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Malaysia Tourism Demand Forecasting by Using Time Series Approaches

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Abstract: In the case of tourism demand, better forecast would help directors and investors to make operational, tactical and strategic decisions. Besides that, government bodies need accurate tourism demand forecasts in the planning of the required tourism infrastructures such as accommodation, site planning, transportation development and other needs. Error magnitude measurements are commonly used to assess various forecasting models or methods. However, accuracy in terms of error magnitude alone is not enough especially in the field of economics. The information on the directional behaviour of the data is very important since if the forecast fails to predict the directional change effectively, it could cause huge negative impact on economic activities. Thus, in assessing economic forecast value, it is important to consider both the magnitudes and directional movements. This research aims to demonstrate the application of time series forecasting on Malaysia tourism demand data. Several time series methods were used, that are Box Jenkins, time series regression and Holt Winters. The forecast accuracy were evaluated by using MAPE, MAD, RMSE, Fisher's exact test, mean directional accuracy and mean directional value. It was found that Holt Winters gave the most accurate forecast in terms of error magnitude. Meanwhile, in terms of directional accuracy, time series regression gave the most accurate forecast. The best model in terms of error magnitude does not necessarily give the most accurate directional forecast and vice versa.

Key words: Tourism demand forecasting, time series forecasting, forecast accuracy evaluation, vice versa, economic forecast

INTRODUCTION

Time series can be interpreted as a sequence of data points that are measured or recorded at uniform time intervals. Time series are used in various fields of studies such as economics, engineering, environmental and business. One of the most important application areas of time series is forecasting; where it uses a model to predict or estimate future values by using previous observed data. In organizations of many fields, forecasting provide valuable information in decision-making. Realizing this fact, researchers are always searching for forecasting methods that are able to improve forecast accuracy.

In the case of tourism demand, better forecast would help directors and investors to make operational, tactical and strategic decisions. Besides that, government bodies need accurate tourism demand forecasts in the planning of the required tourism infrastructures such as accommodation, site planning, transportation development and other needs. In Malaysia, tourism has been identified as an economic development tool, generating employment, income and tax revenue. The Malaysian government has a serious intention in developing tourism industry after the price of oil palm decreased and the world's economy experienced a recession in the middle of 1980s. For instance, numerous incentives and assistances were provided especially to the private sectors to stimulate their participation in tourism.

During the UNWTO/WTTC Global Leaders for Tourism Campaign, (Kuala Lumpur, Malaysia, 17 October 2011) Malaysian Prime Minister, Datuk Sri and Mohd. Najib andbin Tun Abdul Razak had stated that tourism has a crucial role in transforming Malaysia into a high-income country by 2020. The travel and tourism sector contributed 5% or RM124.7 billion of GDP in 2011

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to the Malaysian economy and supports 1.6 million jobs or 13.8% of total employment. Out of a global total of 940 million tourists, Malaysia ranked at the 9th place in the top ten international tourism destinations in 2010 with 24.58 million tourist arrivals. In comparison to 2006, Malaysia was ranked at 14th place with 17.4 million tourist arrivals.

Literature review: Forecasting is very important to many types of organizations since prediction of future events is one of the crucial information that strongly influence decision-making process. Slight improvement in forecast accuracy could give huge improvement in the effectiveness of service, capital investment and resources usage (Makridakis and Hibon, 2000). Realizing this fact, many forecasting methods have been introduced and paidly enhanced in order to provide a more accurate forecast. However, according to Bowerman, there is Ano single best forecasting model exists.

Song and Song and Li (2008) who reviewed published researches in tourism demand forecasting, found that there is no single model that can always outperform other models in all situations. Their findings are consistent with one of the conclusions in M3 competition by Makridakis and Hibon (2000). In their study, it was concluded that the performance of forecasting methods depends on the type of data (fields and frequencies). In tourism, the inconsistency might be due to the different types of data (the origin country and the periodical of the data) and forecasting horizon used (Lim and McAleer, 2001). Moreover, the choice of forecast accuracy measurement may also produce different conclusion from the empirical results (Witt and Witt, 1995). Recently, Nor which used Malaysia tourism data has shown that different measurements give different performance rankings.

