ERROR MAGNITUDE AND DIRECTIONAL ACCURACY FOR TIME SERIES FORECASTING EVALUATION

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To ALLAH

To my husband & daughters

To my mother & family

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ABSTRACT

Evaluation of forecast accuracy is very much influenced by the choice of accurate measurement since it can produce different conclusion from the empirical results. Thus, it is important to use appropriate measurement in accordance to the purpose of forecasting. Commonly, accuracy is measured in terms of error magnitude. However, directional accuracy is as important as error magnitude especially in economics since it considers directional movement of the data. This research attempted to combine the two types of measurement~~s~~ by introducing a new element, the slope value. This proposed measure is known as square error modified of directional accuracy (SE-mDA). Before that, the existing directional change error measurement was modified by comparing the direction of two subsequent forecasts data with two subsequent observed data. Empirical application utilizing the monthly data of Malaysia and Bali tourism demand was used to compare the forecast performance between SARIMA, time series regression, Holt-Winter, intervention neural network and fuzzy time series. The root mean square error, mean absolute percentage error, mean absolute deviation, Fisher's exact test, Chi-square test, directional accuracy, directional value and the modified of directional change error were used in forecast accuracy evaluation. The best forecast model in terms of SE-mDA for the data of Malaysia and Bali are Holt-Winters and neural network, respectively. The main conclusion from this study is that SE-mDA is able to improve the forecasting performance assessment of error magnitude measurement by considering the directional movements. At the same time it also enhances the available directional accuracy measurement by taking into account the difference between slopes of forecast data and observed data. These improvements will help forecaster to choose the best forecasting method or model so as to produce the most accurate forecast.

ABSTRAK

Penilaian terhadap ketepatan ramalan sangat dipengaruhi oleh pilihan pengukuran ketepatan kerana ia boleh memberi kesimpulan yang berbeza untuk keputusan-keputusan empirikal. Oleh itu, adalah penting untuk menggunakan pengukuran yang sesuai mengikut tujuan peramalan. Biasanya, ketepatan ramalan adalah berpandukan kepada ralat magnitud. Walau bagaimanapun, ketepatan arah adalah sama pentingnya dengan ralat magnitud terutama dalam bidang ekonomi kerana ia mengambil kira pergerakan arah data. Kajian ini cuba untuk menggabungkan kedua-dua jenis ukuran dengan memperkenalkan satu elemen baru iaitu nilai cerun. Pengukuran yang dicadangkan ini dikenali sebagai ralat kuasa dua ketepatan arah diubahsuai (SE-mDA). Sebelum itu, ukuran ralat perubahan arah yang sedia ada telah diubahsuai dengan membandingkan arah antara dua data ramalan yang berturutan dengan dua data sebenar yang berturutan. Aplikasi empirikal dengan menggunakan data bulanan permintaan pelancongan di Malaysia dan Bali telah digunakan untuk membandingkan ketepatan ramalan antara model peramalan SARIMA, regresi siri masa, Holt-Winter, intervensi, rangkaian neural dan siri masa kabur. Punca min ralat kuasa dua, ralat peratus min mutlak, ralat min mutlak, ujian Fisher, ujian khi-kuasa dua, ketepatan arah, nilai arah, ralat perubahan arah diubahsuai telah digunakan dalam penilaian ketepatan ramalan. Model ramalan terbaik dari segi SE-mDA bagi masing-masing data Malaysia dan Bali adalah Holt-Winters dan rangkaian neural. Kesimpulan utama daripada kajian ini ialah SE-mDA dapat meningkatkan kebolehan penilaian ramalan oleh pengukur ralat magnitud dengan mengambil kira pergerakan arah. Pada masa yang sama, ia juga meningkatkan ketepatan pengukuran arah yang sedia ada dengan mengambil kira perbezaan kecerunan antara data ramalan dan data sebenar. Peningkatan ini akan membantu peramal untuk memilih kaedah atau model ramalan terbaik yang dapat memberikan ramalan yang paling tepat.

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LIST OF ABBREVIATIONS

MAPE	Mean absolute percentage error
MAD	Mean absolute deviation
RMSE	Root mean squared percentage error
AR	Autoregressive
MA	Moving average
ARIMA	Autoregressive integrated moving average model
SARIMA	Seasonal autoregressive integrated moving average model
ACF	Sample autocorrelation fuction
PACF	Sample partial autocorrelation fuction
NN	Neural network
MLP	Multilayer perceptron
FTS	Fuzzy time series
DCE	Directional change error
DA	Directional accuracy
MDA	Mean directional accuracy
DV	Directional forecast value
MDV	Mean directional value
SE-DA	Standard error directional error
mDCE	Modification of directional change error
mChi-square	Modified of Chi-square test
mFisher’s	Modified of Fisher’s exact test
mMDA	Modified of MDA
mMDV	Modified of MDV
SE-mDA	Standard error modified directional error
ID	Indication number of series
SE-mDA(c)	SE-mDA values for correct directional

