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Forecasting International Tourism Demand in Malaysia Using Box Jenkins Sarima Application

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ABSTRACT

The main aim of this paper is to generate one-period-ahead forecasts of international tourism demand for Malaysia. An appropriate ARIMA model or well known as Box-Jenkins model has been applied in this paper to generate the forecast of international tourism demand. Before selecting an appropriate model, formal stationary tests has been applied in this paper and finds that, the series are stationary at level. Secondly, in order to get a good estimation, this paper has identified the autoregressive (AR) and moving average (MA) of the entire period of the data. Therefore, the future demand of tourism is forecast based on the combination of AR and MA, which known as ARMA model. In this paper, the competing models have been thoroughly investigated when the model adequacy has been checked before the best combination of ARIMA model was selected. Thus, the best fitted ARIMA (1,0,1) with seasonal effects or well known as SARIMA approaches has been suggested through this study and the forecasting process is based on this combination. The forecasts generated by the ARIMA model suggest that Malaysia will face increasing tourism demand for the period of 2009:Q1-2009:Q4. Besides that, this paper found the Box-Jenkins model has offered valuable insights and provide reliable forecasts of tourism demand for Malaysia.

KEYWORDS: *Tourism Demand, Box-Jenkins Method, ARIMA, SARIMA*

INTRODUCTION

According to World Tourism Organization, international tourism can be define as an activity of visitors who make temporary visits across international borders and remains for more than 24 hours. The purpose of visits can be visiting relatives and friends; leisure, business meeting or conventions, education, healthcare and sports. In 2008, international tourist arrivals reached 924 million, up 16 million over 2007, representing a growth of 2%. As a result of the extremely volatile world economy (financial crisis, commodity and oil price rises, sharps exchange rate fluctuations), tourism demand slowed significantly through the year. The last six months of 2008, in particular, showed an abrupt shift in trends, with international tourist arrivals flat or showing negative growth. Overall, the 5% growth between January and June gave way to a 1% decline in the second half of the year. After the economic crisis and the swine flu pandemic produced "one of the most difficult years" for the sector in 2009, global tourism is set to rebound in coming years.

TOURISM DEMAND IN MALAYSIA

Tourism is one of the major contributing sectors for Malaysia's economic growth for several years. Year by year, number of international tourist arrivals to Malaysia showing an upward trend and this supported with the country's political stability, besides several program and package introduce by the Malaysian government to encourage international tourist visit Malaysia. Malaysia recorded 23.65 million tourist arrivals last year in 2009, higher than the 22.05 million arrivals in 2008 and the scaled-down target of 19 million set for last year due to the global economic downturn. The top 10 tourist-generating markets for Malaysia last year were Singapore, Indonesia, Thailand, Brunei, China, India, Australia, Philippines, United Kingdom and Japan. The Malaysian tourism industry will continue to grow rapidly in coming years on the back of increasing promotional activities by the government and growing reputation of the country as a shopping hub. According to a research report by RNCOS, "Opportunities in Malaysian Tourism Industry (2007-2009)", Malaysian tourism industry continues to grow rapidly, where:

- Singapore, Thailand and Indonesia are important sources of visitors for Malaysia. Beyond ASEAN, tourist arrivals from China and India will remain an important influence throughout the forecast period (2008-2012).
- The promotion of Education Tourism will continue to be expanded to expedite the development of Malaysia as a preferred destination for international students. The projected foreign exchange earnings from this potential source of growth are estimated at RM 900 Million by 2010.
- It is expected that expenditure by international tourists in Malaysia will increase at a CAGR of 6.63% during the forecasted period.
- Increasing disposable income in Malaysia will open the opportunities for both outbound and domestic tourism.

Tourist arrivals to Malaysia are poised to reach 24.6 million by 2010, with the bulk of travelers comprising intra-regional tourists. By the year 2010, the target is to attract 24.6 million tourists per annum especially youth travelers from Middle-East and East-Asia. The projected foreign exchange earnings from this potential source of growth are estimated at RM 900 Million by 2010. According to the new RNCOS report Malaysian Tourism Industry Forecast to 2012, international tourist arrivals in Malaysia will grow at a CAGR of around 9% during 2009-2012, and tourism receipts from overseas tourists are expected to rise at a CAGR of around 10% to RM 70 Billion (US$ 19.6 Billion) in the same period.

