international tourism demand in Taiwan in 2013

Month	Forecasted *(Arrivals)*	Month	Forecasted *(Arrivals)*
Jan-13	522,187	Jul-13	612,970
Feb-13	574,426	Aug-13	648,845
Mar-13	668,861	Sep-13	563,180
Apr-13	687,103	Oct-13	576,240
May-13	619,615	Nov-13	669,091
Jun-13	617,498	Dec-13	743,497

CONCLUSION AND POLICY IMPLICATIONS

Due to the hard assessment of relevant data about key determinants of the international tourism demand, this paper discusses the possible application of the three forecasting models, including linear regression, autoregressive integrated moving average (ARIMA) and Grey model. So as to improve their accuracy, their residual series are suggested to be modified with Fourier series. In the case of the international tourism demand in Taiwan, Fourier residual modification has proved to substantially enhance the accuracy of the models. Among them, Fourier modified seasonal ARIMA model $FSARIMA\ (2, 1, 2)\ (1, 1, 1)_{12}$ is considered the most appropriate to forecast the international tourism demand in Taiwan. The low value of the mean absolute percentage error (MAPE) in comparing the forecasted values obtained from the selected model and the actual values in the time series is a sufficient indicator supporting the reliable accuracy in the forecasted values of the international tourism demand in Taiwan in 2013. Trustworthy forecasting result is of great importance in helping 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 sustainable growth of the industry.

REFERENCES

Askari, M. and Fetanat, A. (2011). Long-term load forecasting in power system. Grey system prediction-based models. *Journal of Applied Sciences,* Vol. 11, pp. 3034-3038.

Chang, Y. W. and Liao, M. Y. (2010). A seasonal ARIMA model of tourism forecasting. The case of Taiwan. *Asia Pacific journal of Tourism research,* Vol. 15, pp. 215-221.

Dritsakis, N. (2004). Co-integration analysis of German and British tourism demand for Greece. *Tourism Management*. Vol. 25, pp. 111-119.

Etuk, E. H. (2012). A seasonal ARIMA model for daily Nigerian Naira-US Dollar exchange rates. *Asian Journal of Empirical Research*, Vol. 2, pp. 219-227.

González, P. and Moral, P. (1995). An analysis of the international tourism demand in Spain. *International Journal of Forecasting*. Vol. 11, pp. 233-251.

Guo, Z., Song, X. and Ye, J. (2005). A Verhulst model on time series error corrected for port throughput forecasting. *Journal of the Eastern Asia society for Transportation studies,* Vol. 6, pp. 881-891.

Habibi, F., Rahim, K. A., Ramchandran, S. and Chin, L. (2009). Dynamic Model for International Tourism Demand for Malaysia. Panel Data Evidence. *International Research Journal of Finance and Economics,* Vol. 33, pp. 207-217.

Hanke, J. E. and Wichern, D. W. (2005). *Business Forecasting*. 8th Ed. Pearson, Prentice Hall, New Jersey.

Hsu, C. C. and Chen, C. Y. (2003). Applications of improved grey prediction model for power demand forecasting. *Energy Conversion and Management.* Vol. 44, pp. 2241-2249.

Hsu, L. C. (2003). Applying the grey prediction model to the global integrated circuit industry. *Technological forecasting & Social change.* Vol. 70, pp. 563-574.

Hsu, L. C. and Wang, C. H. (2008). The development and testing of a modified Diffusion model for predicting tourism demand. *International Journal of Management*. Vol. 25, pp. 439-445.

Hua, J. and Liang, Q. (2009). Application research of the Grey forecast in the Logistics demand forecast. *First International Workshop on Education Technology and Computer Science*. Vol. 3, pp. 361-363.

Huang, Y. L. and Lee, Y. H. (2011). Accurately forecasting model for the Stochastic Volatility data in tourism demand. *Modern economy*. Vol. 2, pp. 823-829.

Kan, M. L., Lee, Y. B. and Chen, W. C. (2010). Apply grey prediction in the number of Tourist, In: *The fourth international conference on Genetic and Evolutionary computing in Shenzhen, China*, 2010, pp. 481-484.

Kulendran, N. and Witt, S. (2001). Co-integration versus least squares regression. *Annals of Tourism Research*. Vol. 28, pp. 291–311.

Lagos, D. G. (1999). Exploratory forecasting methodologies for tourism demand. *Ekistics Journal*, Vol. 396, pp. 143-154.

Li, G. D., Wang, C. H., Masuda, S. and Nagai, M. (2011). A research on short term load forecasting problem applying improved grey dynamic model. *Electrical power and Energy systems*, Vol. 33, pp. 809-816.

Lim, C. and Mc Aleer, M. (2001). Monthly seasonal variations. Asian tourism to Australia. *Annals of Tourism Research*. Vol. 28, pp. 68–82.

Liu, S. F. (2007). Advances in Grey system theory and its applications, In. Proceedings of 2007 IEEE International Conference on Grey Systems and Intelligent Services in Nanjing, China, 2007.

Ma, H. and Zhang, Z. (2009). Grey prediction with Markov-Chain for Crude oil production and consumption in China. *Advances in Intelligent and Soft Computing*. Vol. 56, pp. 551-561.

Ministry of Transportation and Communication R. O. C. (2013). Monthly Statistics. www.motc.gov.tw.

Morley, C. L. (1998). A dynamic international demand model. *Annals of Tourism Research*, Vol. 23, pp. 70-84.

Naude, A. W. and Saayaman, A. (2005). Determinants of tourist arrivals in Africa. A panel data regression analysis. *Tourism Economics*, Vol. 11, pp. 365-391.

Nonthapot, S. and Lean, H. H. (2013). Demand of Thai tourists to Lao PDR. An ARDL approach. *Asian Journal of Empirical Research*, Vol. 3, pp. 279-285.

Ouerfelli, C. (2008). Co-integration analysis of quarterly European tourism demand in Tunisia. *Tourism Management*, Vol. 29, pp. 127-137.

Song, H. and Witt, S. F. (2003). General-to-specific modeling to international tourism demand forecasting. *Journal of Travel Research,* Vol. 42, pp. 65-74.

Song, H., Witt, S. F. and Li, G. (2003). Modelling and forecasting the demand for Thai tourism. *Tourism Economics*, Vol. 9, pp. 363–387.

Tan, Y. F., McCahon, C. and Miller, J. (2002). Modelling tourist flows to Indonesia and Malaysia. *Journal of Travel and Tourism Marketing*, Vol. 12, pp. 63–84.

Tsaur, R. C. and Kuo, T. C. (2011). The adaptive fuzzy time series model with an application to

Taiwan's tourism demand. *Expert systems with Applications,* Vol. 38, pp. 9164-9171.

Wang, S. J., Wang, W. L., Huang, C. T. and Chen, S. C. (2011). Improving inventory effectiveness in RFID-enabled global supply chain with Grey forecasting model. *Journal of Strategic Information Systems,* Vol. 20, pp. 307-322.

Witt, S. F. and Witt, C. A. (1995). Forecasting tourism demand. A review of empirical research. *International Journal of Forecasting,* Vol. 11, pp. 447-475.

World Travel and Tourism Council (2013 a, b). *Annual Research*. *Key Facts*. *http://www.wttc.org/research/economic-impact-research/regional-reports/world/*.