Evaluation forecast accuracy in terms of directional change error is less used compare with error magnitude measurement. However, the fact is directional forecasting has very important role in economic filed as it gives valuable information in decision making process on asset allocation and investment (Nyberg, 2011; Pesaran and Timmermann, 2004). Moreover, Gordon and Tanner and Granger (1999) emphasize that error measures that have been widely used failed to give conclusion (or chose the best forecast) that can be relate to forecast profit in economic.

Witt *et al.* (2003) pointed out that failure to predict the directional change in tourism demand could give serious financial consequences. They suggested that researchers be certain with their forecasting objective; whether it is to minimize the error magnitude or the directional change error. Previously, Granger and Pesaran also emphasized that the choice of forecast assessment measures should rely on the objective of forecasting. However, in assessing the economic forecast value, it is important to consider both the magnitudes and directional movements.

Henriksson and Merton (1981) have developed a method for evaluating the market timing of financial investments which known as HM test. This method is hypothesis testing on dependency between two binary variables that are directional change of observed data and that in forecast. Among previous studies that utilize this testing are Cumby and Modest (1987), Dorfman and Mcintosh (1990) Witt *et al.* (2003) and Blaskowitz and Herwartz (2011).

HM test can be simplified by using 2×2 contingency table and it has been demonstrated that HM test can be simplified into simple Chi-square test of independency using contingency table by Cumby and Modest (1987), Schnader and Stekler (1990) and Witt *et al.* (2003). Example of previous studies that used such method in economic forecasting are Sinclair *et al.* (2006), Blaskowitz and Herwartz (2011) and Baghestani (2009). Ash *et al.* (1998) found that Fisher's exact test and Chi-square test give the same conclusion in general. Cicarelli (1982) proposed the probability of correctly forecast directional change is known as Directional Accuracy (DA). Some examples of previous research that used such evaluation can be found in Lai (1990), Gordon and Tanner and Blaskowitz and Herwartz (2008, 2011).

Recently, the studies on Malaysia tourism just started getting attention from researchers and generally the methodology that have been mainly used are traditional time series and econometrics method. Meanwhile, in the context of variables under study most researches are focused on the factors that influence tourism demand instead of the tourism demand itself or the forecasting on the arrivals. Loganathan and Ibrahim (2010) and Nanthakvmar *et al.* (2012) used Box *et al.* (1994) approach to forecast quarterly data of international and Asian tourist arrivals to Malaysia respectively. Box-Jenkins approach also had been used by Shitan to forecast aggregate monthly tourist arrivals from July 2007 until December 2008. Particularly, the study used ARMA and Autoregressive Fractionally Integrated Moving Average Models (ARFIMA) models.

Tan *et al.* (2002a) used econometric models to examine the major factors that influence inbound tourism demand to Malaysia and Indonesia from six market countries. Econometric models also used by Tan *et al.* (2002b) to investigate the implications of formation of tourism development organizations in Malaysia and Indonesia whether it give important marketing for the tourism industries in both countries.

The long run demand for tourist arrivals from United Kingdom and United States to Malaysia was examined by Habibi. They used cointegration analysis on annual data from 1972 until 2006 to study the relationship between macroeconomic variables and the tourism demand. The same study also had been carried out by Arsad *et al.* (2010) by using monthly data of tourist arrivals from three European countries to Malaysia. Hanim *et al.* (2010) also did such study but they used data of tourist arrivals from Asian countries. Moreover, they also consider short run effect of outbreaks and economic crisis on the tourism demand. Then, Salleh *et al.* (2000) proceeded the study by focusing on the increment of Chinese tourists arrivals to Malaysia. Kadir *et al.* (2013) used panel data econometric technique to analyze the factor that influence the tourist arrivals to Malaysia.