Malaysia expected to benefit from the greater intra-Asean travel trade through intense regional co-operation, cultural and information exchanges, development of joint tour packages and establishment of special arrangements for youth travelers from Asean. Apart from the ASEAN countries, tourist arrivals from China, India and the Middle East will strongly grow during the forecast period (2009-2012). In the 9th Malaysia plan, Malaysia targeted as a main international tourist destination. The main programs that implemented by the Government include enhancing access and facilities for tourist arrivals, and improvising as well as maintaining amenities and infrastructure. An expenditure of RM1 billion has been allocated for the purpose of maintenance. Within this plan, government's focus is on the development of rural tourism as based on research, foreign tourists who came to Malaysia spent 15% of their stay in rural areas. In tne near future, MICE (Meetings, Incentives, Conventions and Exhibitions) industry also expected will be one of the major contributors to the Malaysian tourism industry

LITERATURE REVIEWS

Over the past 3 decades, we have seen many studies of international tourism demand forecasting by both tourism researchers and practitioners as well. Basically, the literature on modeling and forecasting tourism demand is huge with various type of empirical analysis. Some of the researchers apply cross-sectional data, but most of forecasting tourism demand used pure time-series analytical models. One of the important time-series modeling used in forecasting tourism forecasting is ARIMA modeling, which specified based on the standard Box-Jenkins method is a famous modeling approach to forecasting demand. Many studies has applied this methodology, such as Chu (2008a), Lee et al. (2008), Coshall (2008), Wong et al. (2007), Akal (2004), Preez and Witt (2003); and Kulendran and Witt (2001).

Basically, this ARIMA model has been proved to be reliable in modeling and forecasting tourism demand with monthly and quarterly time-series. Wong (2007) has used four types of model, such as seasonal auto-regressive integrated moving average model (SARIMA), auto-regressive distributed lag model (ADLM), error correction model (ECM) and vector-autoregressive model (VAR) to forecast tourism demand for Hong Kong by residents from ten major origin countries. The empirical results shows that forecast combinations do not always outperform the best single forecasts. Therefore, combination of empirical models can reduce the risk of forecasting failure in practical. Coshall (2008) meanwhile has used univariate analysis, combined the ARIMA-volatility and smoothing model, which is a term of finance to forecast United Kingdom demand for international tourism. Generally, from this study we can find that the ARIMA volatility models tend to overestimate demand, and the smoothing models are inclined underestimate the number of future tourist arrivals.

Chu (2008a) has modified ARIMA modeling to fractionally integrated autoregressive moving average (ARFIMA) in forecasting tourism demand. This ARFIMA model is ARMA based methods. Three types of univariate models have applied in the study with some modification in ARMA model become ARAR and ARFIMA model. The main purpose of the study is to investigate the ARMA based models and its usefulness as a forecast generating mechanism for tourism demand for nine major tourist destinations in the Asia-Pacific region. This study is different from various forecasting tourism study which been publish earlier, because we can identify the ARMA based model behaviors and the outperforming of the ARFIMA model with other ARMA based models.

Again, Chu (2008b) has study the ARIMA based model using ARAR algorithm model in order to analyze and forecasting tourism demand for Asia-Pacific region using monthly and quarterly data. The major findings of the studies show the comparison between forecasts generated by monthly and quarterly data reveals that the performance is broadly similar. Besides forecasting tourist arrivals, prediction of tourism revenue also can done using empirical modeling. Mustafa (2004) has used autoregressive integrated moving average cause-effect (ARMAX) modeling to forecast international tourism demand for Turkey. The ARMAX model is actually derived from the ARIMA approaches. The forecast estimations are an important benchmark for Turkey’s government to strength-out the tourism sector becoming a major contributing sector for economic development in future.

Chong et al. (2003) has introduce general-to-specific modeling approach to forecasts international tourist arrivals from 16 major countries to Hong Kong for the period 2001-2008. The specification of econometrics model is known as auto-regressive distributed lag model (ADLM). The findings shows that, the most important factors that determine the demand for Hong Kong tourism are the cost of tourism in Hong Kong, the economic scenario in the origin countries, the costs of tourism in the competing destinations and the ‘world of mouth’ effect. Again, ADLM measurement of tourism forecasting is suitable for multivariate modeling and by using this method, we able to determine various factor causes on tourist arrivals in the future. Meanwhile, Greenidge (2001) has used structural time-series modeling (STM) to evaluate forecasting tourism demand in Barbados. STM modeling has its own capability, which is can include time-varying components in the regression equation and capture the movement of tourist arrivals using explanatory variables. Besides using basic structural modeling (BSM), STM model also able to include general structural modeling (GSM) with seasonal effect. Therefore, the findings offered valuable insights into the stylized facts of tourism behavior and provide reliable out-of-sample forecasts of tourism demand.