SE-mDA(i) SE-mda values for incorrect directional

LIST OF SYMBOLS

λ	Parameter in Box-Cox transformation
B	Where B is the backshift operator
a_t	White noise process
θ_q	Non-seasonal moving average of order q
ϕ_p	Non-seasonal autoregressive of order p
Φ_P	Seasonal autoregressive of order P
Θ_Q	Seasonal moving average of order Q
$M_1, M_2, \ldots, M_{12}$	Dummy variables for January, February, … , December
L_t	Estimate for the level factor of the time series at time t
T_t	Estimate for the growth rate (or trend) factor of the time series at time t
S_t	Estimate for the seasonal factor of the time series at time t
α	Weight for level
γ	Weight for trend
δ	Weight for seasonal
b	Delay time for the effect of an intervention
s	Time that is needed for the effect of an intervention to be stable
r	Pattern of an intervention
P_t	Pulse function of intervention
S_t	Step function of intervention
b_i	Bias, are and are
x_j	Independent variables or inputs
n_i	i^{th} neuron in hidden layer

$w_{i,j}$	Weight from input x_j to n_i
γ_0	Bias for output
γ_j	Weight from n_i to output
U	Universe of discourse
$Y(t)$	Universe of discourse by which fuzzy sets $f_i(t)$ are defined
A_j	Fuzzy set of U
f_{Aj}	Membership function of the fuzzy set A_j
$F(t)$	Fuzzy time series defined on $Y(t)$
$A_{j_1}, A_{j_2}, \ldots, A_{j_k}$	Forecast of $F(t)$
$M(t) = [m_{1_1}, m_{1_2}, \ldots, m_{1_k}]$	Midpoints of $A_{j_1}, A_{j_2}, \ldots, A_{j_k}$ in matrix form
$W(t) = w_1^{'}, w_2^{'}, \ldots, w_k^{'}$	Corresponding weight for $A_{1_1}, A_{1_2}, \ldots, A_{1_k}$ in matrix form
T	Time of in-sample data
T*	Time of out-sample data
t	Time for the last data in in-sample data
Y_{T*}	Out-sample data in error measures
n	Number of forecast data
$\hat{y}_{T*}$	Forecast of y_{T*} at time $T*$
$L(e_{T*})$	Loss function for forecast error magnitude
A_{T*}	Directional of actual data between time $T*$ and $T*+1$
F_{T*}	Directional of forecast data between time $T*$ and $T*+1$
p_1	Probability of directionally correct forecast given the conditional of there is fall at time T*
p_2	Probability of directionally correct forecast given the conditional of there is no fall of the actual data at time T*
n_1	Number of observations for which $A_{T*} < 0$
n_2	Number of observations for which $A_{T*} \geq 0$
m_1	Number of correct forecasts given $A_{T*} < 0$
m_2	Number of incorrect forecasts given $A_{T*} \geq 0$

$\underline{m}_1$	Minimum value of m_1
$\overline{m}_1$	Maximum value of m_1
β	Test statistics of the right tail test
χ^2	Corrected version of the Chi-square test statistic
$L_{DA,T*}$	Loss function for directional accuracy
$L_{DV,T*}$	Loss function for directional forecast value
$A_{m,T*}$	Modified directional movement of actual data
$F_{m,T*}$	Modified directional movement of forecast data
$L_{mDA,T*}$	Modified loss function for directional accuracy
$L_{mDV,T*}$.	Modified of loss function for directional value
m_A	The slope of line for two consecutive actual data
m_F	The slope of line for two consecutive forecast data
e^2_{T*}	Loss function for square forecast error magnitude
$L_{S,T*}$	Loss function for difference in slope values of actual and forecast data
$L_{SE\text{-}mDA,T*}$	Conditional loss function that combines the error magnitude and the difference in slope values
μ	Mean of absolute first different value of N2575 series
ρ	Spearman correlation coefficient
$R(X_i)$	Rankings for item i by X
r	Sample Spearman correlation coefficient
y_t	Monthly data of tourist arrivals
$y1_t$	In-sample data for tourist arrivals data
$y2_t$	Out-sample data for tourist arrivals data
z_t	Transformed data of $y1_t$

CHAPTER 1

INTRODUCTION

1.1 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 (Bowerman *et al.*, 2004). Realizing this fact, researchers are always searching for forecasting methods that are able to improve forecast accuracy.

