Forecasting with Fourier Residual Modified ARIMA Model- An Empirical Case of Inbound Tourism Demand in New Zealand

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Abstract: Tourism, one of the gigantic industries in a country, has been considered as a complexly integrated and self-contained economic activity. Key determinants of the tourism demand have not been being fully identified in literature, so varied levels of the forecast accuracy existing in distinct formations of forecasting models, such as the autoregressive integrated moving average (ARIMA) and its joint Fourier modified model, are investigated in this paper. With a certain degree of Fourier-modification factors joined, the model performance is found to be significantly boosted. In an empirical study for the inbound-tourism demand forecasting in New Zealand, the Fourier-modified seasonal $ARIMA$ model, named $FSARIMA(1, 0, 1)(1, 1, 1)_{12}$, is highly recommended due to its satisfactory forecasting power for the historical data. We further employ this model to provide the New Zealand's tourism projecting demand in 2013 so as to assist policy makers as well as related organizations in early establishing their appropriate strategies for sustaining growth in this extremely-intensified competitive industry.

Key–Words: ARIMA model, Tourism demand, Fourier modification, New Zealand tourism, Tourism forecasting

1 Introduction

Tourism, a "smokeless" industry, is one of the world's most important and fastest growing economic sectors, generating quality jobs and substantial wealth for economies around the globe. According to the data collected from World Travel & Tourism Council (WTTC) [1], in 2012, the direct contribution of Tourism to worldwide GDP was more than USD 2,056 billion, accounting for 2.9% of total GDP while its total contribution to GDP, including its wider economic impacts, was more than USD6,630 billion (9.3% of total GDP). It also directly supported more than 101 million jobs (3.4% of total employment) in 2012; besides, including jobs indirectly supported by the industry, its total contribution was about 261 million jobs (8.7% of total employment).

In New Zealand, the number of international tourist arrivals in 2012 was about 50% higher than that in 2000. In 2012, the total contribution of the tourism industry to New Zealand GDP was about NZD31.1 billion; accounting for 14.9% of GDP; and it supported 19.1% of the total employment with about 426.5 thousand jobs. In regarding to its direct contribution, the tourism contributed about NZD7.0 billion; accounting for 3.4% of total GDP and supported 133 thousand jobs (6% of total employment) [2]. These figures indicate that the tourism industry has played an important role in the development of New Zealand's economy. In term of total contribution to GDP of New Zealand, its national tourism industry was ranked 38 among the 184 countries and territories, and ranked 41 in regarding to the number of visitor exports [2].

While its importance to the national growth has been well recognized, the core issue of an accurate forecast of the tourism demand to assist policy-makers creating proper early strategies in sustainability of the tourism-industry development has not been completely resolved. The tourism has been considered as not only an integrated and self-contained economic activity 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, among others [3].

Since there has been no strong economic theory to support the vital determinants for predicting the tourism demand in literature, over the past decades, diverse models have been developed in identifying the adequate variables that impact the tourism demand [4]. However, it has been a tough topic in fully identifying the determinants of the inbound tourism demand. Gonzlez & Moral [5] listed them as the cost of travel to and the cost of living for the tourist at the destination (briefly mentioned as tourism price), the price and the income indexes, marketing expenditures, demographic and cultural factors, the quality-price ratio, and other factors [6]; whereas, Witt and Witt [7] proposed other determinants, such 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 [6]), substitute prices, one-off events, trend, etc. But Hsu & Wang [6] approached with some marketing aspects which were tour prices, distribution channel of the travel agents, traveller's income. Besides, many of these determinants are neither easily measured nor collected due to their availability [3,6-8].

Furthermore, "tourism demand" is a vague concept which is not easily measured by a certain standard. It was suggested that inbound tourism demand be measured in terms of the number of tourist arrivals, tourist expenditure (tourist receipts) or the number of nights tourists spent [7, 8]. But, due to their complexities in collecting the data of tourist expenditure as well as the number of nights tourists spent, the number of tourist arrivals has been widely used as an appropriate indicator of inbound tourism demand in many researches [4,5,8-15]. Therefore, in this study, the monthly arrivals of inbound tourists to New Zealand from January 2000 to March 2013 are used to denote the inbound tourism demand in New Zealand.

As tourism is season-sensitive with the inherent characteristic of a time series, it is therefore suggested to use autoregressive integrated moving average (ARIMA), a well-known forecasting model dealing with time series, to predict the demand. Unlike other methods, the ARIMA approach can efficiently work with unknown underlying economic model or structural relationships of the data set which are assumed that past values of the series plus previous error terms contain information for the purposes of forecasting. The key advantage of ARIMA forecasting model is that it only requires data of the interested variables in a time series. ARIMA model has been found relatively robust especially when generating short-run forecasts, which makes ARIMA model frequently outperform more sophisticated structural models in providing short-term forecast [17, 18]. Therefore, the ARIMA forecasting technique selected and presented in this paper is believed to be an appropriate forecasting model in the case of tourism demand [19, 20].