On the other hand, Athanasopoulos and Hyndman (2008) have modeled Australian domestic tourism demand using regression model, exponential smoothing via innovations state space model and innovations state space model with exogenous variables. Cross-sectional data has been applied in this study, and the data were collected using computer-assisted telephone interview with 120,000 Australians aged from 15 years onward. All the models been used in the studies also highlighted the impact of world events on Australian domestic tourism such as the increase in business travel immediately after the Sydney Olympic in the year 2000; and the significant increase in visiting relatives and friends after the 2002 Bali bombings. One of the interesting this we can find from this study is that, all of three statistical models used in this study outperform the Tourism Forecast Committee (TFC) results for short-term demand of Australian domestic tourism. Meanwhile, the long-term forecasts results from this study also indicate that the TFC forecasts may be optimistic. Finally, from the forecasts outputs, this study finds that the Australian domestic tourism is on the decline stage.

Unlike most of the forecasting tourism studies discussed earlier, forecasting expo demand involves both qualitative technique and quantitative forecasting models (Lee et al., 2008). The main reason using both techniques is because of the limitation of the available data. Combining quantitative technique with willingness-to-visit (WTV) surveys has predicted number of visitors to international tourism expo which to be held in Korea in 2012. Preez and Witt (2003) have also compared two types of methods analyzing forecasting tourism. In their study, univariate and multivariate modeling has been used separately to forecasts tourism demand from four European countries to Seychelles. The findings of the study shows clearly the univariate forecasting models had outperformed multivariate models. Empirical results from the study shows an absence of structural and that ARIMA exhibits better forecasting performance than univariate and multivariate state space modeling.

According to Kim and Wong (2006), the volatility in tourism demand data can be influenced by the effects of new shocks such as economic crises, natural disaster or war. In tourism literature, modeling the volatility in tourism demand is important because it can capture the occurrence of unexpected events. Actually, volatility of tourism demand is modeled using conditional volatility models, and the models that appears in tourism literature are univariate generalized autoregressive conditional heterokedasticity (GARCH), univariate asymmetric GARCH, vector autoregressive moving average GARCH (VARMA-GARCH); and VARMA asymmetry GARCH (VARMA-AGARCH) models (Chan et al. (2005), Kim and Wong (2006), Shareef and McAleer (2005), Shareef and McAleer (2007).

In middle of 1990s, dynamic specification such as vector autoregressive model (VAR), error correction model (ECM) and autoregressive distributed lag model (ADLM) began to appear in the tourism literature. VAR model able to apply various type of independent variables to determine tourist arrivals and from there we able to forecast future tourist arrivals. Besides that, VAR model able to provide with innovative use of the impulse response analysis in tourism context, besides provide results on co-integrating analysis and forecasting. Song and Witt (2004) have used this VAR model to forecast international tourist flows to Macau for the period 2003-2008. The forecasts generated by the VAR models suggest that Macau will face increasing tourism demand by residents from mainland China. Secondly, the ECM model also been used to measuring tourism forecasting but lately this ECM model has modified become vector error correction model (VECM) which can test and impose weak exogeneity restriction. Bonham et al. (2008) have used VECM technique to identify reasonable long-run equilibrium relationship; and have take into account Diebold-Mariano tests for forecast accuracy demonstrate satisfactory forecasting performance for Hawaii. The main purpose of this study is to provide a much more comprehensive examination on tourism forecasting using seasonal ARIMA modeling. However, existing literature of forecasting international tourism demand for Malaysia so far had not been adopted using seasonal auto-regressive integrated moving average (SARIMA) modeling; therefore this paper will fill this gap.

METHODOLOGY

All data for this study were collected from Malaysia tourism arrivals dataset provided by the Ministry of Tourism Malaysia. The time-series data used in this study are quarterly data and it's covered from 1995:Q1-2008Q4. This study focuses on the demand for international tourism for Malaysia and forecast 4 quarters ahead, which is 2009:Q1-2009:Q4. In this study, we used ARIMA and seasonal ARIMA (SARIMA) models to forecast one-period ahead of the series by applying Box-Jenkins approach. An ARIMA model is a generalization of an ARMA model. These models are fitted to time-series data either to better understand the data or to predict future points in the series (Chu, 2008a). The model is generally referred to as an ARIMA (p, d, q) model where p, d and q are integers greater than or equal to zero and refer to the order of the autoregressive, integrated and moving average aspects. In this study we applied Augmented Dickey-Fuller and Phillip-Perron stationary tests to identify the level *d* in time series of international tourist arrivals to Malaysia. The resultant univariate time series mode can be written as