The global tourism industry is vulnerable to the effect of massive crises. These massive crises could be related to environmental, economic, political or health (Aramberri, 2009). These unexpected events also known as intervention and several researchers have took concern of this in their studies. For instance, Kuo *et al.* (2008) investigate the effects of outbreaks namely Avian Flu and Severe Acute Respiratory Syndrome (SARS) on tourist arrivals in Asian countries (including Malaysia and Indonesia) by using monthly data of international tourist arrivals to 14 Asian countries. They used panel data procedures and autoregressive moving average model together with an exogenous variables which known as ARMAX model. Meanwhile, panel data together with random effects method also had been used by Salleh *et al.* (2000). They examined the impact of the 11th September incident on the increment of Middle East tourist arrivals to Malaysia.

MATERIALS AND METHODS

Time series forecasting: Several classical methods have been selected based on their potential to model the pattern of the available time series data. According to Bowerman an appropriate method could be selected when the pattern of historical data is well defined. They proposed a guideline to identify the pattern of data by considering four components:

- Trend: upward or downward movement that is, actual characteristic over period of time
- Cycle: repeated up and down movements around trend levels or the same time interval
- Seasonal variations: periodic pattern that could be repeated for example according to week, month, quarter year or four season weathers. These pattern are then repeated on yearly basis
- Irregular fluctuations: can be interpreted as intervention or outliers. It does not follow any regular pattern such for trend, cycle or seasonal variations

Based on these characteristics, the following methods have been chosen.

Box-Jenkins: The Box-Jenkins methodology was introduced by George and Jenkin. It is most suitable to be applied when the components of a time series are changing over time. This method is consisted of iterative four-stage process, namely model selection or identification, parameter estimation, diagnostic checking and finally forecasting. The identification step consists of the identification of appropriate data transformation and the determination for order of the model. As this method has stationary assumptions, the time series need to be examined as to whether their mean and variance are stationary. If the series do not fluctuate around constant mean or without constant variation, then the time series can be classified as nonstationary. By refering Box *et al.* (1994), the general Box-Jenkins model which allocates seasonality can be written as follows:

$$\phi_p(B)\Phi_P(B^S)\nabla^d\nabla_s^D y_t = \theta_q(B)\Theta_Q(B^s)a_t$$

Where:

$\nabla = \nabla_1 = 1\text{-}B,$

$\phi_P(B) = 1-\phi_1 B\text{-}\phi_2 B^2 - \cdots - \phi_P B^P$

$\Phi_P(B^s) = 1-\Phi_1 B^s\text{-}\Phi_2 B^{2S} - \cdots - \Phi_P B^{pS}$

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

$\Theta_Q(B^S) = 1-\Theta_1 B^S-\Theta_2 B^{2S}-\cdots-\Theta_Q B^{QS}$

$B^j y_t = y_{t-j}$

This model is known as Seasonal Autoregressive Integrated Moving Average (SARIMA) where B is the backshift operator a_t is a white noise process are unknown parameters relating to y_i that indicate the non-seasonal Autoregressive (AR) of order p and ϕ_p indicate the Seasonal Autoregressive (SAR) of order P. The term for non-seasonal Moving Average (MA) of order q is denoted as θ_q and for the seasonal moving average (SMA) is Θ_Q The term d and D represent the non-seasonal and seasonal differences, respectively. There are many types of Box-Jenkins model, however the tentative model, or the order of autoregressive and moving average process can be particularly identified based on the ACFs and PACFs plots.

Time series regression: A standard regression model could be used to model the mean function of a nonstationary process. This is because such mean function is able to be explained by a deterministic trend of time (Wei, 2006). Time series regression explains the relationship between the dependent variable y_t to function of time. This method is appropriate to model time series data that have linear trend and the trend remains the same at all t.