In order to improve the performance of the selected model, we propose combining the conventional model with a modification technique of Fourier series. To achieve this, the residual series obtained from ARIMA model is then modified with Fourier series so as to improve the model accuracy. In order to evaluate the forecasting power of the Fourier modified model, we compare the forecast values obtained from this modified model with the actual ones in a period of time before being further employed to have a longer forecast.

1.1 ARIMA Model

The ARIMA model was first introduced by Box and Jenkins in 1960s to forecast a time series which can be made stationary by differencing or logging. A time series may have non-seasonal or seasonal characteristics. Seasonality in a time series is defined as a regular pattern of changes that repeats over S time-periods. With a seasonal time series, there is usually a difference between the average values at some particular times within the seasonal intervals and the average values at other times; therefore, in most cases, the seasonal time series is non-stationary.

1.1.1 Non-seasonal ARIMA model

The non-seasonal ARIMA model usually has the form of $ARIMA(p, d, q)$, where:

- p is the number of lags of the differenced series appeared in the forecasting equation, called autoregressive parameter,
- d is the difference levels to make a time series stationary, called integrated parameter, and
- q is the number of the lags of the forecast errors, called moving-average parameter. "Auto-Regressive" term refers to the lags of the differenced series appeared in the forecasting equation and "Moving Average" term refers to the lags of the forecast errors. This "Integrated" term refers to the difference levels to make a time series stationary.

1.1.2 Seasonal ARIMA model

Seasonality is one of the most important factors affecting the variations of a time series. In several non-stationary time series, the variations induced by seasonal factor sometimes dominate the variations of the original series. This issue often occurs due to the environmental influence, such as periodic trend. A seasonal time series can be considered as a non-stationary time series that follow some kind of seasonal periodic trend.

With a seasonal time series, it can be made stationary by seasonal differencing which is defined as a difference between one value and another one with lag that is a multiple of 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, q are the parameters in non-seasonal ARIMA model as mentioned above.
- P is the number of seasonal Autoregressive order,
- D is the number of seasonal differencing,
- Q is the number of seasonal Moving Average order, and
- S is the time span of repeating seasonal pattern.

There are three basic steps in the overall procedures to obtain an ARIMA or SARIMA model [21], including:

Step 1: Identifying the possible models

- Examine the Auto-Correlation Function (ACF) and Partial Auto-Correlation Function (PACF) graphs to identify non-seasonal terms.
- Before identifying possible ARIMA models for a time series, it is critical to make sure that the series is stationary. If it is not, it must be transformed by either differencing or logging to become stationary. For auto-regression (AR) or auto-regression moving average (ARMA) models, it is mandatory that the modulus of the roots of the AR polynomial be greater than unity, and, for the moving average (MA) part to be invertible, it is also crucial that the roots of the MA polynomial lie outside the unit circle [17].
- By differencing the seasonal time series to make it stationary, we can easily determine the difference order of differencing required rendering the series stationary before identifying an appropriate ARMA form to model the stationary series. Traditionally, Box-Jenkins procedure is frequently used, which is a quasi-formal approach with model identification relying on subjective assessment of plots of auto-correlation function (ACF) and partial auto-correlation function (PACF) of the series [17]. A time series is considered stationary if the lag values of the ACF cut off or die down fairly quickly. If the series is not stationary, it should be differenced gradually until it is considered stationary. Then, the d value in the model is obtained. If ACF graph cut off after lags q fairly quickly and PACF graph cut off after lags p fairly quickly, $ARMA(p,q)$ is achieved. $ARIMA(p,d,q)$ is accordingly identified.
- Examine the patterns across lags that are multiples of S to identify seasonal terms. Judge the ACF and PACF at the seasonal lags in the same way.

Step 2: Fitting the model

In this step, the parameters of the model are estimated. Nowadays, with the advancement of the science and technology, the parameter estimation is usually done with the assistance of computational software, such as STATA, Eviews, SPSS, etc.

Step 3: Testing the model for adequacy

This step formally assesses each of the time series models, and involves a rigorous evaluation of the analytical tests for each of the competing models. Because different models may wisely perform similarly, their alternative formulations should be retained for further assessment at the stage of checking forecasting power of the models.

There are several analytical methods available for testing the models. Among them, there are two popularly used, including plotting the residuals of the estimated model to detect either any outliers that may affect parameter estimates or any possible auto-correlation or heteroskedacity problems; and, plotting the ACF and PACF of the residuals to check the model adequacy. The residuals from the model must have normal distribution and be white-noise (also known random). This test can be done with one of the following ways:

- Testing the normal distribution of the residuals by considering the normal probability plot and testing the white-noise of the residuals by considering its ACF and PACF graphs where individual residual autocorrelation should be small and its value is within $\pm 2/\sqrt{n}$ from the central point of zero.