Mean absolute percentage error (MAPE), mean absolute deviation (MAD) and root mean squared percentage error (RMSPE) are among the error magnitude measurements commonly used to assess forecast accuracy. Generally, this type of measurement evaluates on how vast the difference is between the forecasted and the actual or observed data. However, accuracy in terms of error magnitude alone is not enough especially in the field of economics as it needs to relate with decision making. Moreover, in the discovery of directional accuracy (which enables researchers, economists and investors to have information on the directional behaviour of data) according to Blaskowitz and Herwartz (2011) is the variable under study that is likely to have upward or downward movements. The forecast accuracy in terms of these movements is known as directional change error or directional accuracy. In this study, we use the term directional change error to avoid confusion with one of the measurements which is named directional accuracy.

The information on the upturn and downturn could be more crucial than the error magnitude accuracy in economics (Cicarelli, 1982). Witt *et al.* (2003) found that error magnitude and directional change error measurement give different performance rankings to competitive models. The same conclusion can also be found in Cicarelli (1982), Witt & Witt (1991), Witt *et al.* (2003) and Blaskowitz & Herwartz (2011).

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 Mohd. Najib bin 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 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.

1.2 Research Background

In tourism forecasting, an accurate forecast is very crucial as it influences the decision- making process that involves with large capital and investment. If the forecasts overestimate the tourist arrivals, government and private sectors related to tourism will have to face with overspending. They have to bear low returns as compared to what they have invested as the accommodation, facilities and transportations provided have not been fully utilised. In contrast, if the forecast underestimates tourist arrivals, the accommodation and facilities offered might be imperfect and inadequate. This may affect the tourists' perception and eventually the reputation of the country. Thus, resulting them not being interested to choose this country as their future vacation destination. Hence, an accurate prediction of tourist arrivals is crucial in order to sustain the future growth of tourism industry.

Witt and Witt (1995) and Song and Li (2008) who reviewed a large number of published works in tourism demand forecasting found that there is no single model that can outperformed other models consistently in all situations. Hence, usually researchers will use various methods or models, and chose the best method through comparison study. However, there is a problem when it comes to decision-making on how to choose the best model since it is highly influenced by the choice of accuracy measurement (Witt and Witt, 1995).

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 (2000) 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.

Granger (1999a) studied the relationship between forecast evaluation in statistical and economic methods. He proposed to present forecast as a predictive distribution. This approach has its limitation since not all studied variable could be estimated. Hartzmark (1991) introduced a criteria known as 'big hit ability' which considers forecast ability to obtain large profit in economic value by giving preference for model that is able to predict large price changes instead of small ones. Although it claimed that it is able to capture the sign and magnitude of data movements, it omits the distance between the forecasted and observed data. It becomes inappropriate when competitive methods have similar performance in terms of direction.

This study attempts to solve these problems by introducing a forecast accuracy evaluation that is able to simultaneously measure the error magnitude and direction. In this measure, we introduced a new element in assessing forecast accuracy that is the value of different slope between observed and forecasted data. This value will cause the measure to be able to evaluate and differentiate forecasts that have identical direction but different error magnitude, and vice versa.

1.3 Problem Statement

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. Thus, in assessing economic forecast value, it is important to consider both the magnitudes and directional movements. 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. It is found that error magnitude and directional change error measurement give different performance rankings of competitive models (Cicarelli, 1982; Witt and Witt, 1991; Witt *et al.*, 2003; Blaskowitz and Herwartz, 2011).

1.4 Research Questions

(a) What are the drawbacks of MAPE, MAD, RMSE, Fisher's exact test, Chi-square test, mean directional accuracy (MDA) and mean directional value (MDV) in evaluating forecast accuracy for economic data.

(b) Is there any other element that could be considered in evaluating forecast accuracy and subsequently improve the forecast evaluation by MDA.

(c) What is the most appropriate forecasting method among classical methods (Box-Jenkins, Holt-Winters, intervention analysis and time series regression) and modern methods (neural networks and fuzzy time series) in order to forecast Malaysia's tourism data.

1.5 Objectives of the Study

This study embarks on the following objective:

(a) To develop an alternative forecast accuracy measurement by combining square error and directional accuracy.

(b) To propose new approach of directional change error and then reconstruct the existing directional change error measurements according to the proposed approach.

(c) To assess the ability of MAPE, MAD, RMSE, fisher's exact test, Chi-square test, MDA, MDV and the propose measurement in evaluating forecast accuracy.

(d) To evaluate the forecasting performance of classical methods (Box-Jenkins, Holt-Winters, intervention analysis and time series regression) and modern methods (neural networks and fuzzy time series) in order to forecast tourist arrivals.

1.6 Significance of the Study

Forecast accuracy measures will influence the decision for choosing the best forecast model. Existing measures requires the researchers to choose whether to assess the forecast performance in terms of error magnitude or directional errror. The SE-mDA which could conduct a simultaneous assesment on error magnitude and directional error will cause such critical decision and conclusion be made with more precision and confidence. Moreover, the proposed measure does not require highly complex computer programme and the model is selected only through ranking.