The seasonal patterns were modeled by employing dummy variables to make sure that an appropriate seasonal parameters are included in the regression model at each time period. This dummy variables model assumed that the seasonal components are unchanged from year to year. For instance, in the case of monthly data there are 12 dummy variables. By referring Bowerman, the forecast model at t+1 can be written as follow:

$$\hat{y}_{t+1} = \hat{\delta}_1 t + \hat{\beta}_1 M_1 + \hat{\beta}_2 M_2 + \hat{\beta}_3 M_3 + \hat{\beta}_4 M_4 + \hat{\beta}_5 M_5 + \hat{\beta}_6 M_6 + \hat{\beta}_7 M_7 + \hat{\beta}_8 M_8 + \hat{\beta}_9 M_9 + \hat{\beta}_{10} M_{10} + \hat{\beta}_{11} M_{11} + \hat{\beta}_{12} M_{12}$$

Where, $M_1, M_2,...,M_{12}$ are dummy variables that define as follows:

$$M_1 = \begin{cases} 1; \text{ if time period t is January} \\ 0; \text{ otherwise} \end{cases}$$

$$M_1 = \begin{cases} 1; \text{ if time period t is Febuary} \\ 0; \text{ otherwise} \end{cases}$$

$$\vdots$$

$$M_{12} = \begin{cases} 1; \text{ if time period t is December} \\ 0; \text{ otherwise.} \end{cases}$$

For example, when the forecast data is for March, all dummy variables are zero except for M_3.

Holt-winters: Exponential smoothing methods are appropriate to forecast on time series with the trend and seasonal factors may be changing over time. Triple exponential smoothing (well known as Holt-Winters method) which was introduced by Winters (1960) is an exponential smoothing procedure for seasonal data. There are 15 exponential smoothing methods and Holt-Winters is the best method for seasonal data (De Gooijer and Hyndman, 2006). There are two types of Holt-Winters method namely the additive and multiplicative Holt-Winters methods.

Additive Holt-Winters model is used when the magnitude of andthe seasonal pattern in the anddata does not depend on andthe magnitude of andthe data or the series can be described as having constant seasonal variation. A forecast at time t +1 for this method is written by the following equations:

$$\hat{y}_{t+1} = L_t + T_t + S_{t+1-p}$$

where S_{t+1-p} is the most recent estimate of the seasonal factor with p denoting the number of season in a year, for example p = 12 for data that has monthly seasonality. The parameters L_t, T_t and S_t are the estimate for the level, growth rate (or trend) and seasonal factor of the time series at time t, respectively. Their smoothing equations are given by:

$$L_t = \alpha(y_t - S_{t-p}) + (1-\alpha)(L_{t-1} - T_{t-1})$$
$$T_t = \gamma(L_t - L_{t-1}) + (1-\gamma)T_{t-1}$$
$$S_t = \delta(y_t - L_t) + (1-\delta)S_{t-p}$$

Where:

α = Is weight for the level
γ = Is weight for the trend
δ = Is weight for the seasonal

Meanwhile, multiplicative Holt-Winters model is appropriate to use when the time series has increasing seasonal variation. The magnitude of the seasonal pattern in andthe data depends on the magnitude of the data where the magnitude of the andseasonal pattern increases when the values of data increase and decreases when the values of data anddecrease.

Measures of forecasting accuracy: The information from available history data was used to predict the future data by forecasting methods. These predicted or forecast values commonly have different values than the actual values of the forecasted variable. Hence, every forecast results need to be evaluated so that their accuracy could be measure. Then, the most accurate forecast results from the corresponding forecasting model could be chosen and an appropriate conclusion could be made.

Error magnitude measurements are used to quantify the differences between the actual values with the forecast or predicted values produced by a forecasting model. Let $\check{y}_{T^*}$ is the forecast of y_{T^*} at time T* by using the information that available in T time where T = 1,2,...,t. Thus, the loss function for forecast error magnitude is $L(e_{T^*}) = L(yT^* - \check{y}_{T^*})$. This loss function will arise as this difference getting larger.