- Ljung-Box Q statistic [22]:

$$Q_m = n(n+2)\sum_{k=1}^{m}\frac{e_k^2}{n-2} \tag{1}$$

  where: e_k is the residual autocorrelation at lag k; n is the number of residuals; and, m is the number of time lags includes in the test.
  The model is considered adequate only if the p-value associated with the Ljung-Box Q Statistic is higher than a given significance.

1.2 Fourier Residual Modification

Grey forecasting models have been proved to be significantly improved after their residual series are modified with Fourier series [21-25]. So, this effective methodology should also be considered in the case of ARIMA model. The procedure to obtain the modified model is as the following.

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

$$\varepsilon^{(0)} = \{\varepsilon_2^{(0)}, \varepsilon_3^{(0)}, \ldots, \varepsilon_n^{(0)}\} \tag{2}$$

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

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

$$\varepsilon_k^{(0)} = \frac{a_0}{2} + \sum_{i=1}^{F}\left[a_i\cos\left(\frac{2ik\pi}{n-1}\right) + b_i\sin\left(\frac{2ik\pi}{n-1}\right)\right] \tag{3}$$

where: $F = [(n-1)/2 - 1]$ is called the minimum deployment frequency of Fourier series [27] and only take integer number [23, 24, 26]. And therefore, the residual series is rewritten as:

$$\varepsilon^{(0)} = P \cdot C \tag{4}$$

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:

$$C = (P^T P)^{-1} P^T \left[\varepsilon^{(0)}\right]^T. \tag{5}$$

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

$$\hat{\varepsilon}_k^{(0)} = \frac{a_0}{2} + \sum_{i=1}^{F}\left[a_i\cos\left(\frac{2ik\pi}{n-1}\right) + b_i\sin\left(\frac{2ik\pi}{n-1}\right)\right] \tag{6}$$

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

$$\tilde{x}^{(0)} = \{\tilde{x}_1^{(0)}, \tilde{x}_2^{(0)}, \ldots, \tilde{x}_k^{(0)}, \ldots, \tilde{x}_n^{(0)}\} \tag{7}$$

where

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

In order to evaluate the accuracy of the forecasting model, the residual error (ε) and its relative error ($\wp$) are used [24, 28]. ε and $\wp$ of the k^{th} entry are expressed as:

- Residual error:

$$\varepsilon_k = x_k^{(0)} - f_k^{(0)} \qquad (k = \overline{1,n})$$

  where $f_k^{(0)}$ is the forecasted value at the k^{th} entry.

- Relative error:

$$\wp_k = \frac{|\varepsilon_k|}{x_k^{(0)}}$$

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

- The mean absolute percentage error (MAPE) [6, 22-25, 27-31]:

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

- The post-error ratio C [34, 35]:

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

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 [34, 35]:

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

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 [35]. Thus, the higher the P value, the higher accuracy the model has.

- The forecasting accuracy ρ [35]:

$$\rho = 1 - MAPE.$$

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

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

2 Empirical Study

Historical data of the inbound tourism demand in New Zealand from January 2000 to March 2013 (totally 160 observations) are obtained from the monthly statistical data published by Statistics New Zealand [36] as shown in the Appendix. The data between January 2000 and December 2012, plotted on Fig.1, show that the time series has seasonal characteristic; hence, in this investigated period, an $ARIMA/SARIMA$ model is appropriately suggested. The traditional model is then modified with Fourier series to become a modified model with higher accuracy. Data from January 2013 to March 2013 are used to check the forecast power of the modified model before it is employed to forecast the demand in other three quarters of 2013.