$$\phi_p(L)y_t = \theta_q(L)\varepsilon_t,\ t = p+1, p+2, \ldots n \qquad (1)$$

With;

$$\phi_p(L) = 1 - \Phi_{1L} - \ldots - \phi_p L^p$$

$$\phi_q(L) = 1 - \Phi_{1L} - \ldots - \phi_q L^q \qquad (2)$$

Where, the last notational conventional as chosen such that the model in (1) amounts to the regression model

$$y_t = \phi_1 y_{t-1} + \ldots + \phi_p y_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \ldots + \theta_q \varepsilon_{t-q}$$

Therefore, this model is called an autoregressive moving average model of order (p,q), or briefly ARMA(p,q). When the y_t series replaced by $\Delta_1^d y_t$, we say that y_t is described by an autoregressive integrated moving average model of order (p,d,q), or briefly ARIMA(p,d,q). This can express as Box-Jenkins approach. The autocorrelation functions (ACF) of a time series y_t can be define as $\rho_k = \gamma_k / \gamma_0$. Where γ_k is the k order of auto-covariance of y_t, that is

$$\gamma_k = E[(y_t - \mu)(y_{t-k} - \mu)],\ k = \ldots, -2, -1, 0, 1, 2 \ldots, n \qquad (3)$$

Given equation (3), it is easily seen that for the autocorrelation it holds that $\rho_0 = 1$, $\rho_{-k} = \rho_k$ and that $-1 < \rho_k < 1$. Therefore, this ACF can be useful to characterize ARIMA time series models. Let say for example, a simple white noise series ε_t for which $E(\varepsilon_t) = 0$ and $\rho_k = 0$ for all $k \neq 0$. For the AR(1) model

$$y_t - \mu = \phi_1(y_{t-1} - \mu) + \varepsilon_t,\ t = 1, 2, 3 \ldots, n \qquad (4)$$

Meanwhile, the ACF may not be particularly useful to identify whether an AR of specific order is a suitable model. In fact, the ACF is more useful in case of MA(q) models. For the MA(1) process, it can be shown as follows with PACF at lag h:

$$\alpha(h) = \phi_{hh} = -(-\theta)^h / (1 + \theta^2 + \ldots + \theta^{2h}) \qquad (5)$$

Forecasting SARIMA processes is completely analogous to the forecasting of ARIMA processes. This can be expressed as ARIMA(p,d,q)(P,D,Q)$_{12}$ [ARIMA(p,d,q) (P,D,Q)]$_4$ for quarterly data. Which p and P are the orders of autoregressive operator; d and D are the differences; and q and Q are the orders of moving average operator of non-seasonal and seasonal components respectively. The first steps in identifying SARIMA models for a data set are to find *d* and *D* so as to make the differenced observations:

$$y_t = (1 - B)^d (1 - B^s)^D X_t \qquad (6)$$

In this study we used one-period-ahead forecasting using seasonal ARIMA modeling. In order to forecasting SARIMA model, the mean absolute percentage error (MAPE) is a useful measure for comparing the accuracy of forecasts between different forecasting models since it measures relative performance. If an error is divided by the corresponding observed value, we have a percentage error. In many empirical studies it appears that the models that tend to do best for within-sample data do not necessarily forecast better out-of-the sample. There is no strict rule for that, but empirical experience suggests that if may be better to select few models on the Akaike Information Criterion (AIC) and Schwarz Information Bayesian (SBC), and to evaluate these on the forecast data. The last evaluation can be based on root the mean square error (RMSE). The RMSE can be express as follow:

$$\mathrm{RMSE} = (1-\mathrm{m})\left[\sum_{h=1}^{m}(\hat{y}_{n+h} - y_{n+h})^2\right] \quad (7)$$

Meanwhile, in most of previous literatures, mean absolute percentage error (MAPE) has been used to determine suitable models. It should be mentioned that, MAPE is not very useful for very small observation (Franses, 1998). The MAPE can be express as follow:

$$\mathrm{MAPE} = (1-\mathrm{m})\left[\sum_{h=1}^{m}\left|(\hat{y}_{n+h} - y_{n+h})/\, y_{n+h}\right|\right] \quad (8)$$

Therefore, ARIMA-SARIMA model selection in this study is based on AIC, SIC and forecast evolution results, especially referring on the minimum value of RMSE and MAPE.