The mean of absolute value from this loss function is the Mean Absolute Error or Mean Absolute Deviation (MAE or MAD). It is belongs to the general classes of loss functions (Elliott *et al*., 2005). As it takes the absolute value, it does not account for over-forecast or under-forecast. The MAD can be written as follow:

$$MAD = \frac{1}{n}\sum_{i=1}^{n}|y_{T^*} - \hat{y}_{T^*}|$$

Table 1: Intervals of MAPE values that indicate the forecast accuracy level

Lower value (%)	Upper value (%)	Level of accuracy
0	10	Highlyaccurate
10	20	Good
20	50	Reasonable
50	100	Inaccurate

Lewis

It measures the forecast performance by giving value with the same units as the variable under study. Thus, it is not applicable in forecast evaluation across multiple series. Alternatively, for scale-independent measure, the Mean Absolute Percentage Error (MAPE) is the most frequently used measure to compare forecast performance across multiple time series (Hyndman and Koehler, 2006). Its loss function gives relative performance of forecast which given by the following equation:

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{(y_{T^*} - \hat{y}_{T^*})}{y_{T^*}}\right|(100); \quad y_{T^*} \neq 0$$

The MAPE values can reflect the forecast accuracy level according to four intervals as shown in Table 1. The lower and upper values are inclusive and exclusive respectively.

Mean Square Error (MSE) is a loss function that associated with average of quadratic or square error loss. Originally, it was introduced by Carl Friedrich Gauss for estimation problem which it is the variance of unbiased estimator. One of the reasons of its widespread use is because of it has relationship with least square theory (Berger, 1985). In the case of forecast evaluation, this square error loss function is given by. $L(y_{t+1},\check{y}_{t+1}) = L(y_{t+1},\check{y}_{t+1})^2$ It is scale dependent as MAD. Root Mean Square Error or Root Mean Square Deviation (RMSE or RMSD) is the square root of MSE which can be calculated as:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{T^*=t+1}^{t+n}(y_{T^*} - \hat{y}_{T^*})^2}$$

Loss function such MAD, MAPE and MSE are widely applied due to its simplicity and easy to interpret. Such loss function can be computed directly from the actual and forecast values. They do not involve any unknown parameter that need to be estimated (Elliott *et al*., 2005).

Directional change error: The directional change error or directional accuracy (hereafter denote as DCE) was first introduced in market timing forecast evaluation by Merton (1981). This forecasting involves the prediction of time when bonds will outperform stocks and vice versa. In the context of time series forecasting, DCE is referred to the upward or downward movement of the data. The downward movement is also can be referred as fall in the interested variable. Let the out-sample data are at time $T^* = t+1, t+2, \ldots, t+n$. Then, the directional of actual and forecast data between time and is given by A_{T^*} and F_{T^*}, respectively which can be written as:

$$A_{T^*} = y_{T^*+1} - y_{T^*}$$

and

$$F_{T^*} = \hat{y}_{T^*+1} - y_{T^*}$$

Since the forecast data available starts at time t+1, the equations have exception for the directional of actual and forecast data between time t and t+l where the equation are given by:

$$A_t = y_{t+1} - y_t$$

and

$$F_t = \hat{y}_{t+1} - y_t$$

The sign of A_{T^*} and F_{T^*} indicate the downward or no downward movement. No downward movement means that there can be upward movement or no movement. The hypothesis testing on the usefulness of the forecast is well known as HM test. It can be simplified by using 2×2 contingency table and it has been demonstrated that HM test can be simplified into simple Chi-square test of independency using contingency table by Cumby and Modest (1987), Schnader and Stekler (1990) and Witt *et al.* (2003).

Fisher's exact test: Aware of the weaknesses and limitations of Chi-square test, the Fisher's exact test that was introduced by Fisher has been applied in case of Chi-square test fails to evaluate the contingency table. This test is useful for categorical data to examine the significance of dependency or association between two types of classifications.