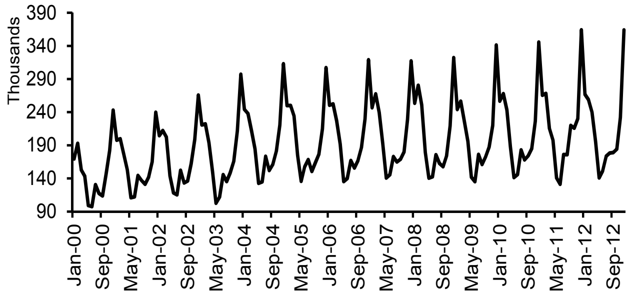


Figure 1: Monthly inbound arrivals to New Zealand

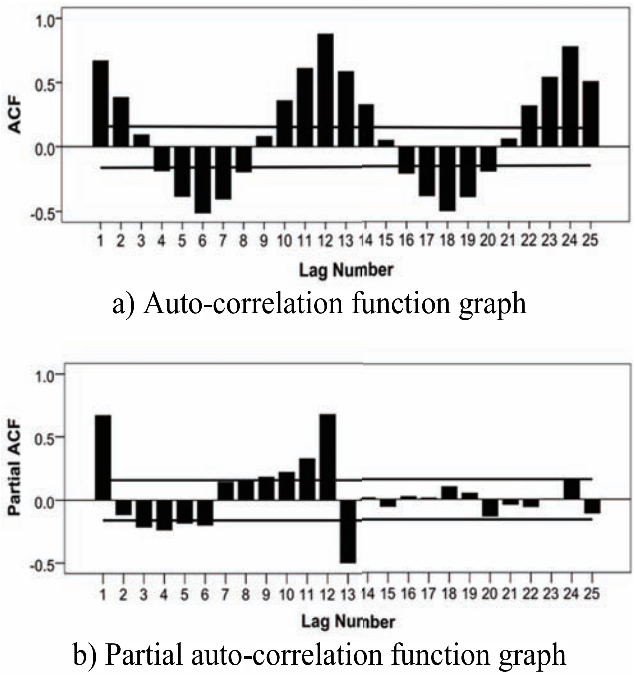
From Fig.1, it can be concluded that seasonality exists in the series of tourism demand. Specifically, the monthly seasonal indexes are shown in Table 2.

Table 2: Monthly seasonal indexes

Month	Seasonal index (%)
January	122.53
February	126.38
March	112.28
April	91.44
May	67.06
June	68.64
July	85.34
August	79.48
September	83.51
October	91.26
November	110.90
December	161.17

It is obvious that there is a high demand of inbound tourists from November, December to the first quarter of the next year; whereas, there are fewer inbound tourists to New Zealand in the period of May-August. This can be explained by the fact that the summer and autumn time in New Zealand from December to February with the most comfortable weather temperature is not only the time that students, especially Australian ones, have their Summer holidays but also the ideal time to travel around the clean and green country with typical destinations such as Milford Sound, Abel Tasman National Park or the Tongariro Alpine Crossing, or join several typical performance activities attracting tourists such as bungee jumping or whale watching; while May-August is the cold winter time which usually doesn't attract people to go sight-seeing. New Zealand is also a high-ranked country with advanced education systems, which is one of the dominant factors appealing international students to choose New Zealand as a suitable destination for their higher education. Their relatives' visits also help the national tourism industry because they take the special opportunity to explore the beauty of New Zealand.

With the existence of seasonal characteristic, only seasonal ARIMA model is considered in this section. The original series of the inbound tourism demand is not stationary as plotted in Fig.2. However, at one degree of seasonal difference, the series becomes stationary as shown in Fig.3.



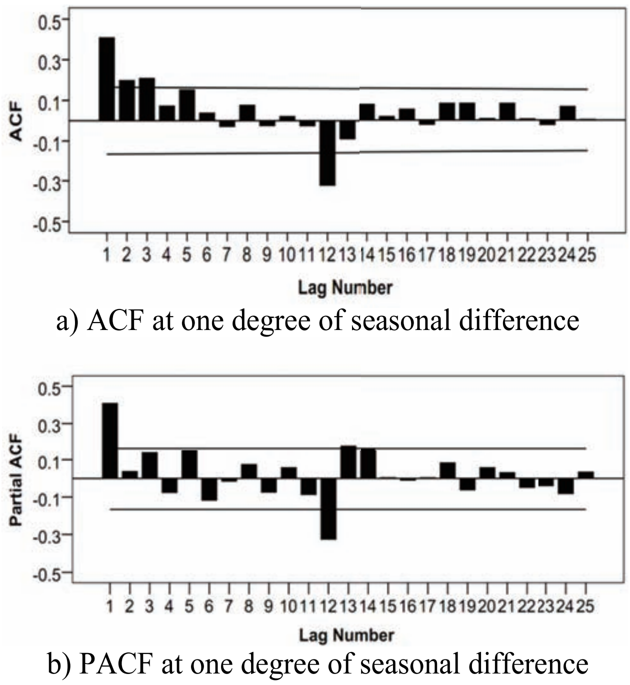
a) Auto-correlation function graph

b) Partial auto-correlation function graph

Figure 2: ACF and PACF graphs

From the Fig.3, there are three possible SARIMA models as the following.

- Model 1: $SARIMA(1,0,1)(1,1,1)_{12}$
- Model 2: $SARIMA(1,0,2)(1,1,1)_{12}$
- Model 3: $SARIMA(1,0,3)(1,1,1)_{12}$



a) ACF at one degree of seasonal difference

b) PACF at one degree of seasonal difference

Figure 3: ACF and PACF at one degree of seasonal difference

The parameters of these models are summarized as in Table 3.

Of the three models shown in Table 4, Model 1 is the best because it has the lowest value of MAPE and MAE. Fig.4 shows that Model 1 is adequate; and, the histogram of the residuals in Fig.5 further emphasizes the white-noise characteristic of the residual series obtained from the traditional SARIMA model. Model 1 is, therefore, selected in this study for further assessment of forecasting power.