EMPIRICAL RESULTS

The data of international tourist arrivals to Malaysia for the period 1995:Q1-2008:Q4 with seasonal effects is shown clearly in Figure 1. Basically, figure 2 has shown clearly the demand of international tourist arrivals to Malaysia is not depending on seasonal effects; because the flow of tourist arrivals to Malaysia for the four quarters is exist same patterns for the past 1 decade. The data of international tourist arrivals with seasonal effects are plotted to examine the pattern of international tourist arrivals in Malaysia. It was found that the plot exhibited a permanent deterministic pattern of long term upward trend.

Figure 1 : Seasonal Stacked Line of Log Total International Tourist
Arrival to Malaysia

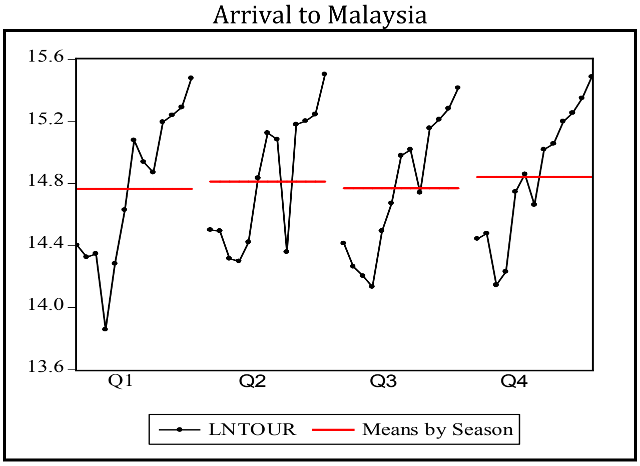

Table 1 summarizes the outcome of the Augmented Dickey-Fuller and Phillip-Perron tests on 1995:Q1-2008:Q4 quarterly tourist arrivals to Malaysia. The null hypothesis tested is that the variable under investigation has a unit root against the alternative that it does not. The lag-length is chosen using the Akaike Information Criterion (AIC) after testing for first and higher order serial correlation in the residuals. In the first half of Table 1, the null hypothesis has a unit root cannot be rejected by both ADF and PP tests. However, after applying the first difference, both ADF and PP tests reject the null hypothesis. Since the data appear to be stationary by applying the ADF and PP tests in first differences, therefore we never perform further tests. In this study we apply stationary tests with trend effects. Therefore, the null hypothesis has a root has been rejected in both ADF and PP tests at levels $I(0)$. Hence, all series are stationary with trend effects analysis and accepts *I* (0). Once stationary has been established, examination of the autocorrelation function plot (ACF) and partial autocorrelation plot (PACF) over several quarterly lags suggests which autoregressive and moving average terms should be included in the ARIMA model (Coshall, 2008). Figure 3 shows clearly the stage of ACF and PACF for tourist arrivals to Malaysia, and from the diagrams, we choose combination of ARIMA (p,d,q) to obtain the most suitable SARIMA model for this study. The standard procedure for identification, estimation, diagnostic checking and over fitting in a Box-Jenkins analysis of time series was performed.

Table 1 : Stationary Tests

Variables	Without Trend		With Trend	
	Level	First Difference	Level	First Difference
ADF Test (τ)	-1.1531(0)	-8.7342(0)*	-3.9420(8)**	-8.6978(0)*
PP Test (Z_τ)	-0.8229[11]	-11.0061[11]*	-3.3444[4]**	-12.3029[19]*

Note: Lag length in ( ) and Newey-West value using Bartlett kernel in [ ], Asterisks (*) and (**) denote statistically significant at 1% and 5% significance levels

The estimation method involved maximum likelihood parameter estimation to obtain initial estimates and then unconditional least-squares estimations to obtain final estimates. It is a fairly common occurrence that differencing a time series introduces moving average terms into the resultant ARIMA model. Two often applied criteria to select between time series models are the Akaike Information Criterion (AIC) and Schwarz Bayesian Criterion (SBC). Both criteria evaluate the fit versus the number of parameters. Table 2 clearly indicates diagnostic correlogram with autocorrelation (ACF) and partial autocorrelation (PACF) for ARMA(1,1). The flow of ACF and PACF shows clearly the effects of autoregressive effects with first different of historical data.