In contrast of Chi-square test, Fisher's exact testcan be applied in small sample size. The hypergeometric distribution is used directly to calculate the probability of independency between the direction of forecast and the actual data. Thus, it does not calculate a test statistics such as Chi-square test. Based on contingency Table Reference source not found. the Fisher's p-value is calculated as follows:

$$\text{p-value} = \frac{\binom{n_{0\cdot}}{n_{0,0}}\binom{n_{1\cdot}}{n_{1,0}}}{\binom{N}{n_{\cdot 0}}}$$

Significant p-value indicate that the forecast able to predict the directional successfully or in other words, it able to give significantly sufficient information on the directional of data. Ash *et al*. (1998) have shown that the Fisher's is identical to HM test. The HM test is linked with the loss function approach but they are not equivalent (Blaskowitz and Herwartz, 2008).

Mean directional accuracy: Probability of correctly forecasting directional change was introduced by Cicarelli (1982). It used ordinary conditional probability. Then, this idea was enhanced by using the loss function to evaluate the Directional Accuracy (DA) where the loss function is given by:

$$\begin{aligned} L_{DA,T^*} &= I\left[(y_{T^*+1} - y_{T^*})(\hat{y}_{T^*+1} - y_{T^*}) > 0\right] \\ &\quad - I\left[(y_{T^*+1} - y_t)(\hat{y}_{T^*+1} - y_t) < 0\right] \\ &= I(A_{T^*}F_{T^*} > 0) - I(A_{T^*}F_{T^*} < 0) \end{aligned}$$

Where:

$$L_{DA,T^*} = \begin{cases} 1 \text{ for correct directional forecast} \\ -1 \text{ for incorrect directional forecast} \end{cases}$$

The I (.) are the indicator function which if it is true, then the value of one is assigned and otherwise the value zero is assigned. Examples of the used of this loss function can be found in Leitch and Ernesttanner (1995), (Greer, 2005), Blaskowitz and Herwartz (2008).

In order to represent the directional change accuracy for all forecast data, the mean of DA is computed and it is known as MDA. It gives the average number of correct forecast in terms of directional. The MDA is calculated as follows:

$$MDA = \frac{1}{n} \sum_{T^*=t+1}^{t+n} L_{DA,T^*}$$

Note here that the larger MDA value indicates the better directional forecast of the data. It may also take negative value.

Mean directional value: Hartzmark (1991) argued that the performance of forecast ability in terms of correct directional should not be justify only based on some statistic significant level. His focus was on daily transactions data on individual investors. He introduced a loss function that gives preference for model that is able to predict large price changes instead of small changes. It is known as "big hit" ability or Directional forecast Value (DV). The loss function of DV can be written as follows:

$$L_{DV,T^*} = L_{DA,T^*}\left|y_{T^*+1} - y_{T^*}\right|$$

It is not only taking into account the sign of the directional (as in the DA) but also the magnitude of changes in the actual data. For instance, if the model forecast the directional correctly when big changes occur in actual data, it will be assigned with large (according to the magnitude of change in actual data) positive number. In contrast, if the model fails, it will be penalized with large negative number. As for MDA, the average of this loss function is calculated in order to evaluate the forecast ability for the entire forecast horizon and it is given as follows:

$$MDV = \frac{1}{n} \sum_{T^*=t+1}^{t+n} L_{DV,T^*}$$

Larger value of MDV value also indicates the better directional forecast of the data.

RESULTS AND DISCUSSION

Data of inbound tourism Malaysia monthly data, y_t starting January 1998 until December 2009 is divided into two parts where the first part, $y1_t$ is for the purpose of estimation and the second part, $y2_t$ is for the purpose of forecasting. The first part consists of 132 data starting January 1998 until December 2008. Meanwhile, the second part consists of 12 data from January 2009 until December 2009.

Time series plot of y_t (in thousand people) is shown in Fig. 1. It shows that the data have linear trend and the mean level depends on time. Thus, the data do not fluctuate around a constant mean. The mean of tourist arrivals through the 12 years was 1,227,085 tourists. Before proceed with SARIMA, the data need to be differenced in order to remove non-stationarity. The Malaysia tourism demand data is a seasonal data with linear trend. It can be observed from Fig. 1 that the data tends to have constant seasonal variation than increasing seasonal variation (multiplicative), hence the additive Holt-Winters model was used.