In order to compare the performance of these three models, we consider some statistics indexes as illustrated in Table 4.

The residual series obtained from the selected model $SARIMA(1,0,1)(1,1,1)_{12}$ is now modified with Fourier series, making the model become a new one- called $FSARIMA(1,0,1)(1,1,1)_{12}$. The evaluation of these two models is shown in Table 5.

In order to evaluate the forecasting power of $FSARIMA(1,0,1)(1,1,1)_{12}$, we now compare the forecast values in January–March 2013 with the actual observations in the same period shown in Table 6.

With the very low value of MAPE of 0.0202, $FSARIMA(1,0,1)(1,1,1)_{12}$ is considered a powerful model to be employed to forecast the number of inbound arrivals from April to December 2013 as shown in Table 7.

Fig. 6 depicts the accuracy of the forecasts ob-

Table 3: Summary of model parameters

Model	Parameters		Estimate	Sig.
1	Constant		5699.593	0.000
	AR	Lag 1	0.770	0.000
	MA	Lag 1	0.355	0.013
	AR Seasonal	Lag 1	-0.459	0.010
	Seasonal Diff.		1	
	MA Seasonal	Lag 1	0.104	0.042
2	Constant		5750.312	0.005
	AR	Lag 1	0.905	0.000
	MA	Lag 1	0.463	0.000
	MA	Lag 2	0.182	0.078
	AR Seasonal	Lag 1	-0.425	0.020
	Seasonal Diff.		1	
	MA Seasonal	Lag 1	0.138	0.034
3	Constant		5707.069	0.000
	AR	Lag 1	0.650	0.001
	MA	Lag 1	0.190	0.355
	MA	Lag 2	0.054	0.666
	MA	Lag 3	-0.154	0.142
	AR Seasonal	Lag 1	-0.434	0.019
	Seasonal Diff.		1	
	MA Seasonal	Lag 1	0.120	0.049

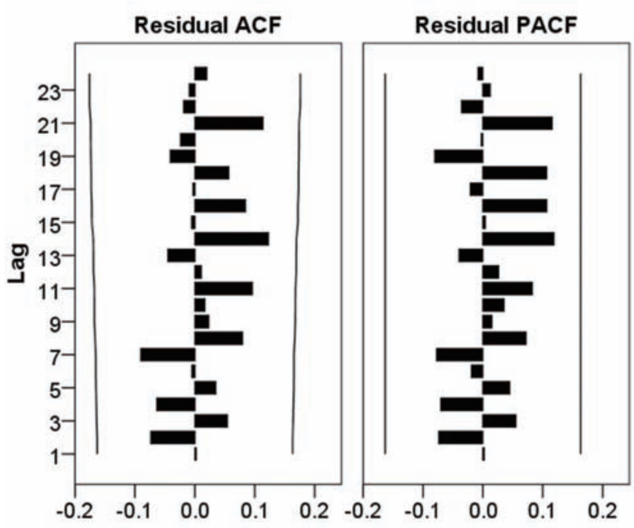


Figure 4: Noise residual ACF and PACF

Table 4: Model summary statistics

Model	Model 1	Model 2	Model 3
R-Squared	0.963	0.963	0.963
MAPE	4.266	4.361	4.376
MAE	8043.843	8143.048	8167.646
LB* Stat.	10.365	11.099	10.909
LB* Df.	14	13	12
LB* Sig.	0.735	0.603	0.537

*: Ljung-Box

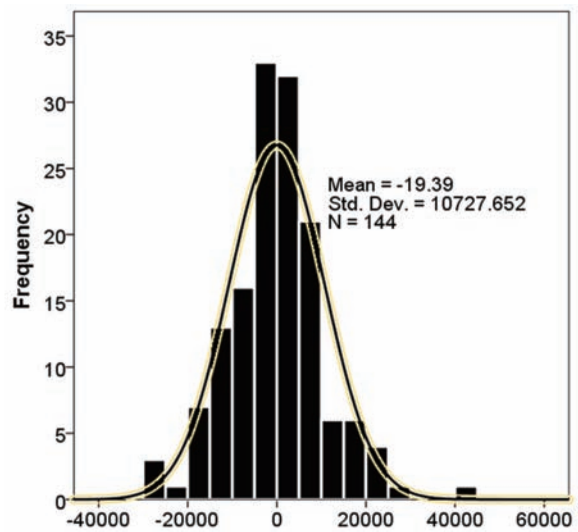


Figure 5: Histogram of Noise residuals of $SARIMA(1,0,1)(1,1,1)_{12}$

Table 5: Evaluation indexes of model accuracy

Index	SARIMA	FSARIMA
$MAPE$	0.0427	0.0069
S_1	55552.12	55552.12
S_2	10690.32	3029.26
C	0.1924	0.0545
P	0.9931	1.0000
ρ	0.9573	0.9931
Forecasting power	Good	Very good