Figure 2 : ARMA(1,1) Diagnostic Correlogram with Autocorrelation (ACF) and Partial Autocorrelation (PACF)

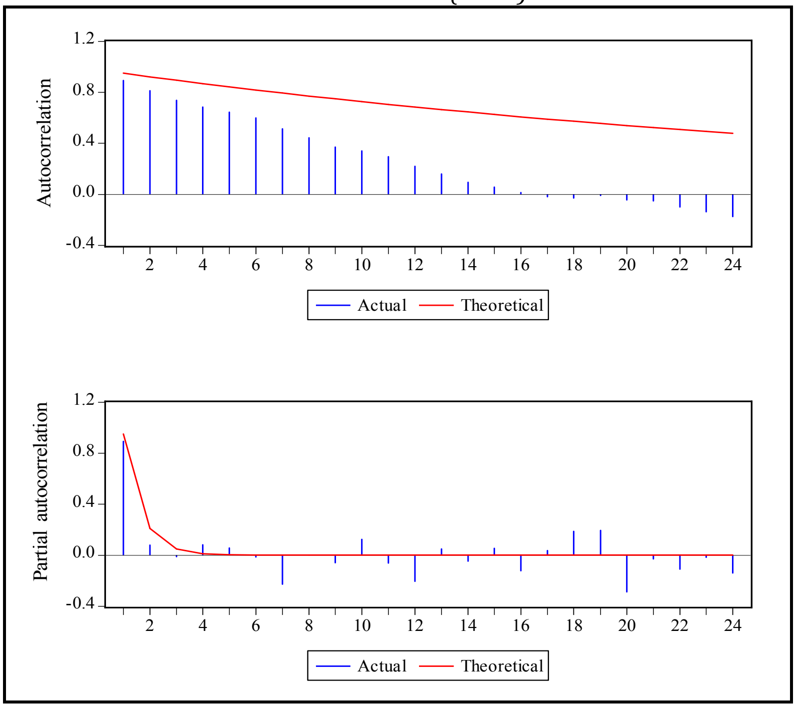

Table 2 : Regression Results and Diagnostic Tests for Seasonal ARIMA Models

Models	Coefficient	ARCH-LM Test[(a)]	H_o: No serial correlation[(b)]	H_o: Normality[(c)]
ARIMA(1,0,1)				
Season (1)	0.045 (1.040)	1.304	1.305	11.051
Season (2)	-0.001 (-0.011)	[0.259]	[0.28]	[0.00]
Season (3)	0.033 (0.723)			
AR(1)	0.970 (19.48)			
MA(1)	-0.230 (-1.447)			
AIC value	-0.520			
SBC value	-0.293			
ARIMA(1,0,2)				
Season (1)	0.050 (1.137)	0.327	1.031	14.087
Season (2)	0.012 (0.237)	[0.569]	[0.364]	[0.000]
Season (3)	0.039 (0.803)			
AR(1)	0.989 (23.51)			
MA(1)	-0.261 (-1.621)			
MA(2)	-0.143 (-0.882)			
AIC value	-0.500			
SBC value	-0.235			
ARIMA(2,0,2)				
Season (1)	0.048 (1.017)	1.987	0.768	9.054
Season (2)	0.018 (0.332)	[1.166]	[0.469]	[0.000]
Season (3)	0.052 (1.033)			
AR(1)	1.440 (5.857)			
AR(2)	-0.441 (-1.777)			
MA(1)	-0.838 (-2.748)			
MA(2)	-0.158 (-0.609)			
AIC value	-0.511			
SBC value	-0.277			

Note: (a), (b) and (c) indicates Autoregressive conditional heterocedasticity (ARCH) LM test, Breusch-Godfrey (BG); serial correlation test and Jarque-Bera (JB) normality test. Figures in ( ) and [ ] indicates t-statistics and probability values

Table 2 clearly indicates the AIC and SBC's values and the decision of selecting most suitable model is by comparing the value of AIC and SBC according to the ARIMA models used in this study. Smaller the value of AIC and SBC, is better and fit the ARIMA model used. Therefore ARIMA(1,0,1) is relevant because the value of AIC and SBC is smaller than other ARIMA models. Besides that, diagnostics tests have been applied in this study to determine the estimated models deviate from the assumptions of the standard linear regression model. Therefore, we tested the autoregressive conditional heteroscedasticity (ARCH), serial correlation using Breusch-Godfrey (BG) test; and normality test using Jarque-Bera (JB) test. Since correlogram of squared residuals from ARMA(1,1) shows autocorrelation pattern in square residuals which could be attributed to volatility clustering, therefore , to test the presence of ARCH effect, we compute ARCH LM test.