The forecasting performances of all the models were being evaluated by using different forecast error measurements and their rankings were compared. The time series plot of their forecast are shown in Fig. 2 and comparison results are presented in Table 1.

Table 2, Inconsistent forecast assessment can be found among the three error magnitude measurements and between the error magnitude measurements and DCE. All the error magnitude measurement (except MAPE) chose Holt Winters as the best method. On the other hand, all the DCE chose time series regression as the best method. All the forecasting methods has MAPE values that are <10% thus, it can conclude that the forecast results are highly accurate. In contrast, when the assertion of no

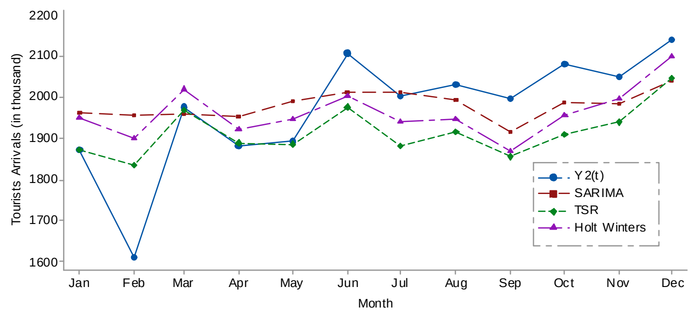

Fig.1: Time series plot for monthly tourist arrivals to Malaysia from January 1998 until December 2009

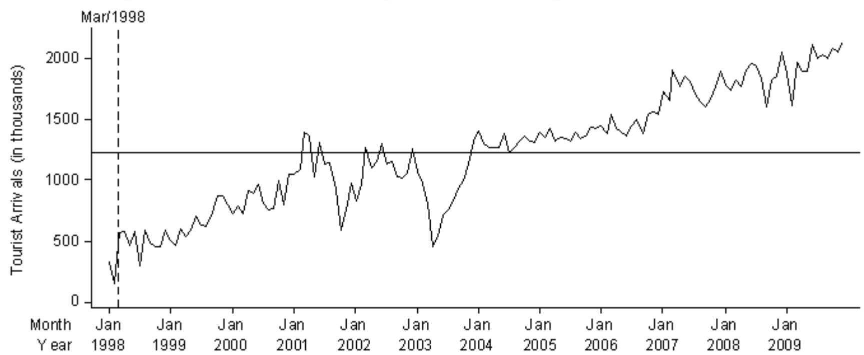

Fig. 2: Time series plot for forecast data

Table 2: Forecast performance of difference forecasting methods for Malaysia tourist arrivals

Model	Forecast accuracy measurement					
	MAD	MAPE	RMSE	Fisher's	MDA	MDV
SARIMA	91.56 (2)	4.917 (3)	122.82 (3)	0.55 (3)	0.33 (2)	47.99 (3)
Time series regression	93.37 (2)	4.80 (1)	116.50 (2)	0.18 (1)	0.50 (1=)	90.96 (1)
Holt Winters	91.4 (1)	4.84 (2)	112.69 (1)	0.24 (2)	0.50 (1=)	63.403 (2)

() ranking

association or independency between the actual and predicted directional changes has been tested through hypothesis testing by using Fisher's exact test, all these methods has p-values that are larger than 0.05.

CONCLUSION

When we compare between the error magnitude measures and DCE, the empirical results on application of tourism demand to Malaysia data supports the finding from previous studies by Witt *et al*. (2003), Cicarelli (1982), Witt and Witt (1991) and Blaskowitz and Herwartz (2011) where they found that error magnitude measurement and directional change error give different conclusion. The best model in terms of error magnitude does not necessarily give the most accurate directional forecast and vice versa. It can be conclude that Holt Winters gave the most accurate forecast in terms of error magnitude. Meanwhile, in terms of directional accuracy, time series regression gave the most accurate forecast.

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