Previous studies showed that existing forecast evaluation measures have their own strengths and weaknessess. Most investigations on these measures only focus on evaluation across multiple time series. Thus, they are limited to scale-free or scale-independent measures. In contrast, this study does not has any scale constraint as we compared the behaviour of measures in evaluating single series. The behaviour of each measures was examined through comparison study involving modification on M3-competition data. This could provide some guidelines so that researchers would be more concious when they utilize the forecast accuracy measurements; particularly when it involves with the assessment for both errors (magnitude and directional).

It has been shown that tourism industry provides important contribution to Malaysia's economic development. Thus, an accurate forecasting of tourism demand is worthwhile to be investigated and studied. This is particularly true for Malaysia as most of the forecast tourism demand studies focus on classical time series methods. This research attempts to fill this gap by examining whether modern methods such as neural networks and fuzzy time series can produce better forecast results as compared to the classical time series methods. The classical time series methods considered are Box-Jenkins method, Holt Winter's, intervention and time series regression.

There is no clear proof in concluding which model is performing better than the other models in all situations. Therefore, it is appropriate that forecasting competitions be applied in order to procure the best forecating model. However, according to Song and Li (2008) (who reviewed 121 published studies since 2000 in tourism demand modelling and forecasting) most of the previous tourism forecasting competition studies are only involved with less than five models. In contrast, the comparative study in this research involves eight different forecasting models. Moreover, their forecast accuracy were also assessed through several aspects, specifically in terms of error magnitude, directional change error and proposed measures. Thus, it may provide a better conclusion in finding the most appropriate model to forecast tourism demand. In the future, this particular model might be studied in greater detail in order to adapt with the data. Hence, it could establish a direction in research on Malaysia's tourism demand forecasting.

This study involves tourist arrivals to two different destinations. The main difference between this data is the presence of outliers data. The changes in forecast performance against the presence of outliers is examined through comparison study. This will provide beneficial information guideline in deciding whether a particular model is appropriate to be applied in forecasting whenever the historical data contains outlier.

1.7 Scope and Limitation of the Study

Classical time series methods that will be applied in this study are Box-Jenkins model, time series regression, intervention analysis and Holt Winter's method. Meanwhile, the modern methods are neural networks and fuzzy time series. Meanwhile, the forecast accuracy of all these methods will be evaluated and compared by using MAPE, MAD, RMSE, fisher's exact test, Chi-square test, MDA, MDV and SE-mDA.

There are several types of directional accuracy assessment such as turning point, directional change error and circle growth. In this research we only focus on directional change error since it is more appropriate in the application of Malaysia's tourism demand data where it is very unlikely to have data that fulfils the trend change pattern. Moreover, directional change error also makes the construction of mixed measurement of error magnitude and directional accuracy possible as it only needs comparison on the directions between two consecutive data.

The data involved in the comparison of forecasting models performance is inbound tourist arrivals to Malaysia and Bali. The data of Malaysia and Bali is consisted of monthly data starting January 1998 until December 2009, and January 1989 until December 1997, respectively. The M3-competition data is used only for simulation study. For simulation purpose, financial data coded as N2575 series from M3-competition data is used. This data is taken from the website of International Institute of Forecasters (http://forecasters.org/resources/time-series-data/m3-competition/). Only 18 data which is the out-sample data from this series was considered.

The limitations of the proposed measures are that they are only appropriate to be applied on univariate series since they are scale dependent. Moreover, they do not take into account the presence of outlier. This study does not attempt to find the best forecasting model in tourism forecasting since it is impossible to have a single model that could give the most accurate forecast in all situations. The most appropriate forecasting model is only for the particular data, forecast horizon and in terms of accuracy measure used.

1.8 Structure of Thesis

This thesis consists of five chapters. The second chapter presents literature review–that covers Malaysia's tourism forecasting and modelling, classical and modern forecasting methods, and forecast accuracy evalution. The following chapter explains in detail the forecasting models and the simulation procedure. Results of the study will be explained and discussed in Chapter 4. This includes the results of simulation studies and comparison of forecast performance by classical and modern forecasting models. Finally, Chapter 5 presents the conclusion, summary and recommendation for future studies.

This research found that NN has a good potential to forecast tourism data effectively in terms of error magnitude. However, it has weakness to forecast the direction (as the propose approach) when there is outliers. Thus, this method is beneficial to be studied more in-depth together with outlier analysis so that it can cope with data that contain outliers such in Malaysia tourism data. Besides, one of the most important properties of NN that could be interesting and beneficial to investigate is the solution to find the optimum input lags of NN. It could give significant improvement of NN forecast performance.

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