The results in Table 2 do not indicate any ARCH effects in all models estimated in this. The Breusch-Godfrey (BG) test of serial correlation indicates that serial correlation hypothesis cannot be rejected in all three ARIMA models. Meanwhile, normality test using Jarque-Bera (JB) test indicates that normality in the errors has be rejected in all there ARIMA models. This indicates that, all there models are not normal distributed because of some seasonal effects. One interesting results can be derived from Table 2 is that, although seasonal effects have been take into account in every ARIMA models, but the results does not exists any significant seasonal effects, either positively or negatively. To choose suitable ARIMA model for this study, we used the inequality coefficients. The inequality coefficient of the ARIMA(1,0,1) model are marginally smaller than those of the ARIMA(1,0,2) and ARIMA(2,0,2). Therefore ARIMA (1,0,1) is the best ARIMA selected in this study. Keep in mind that ARIMA models are very hard to beat, especially when it comes to dealing short-term forecasting. For one-step ahead forecasting which been applied in this study, the MA(1) model is the best because the value of RMSE and MAPE are the lowest. The results illustrated in Table 3 is in the line of AIC and SIC values which been discussed through Table 2 earlier. As a conclusion, we used ARIMA(1,0,1) to forecast one-period ahead tourist arrivals to Malaysia.

Table 3 Summary of Forecast Evolutions of ARIMA Models

Inequality Coefficient	ARIMA Models		
	ARIMA (1,0,1)	**ARIMA (1,0,2)**	**ARIMA (2,0,2)**
RMSE	0.2914	0.3052	0.3241
MAE	0.2075	0.2162	0.2356
MAPE	1.4319	1.5891	1.6269
Theil Coefficient	0.0097	0.0102	0.0108

The ARIMA(1,0,1) model that has been estimated for the sample period can be describe as shown in equation (9) with t-values of the coefficients are in parentheses. Estimated AR(1) and MA(1) were found significant at 1 percent. It is clear that the AR(1) and MA(1) components are significant without any seasonal dummies. Therefore, our selection of ARIMA(1,0,1) model is a right choice:

$$\ln(\text{Tour})_t = 15.607 + 0.974\ln(\text{Tout})_{t-1} - 0.276\varepsilon_{t-1} \quad (9)$$
$$(9.339) \qquad (21.005) \qquad (-3.842)$$

It needs to be noted that, once we accepted ARIMA(1,0,1) as a suitable model for this study, therefore we used the model to forecasting purpose. We applied ARIMA(1,0,1) to forecast one-period ahead using historical data 1995Q1-2008Q4 and predict for short-term period 2009:Q1-2009:Q4 of tourist arrivals to Malaysia. Figure 3 shows clearly the forecasted international tourist arrivals to Malaysia using ARIMA(1,0,1) with one-period ahead forecasting method. In term of using quarterly data with short term forecasting, one-period-ahead procedure slightly better forecast for Malaysia; while seasonal ARIMA generates relatively not accurate in this study because seasonality does not exists in this study.

Figure 3 : Forecasted International Tourist Arrivals to Malaysia with
$\pm$ 2 x S.E *from the ARIMA(1,0,1) Model in Logarithm Form*

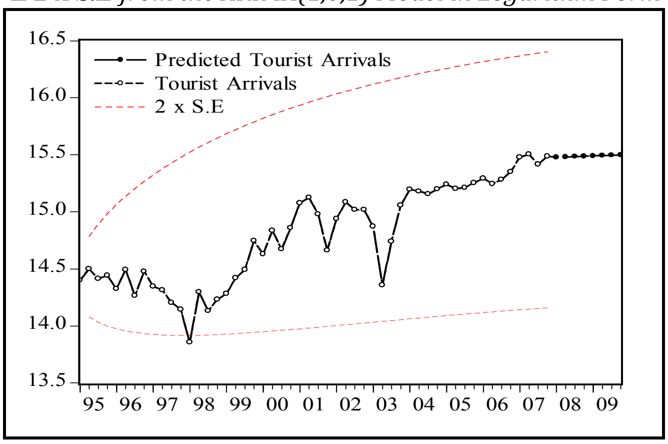

Table 4 displays an ex-post forecast of the international tourist arrivals in Malaysia from 2009:Q1 to 2010:Q4. The forecasted value is according to ARIMA(1,0,1) estimation which minimize mean absolute percentage errors. The trend of forecasted international tourist arrivals for 8 period-ahead indicates an upward trend in lower and upper limits.