Table 6: Checking forecasting power

Month	Actual	Forecast	APE
Jan.2013	260,637	262,918	0.0183
Feb.2013	281,233	273,325	0.0281
Mar.2013	270,740	266,862	0.0143
Mean absolute percentage error			0.0202

Table 7: Forecast in 2013 (Unit: Arrivals)

Month	Forecast	Month	Forecast
Apr. 2013	264,730	May. 2013	209,433
Jun. 2013	209,480	Jul. 2013	244,215
Aug. 2013	245,428	Sept. 2013	268,427
Oct. 2013	269,342	Nov. 2013	299,968
Dec. 2013	372,126		

tained from the modified model compared to the actual observations. Particularly, for the investigated period, January 2000 – December 2012, the forecasted values of the inbound tourism demand in New Zealand closely follow the actual ones with the MAPE value of less than 0.7% which is considered as an excellent indicator of a good forecasting model. Moreover, the MAPE of about 2% for using the modified model to forecast the demand in the first quarter of 2013 further proves the fitness of our proposed model in practice. Therefore, the forecasts of the inbound tourism demand for the last three quarters in 2013 are well believed feasible and practical. As the ultimate purpose of constructing a statistical forecasting model is to provide accurate forecasts, our model is therefore believed in its special forecasting power and strongly suggested for further application in the New Zealand tourism industry. It also points out that there is trend of a stronger demand in the last three quarters of year 2013; even the low season of the year is expecting more inbound tourists than those of previous years. Our forecasts in this paper can draw up an overview of the industry for the whole 2013 so that relevant industries and organizations such as the airport management, transportation facilities, tour guides, restaurants and hotels, etc., should be well prepared in advance to deliver their effectual services for their customers and make them satisfied with their trips.

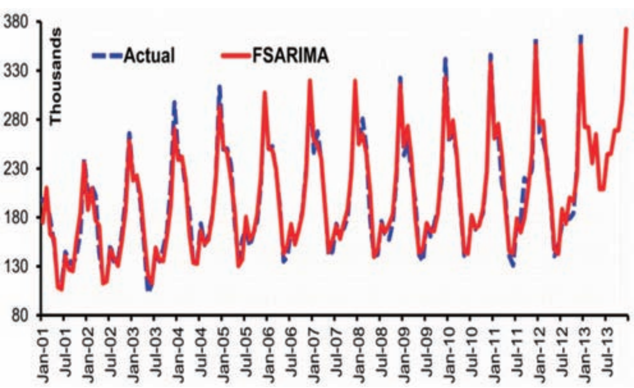


Figure 6: Actual observations versus forecasts

3 Conclusion

In this paper, we have uncovered that the forecasting accuracy of traditional ARIMA models can be substantially ameliorated through the scheme called a Fourier residual modification. For the case of the inbound tourism demand in New Zealand, the monthly demands modeled by its key determinants have been effectively forecasted with a Fourier-modified ARIMA model, $FSARIMA(1,0,1)(1,1,1)_{12}$. For a sustained growth increasing profit in the highly-competitive tourism industry, these precise forecasting results enable the policy-makers of the associated organizations in prior strategic preparations of planning sufficient facilities and attainable human resources in high seasons and making adequate adjustment and holding personnel training in low seasons.

References:

[1] World Travel and Tourism Council, 2013 Annual Research: Key Facts. Available from: http://www.wttc.org/research/economic-impact-research/regional-reports/world/

[2] World Travel and Tourism Council, 2013 Annual Research: Key Facts. Available from: http://www.wttc.org/research/economic-impact-research/country-reports/n/new-zealand/

[3] D. G Lagos, Exploratory forecasting methodologies for tourism demand, *Ekistics J.* 396, 1999, pp. 143–154.

[4] F. Habibi, K. A. Rahim, S. Ramchandran, and L. Chin, Dynamic Model for International Tourism Demand for Malaysia: Panel Data Evidence, *Int. Res. J. Finance Econ.* 33, 2009, pp. 207–217.

[5] P. Gonzlez, and P. Moral, An analysis of the international tourism demand in Spain, *Int. J. Forecasting* 11, 1995, pp. 233–251.

[6] L. C. Hsu and C. H. Wang, The development and testing of a modified Diffusion model for predicting tourism demand, *Int. J. Manage.* 25, 2008, pp. 439–445.

[7] S. F. Witt and C. A. Witt, Forecasting tourism demand: A review of empirical research, *Int. J. Forecasting* 11, 1995, pp. 447–475.

[8] C. Ouerfelli, Co-integration analysis of quarterly European tourism demand in Tunisia, *Tourism Manage.* 29, 2008, pp. 127–137.