Table 4 Actual and Fitted Value of Forecasted International Tourism Demand

Year/Quarter	Lower 90%	Forecasted Tourism Demand	Upper 90%
2009:Q1	3155817	3495901	3835986
2009:Q2	3226178	3583646	3941114
2009:Q3	3008576	3453929	3899281
2009:Q4	2921275	3394656	3868036

CONCLUSION

For the first time, this study demonstrates that seasonality exists in the ARMA of tourist arrivals to Malaysia. To capture the seasonal effects, seasonal dummy variables were included in the conditional ARIMA models. Furthermore, given the seasonal ARIMA models have been widely employed in forecasting tourist arrivals to Malaysia. Overall, this paper concludes that ARIMA model (1,0,1) cannot perform seasonal effects in predicting tourist arrivals to Malaysia because seasonality not affected on the numbers of tourist arrivals to Malaysia. The findings of this study is also in line with previous studies conduct by Chu (2008), Chan and McAleer (2005); and Song et al. (2003) using univariate data with ARMA-ARIMA forecasting techniques. The empirical forecasting method used in this study perform best fit ARIMA model and from a planning perspective, this should be a major research theme in the study of international tourism demand, since incorporation of forecasts into decision making processes would assist development and investment strategies in tourism industry in the future. As a conclusion, more forecasting method should be included in future studies in Malaysia. For example, there was some inconclusive evidence suggesting that smoothing technique performs better than the Box-Jenkins methodology.

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REFERENCES

Akal, M. (2004). Forecasting Turkey's tourism revenues by ARMAX model. Tourism Management, 25, 565-580.

Athanasopoulos, G. & Hyndman, R. J. (2008) Modeling and forecasting Australian domestic tourism. Tourism Management, 29, 19-31.

Bonham, C., Gangnes, B. & Zhau, T. (2008). Modelling tourism: a fully identified VECM approach. International Journal of Forecasting (in press)

Chan, F. , Lim, C. & McAleer, M. (2005). Modelling multivariate international tourism demand and volatility. Tourism Management, 26(3), 459-471.

Chu, F.L. (2008a). Forecasting tourism demand with ARMA-based methods. Tourism Management, x, 1-12.

Chong, C.L. (2003).

Chu, F.L. (2008b). Analyzing and forecasting tourism demand with ARAR algorithm. Tourism Management, 29(6), 1185-1196.

Coshall, J. T. (2008). Combining volatility and smoothing forecast of UK demand for international tourism. Tourism Management (in press)

Franses, P. H. (1998). Time-series models for business and economic forecasting. Cambridge University Press: United Kingdom.

Greenidge, K. (2001). Forecasting tourism demand. An STM approach. Annals of Tourism Research, 28(1), 98-112.

Kim, J. H. & Wong, K. F. (2006). Effects of news shocks on inbound tourists demand volatility in Korea. Journal of Travel Research, 44(4), 457-466.

Kulendran, Nada & Witt, S. F. (2001). Cointegration versus least squares regression. Annals of Tourism Research, 28(2), 291-311.

Lee, C. K., Song, H. J. & Mjelde, J. W. (2008). The forecasting of international expo tourism using quantitative and qualitative techniques. Tourism Management, 29(6), 1084-1098.

Preez, J. & Witt, S. F. (2003). Univariate versus multivariate time series forecasting: an application to international tourism demand. International Journal of Forecasting, 19, 435-451.

Shareef, R. & McAleer, M. (2005). Modelling international tourism demand and volatility in small island tourism economics. International Journal of Tourism Research, 7(6), 313-333.

Shareef, R. & McAleer, M. (2007). Modelling the uncertainty in monthly international tourist arrivals to the Maldives. Tourism Management, 28(1), 23-45.

Song, H., Wong, K. F. & Chon, K. S. (2003). Modelling and forecasting the demand for Hong Kong Tourism. Hospitality Management, 22, 435-451.

Wong, K., Song, H., Witt, S. F. & Wu, D. C. (2007). Tourism forecasting: to combine or not to combine? Tourism Management, 28, 1068-1078.

World Tourism Organization (WTO). 2008. Youth travel matters: Understanding the global phenomenon of youth travel. WTO: Madrid, Spain.

United Nation World Tourism Organization (UNWTO)

RNCOS, reports.research.com Aug 27, 2009 Shortcut:http://prlog.org/10323547