[9] C. L. Morley, A dynamic international demand model, *Ann. Tourism Res.* 23, 1998, pp. 70–84.

[10] C. Lim and M. McAleer, Monthly seasonal variations: Asian tourism to Australia, *Ann. Tourism Res.* 28, 2001, pp. 68-82.

[11] N. Kulendran and S. Witt, Co-integration versus least squares regression, *Ann. Res.* 28, 2001, pp. 291-311.

[12] Y. F. Tan, C. McCahon and J. Miller, Modelling tourist flows to Indonesia and Malaysia, *J. Travel Tourism Marketing* 12, 2002, pp. 63-84.

[13] H. Song and S. F. Witt, General-to-specific modeling to international tourism demand forecasting, *J.Travel Res.* 42, 2003, pp. 65-74.

[14] H. Song, S. F. Witt and G. Li, Modelling and forecasting the demand for Thai tourism, *Tourism Econ.* 9, 2003, pp. 363-387.

[15] N. Dritsakis, Co-integration analysis of German and British tourism demand for Greece, *Tourism Manage.* 25, 2004, pp. 111-119.

[16] A. W. Naude and A. Saayaman, Determinants of tourist arrivals in Africa: a panel data regression analysis, *Tourism Econ.* 11, 2005, pp. 365-391.

[17] A. Meyler, G. Kenny and T. Quinn, Forecasting Irish inflation using ARIMA models, *Technical paper 3/RT/98*, 1998.

[18] S. Abdullah, M. D. Ibrahim, A. Zaharim and Z.M. Nopiah, Statistical Analysis of a Nonstationary Fatigue Data Using the ARIMA Approach, *WSEAS Trans. Math.* 7, No.2, 2008, pp.59-66.

[19] T. L. Nguyen, M. H. Shu, Y. F. Huang and B. M. Hsu, Accurate forecasting models in predicting the inbound tourism demand in Vietnam, *J. Stat. Manage. Syst.* 16, No.1, 2013, pp. 25–43.

[20] T. L. Nguyen, M. H. Shu and B. M. Hsu, Forecasting international tourism demand- An empirical case in Taiwan, *Asian J. Empirical Res,* 3, No.6, 2013, pp. 711–724.

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

[22] G. M. Ljung and G. E. P. Box, On a measure of lack of fit in time series models, *Biometrika* 65, 1978, 297-303.

[23] L. C. Hsu, Applying the grey prediction model to the global integrated circuit industry, *Technol. Forecasting Social Change* 70, 2003, pp. 563-574.

[24] Z. Guo, X. Song and J. Ye, A Verhulst model on time series error corrected for port throughput forecasting, *J. East. Asia Soc. Transp. Stud.* 6, 2005, pp. 881-891.

[25] M. L. Kan, Y. B. Lee and W. C. Chen, 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.

[26] M. Askari and A. Fetanat, Long-term load forecasting in power system: Grey system prediction-based models, *J. Appl. Sci.* 11, 2011, pp. 3034-3038.

[27] Y. L. Huang and Y. H. Lee, Accurately forecasting model for the Stochastic Volatility data in tourism demand, *Modern Econ.* 2, 2011, pp. 823-829.

[28] P. Liang, H. Zhou and J. Zheng, Forecast research of droplet size based on Grey theory, *IFIP Adv. Inf. Commun. Technol.* 258, 2008, pp. 653-658.

[29] C. C. Hsu and C. Y. Chen, Applications of improved grey prediction model for power demand forecasting, *Energy Convers. Manage.* 44, 2003, pp. 2241-2249.

[30] Y. W. Chang and M. Y. Liao, A seasonal ARIMA model of tourism forecasting: The case of Taiwan, *Asia Pac. J. Tourism Res.* 15, 2010, pp. 215-221.

[31] R. C. Tsaur and T. C. Kuo, The adaptive fuzzy time series model with an application to Taiwan's tourism demand, *Expert Syst. Appl.* 38, 2011, pp. 9164-9171.

[32] M. Memmedli and O. Ozdemir, An application of fuzzy time series to improve ISE forecasting, *WSEAS Trans. Math.* 9, No.1, 2010, pp.12-21.

[33] D. Aydin and M. Mammadov, A comparative study of hybrid, neural networks and nonparametric regression models in time series prediction, *WSEAS Trans. Math.* 8, No.10, 2009, pp.593-603.

[34] J. Hua and Q. Liang, Application research of the Grey forecast in the Logistics demand forecast, *First Int. Workshop Edu. Technol. Comput. Sci.* 3, 2009, pp. 361-363.

[35] H. Ma and Z. Zhang, Grey prediction with Markov-Chain for Crude oil production and consumption in China, *Adv. Intell. Soft Comput.* 56, 2009, pp. 551-561.

[36] Statistics New Zealand (2013), *http://www.stats.govt.nz/infoshare/*

Appendix

Monthly inbound tourism arrivals

Month	Arrivals	Month	Arrivals
Jan-2000	169,404	Feb-2000	192,856
Mar-2000	152,910	Apr-2000	143,681
May-2000	99,068	Jun-2000	97,516
Jul-2000	130,571	Aug-2000	117,365
Sep-2000	113,750	Oct-2000	146,610
Nov-2000	182,324	Dec-2000	243,023
Jan-2001	197,765	Feb-2001	199,792
Mar-2001	176,875	Apr-2001	153,186
May-2001	110,936	Jun-2001	112,279
Jul-2001	144,380	Aug-2001	136,864
Sep-2001	131,194	Oct-2001	142,095
Nov-2001	164,636	Dec-2001	239,807
Jan-2002	204,717	Feb-2002	212,233
Mar-2002	202,504	Apr-2002	143,877
May-2002	118,201	Jun-2002	115,194
Jul-2002	152,156	Aug-2002	133,272
Sep-2002	136,085	Oct-2002	162,327
Nov-2002	198,705	Dec-2002	265,691
Jan-2003	220,861	Feb-2003	222,201
Mar-2003	193,853	Apr-2003	150,416
May-2003	102,745	Jun-2003	111,982
Jul-2003	145,564	Aug-2003	135,351
Sep-2003	148,420	Oct-2003	165,821
Nov-2003	211,735	Dec-2003	297,280
Jan-2004	244,333	Feb-2004	238,032
Mar-2004	211,748	Apr-2004	184,379
May-2004	132,715	Jun-2004	134,813
Jul-2004	173,328	Aug-2004	152,104
Jan-2004	244,333	Feb-2004	238,032
Mar-2004	211,748	Apr-2004	184,379
May-2004	132,715	Jun-2004	134,813
Jul-2004	173,328	Aug-2004	152,104
Sep-2004	161,182	Oct-2004	181,371
Nov-2004	220,610	Dec-2004	313,057
Jan-2005	249,933	Feb-2005	250,070
Mar-2005	234,101	Apr-2005	174,757
May-2005	135,708	Jun-2005	157,547
Jul-2005	168,422	Aug-2005	150,656
Sep-2005	163,785	Oct-2005	176,216
Nov-2005	214,694	Dec-2005	307,061

Monthly inbound tourism arrivals - *continued*

Month	Arrivals	Month	Arrivals
Jan-2006	250,554	Feb-2006	252,431
Mar-2006	226,966	Apr-2006	191,648
May-2006	135,279	Jun-2006	139,891
Jul-2006	166,970	Aug-2006	155,699
Sep-2006	166,531	Oct-2006	186,639
Nov-2006	229,913	Dec-2006	319,040
Jan-2007	246,748	Feb-2007	267,569
Mar-2007	239,203	Apr-2007	193,229
May-2007	140,755	Jun-2007	145,498
Jul-2007	173,046	Aug-2007	164,775
Sep-2007	168,838	Oct-2007	179,947
Nov-2007	228,813	Dec-2007	317,259
Jan-2008	253,515	Feb-2008	280,513
Mar-2008	250,806	Apr-2008	179,388
May-2008	140,483	Jun-2008	142,413
Jul-2008	175,738	Aug-2008	162,485
Sep-2008	157,704	Oct-2008	173,938
Nov-2008	219,313	Dec-2008	322,207
Jan-2009	244,030	Feb-2009	256,559
Mar-2009	226,461	Apr-2009	195,883
May-2009	141,916	Jun-2009	135,162
Jul-2009	176,198	Aug-2009	161,100
Sep-2009	172,425	Oct-2009	187,372
Nov-2009	219,939	Dec-2009	341,337
Jan-2010	256,652	Feb-2010	267,855
Mar-2010	243,263	Apr-2010	187,962
May-2010	141,336	Jun-2010	145,825
Jul-2010	182,904	Aug-2010	168,081
Sep-2010	174,157	Oct-2010	184,898
Nov-2010	226,455	Dec-2010	345,656
Jan-2011	265,553	Feb-2011	268,259
Mar-2011	215,553	Apr-2011	197,777
May-2011	140,741	Jun-2011	131,269
Jul-2011	176,084	Aug-2011	175,909
Sep-2011	219,940	Oct-2011	215,902
Nov-2011	230,292	Dec-2011	364,165
Jan-2012	266,839	Feb-2012	259,083
Mar-2012	239,929	Apr-2012	195,668
May-2012	140,841	Jun-2012	151,074
Jul-2012	173,539	Aug-2012	178,298
Sep-2012	179,069	Oct-2012	184,200
Nov-2012	232,119	Dec-2012	363,959
Jan-2013	260,637	Feb-2013	281,233
Mar-2013	270,740		