MULTIPLE LINEAR REGRESSION AND NEURAL NETWORK FOR ELECTRIC LOAD FORECASTING

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Thank you Allah

For my family

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ABSTRACT

Starting from conventional models, researchers have begun to develop advanced techniques. One recent technique is the hybrid model, which improves upon the time series forecast. In this study, a hybrid model combining the multiple linear regression (MLR) model and neural network (NN) model has been developed to enhance the forecast of Malaysian short term load. Considering the data consisted of linear and nonlinear parts, it is first forecasted using the MLR model. The residuals obtained from the in-sample forecast are then forecasted using the NN model. This model has improved the forecast, although at certain hours, neural network model gives better performance. To determine the performance of the models, three performance indicators are used: root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE). To assist in error measurements, we also developed a fractional residual plot to observe goodness-of-fit. A graphical plot could help an analyst see the goodness of the analysis for each of the individual data. Compared to the regular residual plot, this plot provides more information and can be used as a benchmark tool. This study also includes the missing values problem as one of the objectives. In load data, the missing problem always occurs in a set of data. Since it has a seasonal pattern according to days, most of the time, the load usage for the next day is predictable. For this reason, a new model has been developed based on these characteristics. Three imputations are tested with this method: mean (DCM1), mean + standard deviation (DCM2) and third quartile value (DCM3). The data is divided into three parts which are at the front, middle and at the end of the data with 5%, 15%, and 25% of missing values. The results of RMSE show that the proposed techniques, particularly DCM1 and DCM3, are superior to other complex methods when dealing with missing values.

ABSTRAK

Bermula daripada model konvensional, penyelidik mula membangunkan teknik yang lebih canggih. Salah satu teknik yang terbaru adalah model hibrid, yang menambah baik ramalan siri masa. Dalam kajian ini, model hibrid menggabungkan model regresi linear (MLR) dan model rangkaian neural (NN) telah dibangunkan untuk meningkatkan ramalan beban jangka pendek Malaysia. Memandangkan data terdiri daripada bahagian-bahagian linear dan tak linear, ia dimulakan dengan meramal menggunakan model MLR. Ralat yang diperolehi daripada ramalan dalaman sampel kemudiannya diramalkan menggunakan model NN. Model ini telah menambah baikkan ramalan, walaupun pada masa tertentu, model rangkaian neural memberikan prestasi yang lebih baik. Untuk menentukan prestasi model, tiga petunjuk prestasi digunakan: ralat punca min persegi (RMSE), ralat min mutlak (MAE), dan ralat min peratusan mutlak (MAPE). Untuk membantu dalam ukuran ralat, kami juga membangunkan plot ralat pecahan untuk melihat kebaikan prestasi. Sebuah plot grafik dapat membantu seorang penganalisis melihat kebaikan analisis bagi setiap data individu. Berbanding dengan plot ralat biasa, plot ini menyediakan maklumat lanjut dan boleh digunakan sebagai alat penanda aras. Kajian ini juga menkaji masalah nilai yang hilang sebagai salah satu objektif. Dalam beban data, masalah kehilangan nilai sentiasa berlaku dalam bentuk satu set data. Oleh kerana data mempunyai corak bermusim mengikut hari, pada kebanyakan masa, penggunaan beban untuk hari berikutnya boleh diramal. Atas sebab ini, model baru telah dibangunkan berdasarkan ciri-ciri ini. Tiga imputasi diuji dengan kaedah ini: min (DCM1), min + sisihan piawai (DCM2) dan nilai kuartil ketiga (DCM3). Data ini dibahagikan kepada tiga bahagian iaitu jika kehilangan berada di awal, tengah dan di akhir data dengan 5%, 15%, dan 25% nilai-nilai kehilangan. Keputusan RMSE menunjukkan bahawa teknik yang dicadangkan, terutamanya DCM1 dan DCM3, adalah lebih baik daripada kaedah kompleks yang lain apabila berurusan dengan nilai-nilai yang hilang.

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LIST OF ABBREVIATIONS

STLF	-	Short term load forecasting
EMS	-	Energy Management System
ANN	-	Artificial neural network
ARIMA	-	Autoregressive integrated moving average
SARIMA	-	Seasonal autoregressive integrated moving average
MAE	-	Mean absolute error
MAPE	-	Mean absolute percentage error
RMSE	-	Root mean square error
AR	-	Autoregressive
MA	-	Moving average
FLRs	-	Fuzzy logical relationships
FLRG	-	Fuzzy logical relationships group
MLP	-	Multi-layer perceptron
GLM	-	Generalized long memory
PCA	-	Principal component analysis
MCAR	-	Missing completely at random
MAR	-	Missing at random
NI	-	Non-ignorable
EM	-	Expectation maximization
SOM	-	Self-organized maps
EOF	-	Empirical Orthogonal Function
MLR	-	Multiple linear regressions
NN	-	Neural network
ACF	-	Autocorrelation function
PACF	-	Partial autocorrelation function
SAR	-	Seasonal autoregressive
SMA	-	Seasonal moving average

FTS	-	Fuzzy time series
MSE	-	Mean square error
TLSAR	-	Two level seasonal autoregressive
DCM	-	Disaggregation-and-combination-imputation
Q3	-	Third quartile
DCM1	-	$\text{mean}+\lvert 1\sigma \rvert$ imputation
DCM2	-	Mean imputation
DCM3	-	Third quartile imputation
PBJB	-	Pusat Bandar Johor Bahru

LIST OF SYMBOLS

y_t	-	Actual value
ε_t	-	Error or residual
L_t	-	The linear component
N_t	-	The nonlinear component
$\hat{Y}_t$	-	The out-sample forecast
$\hat{Y}_{1,t}$	-	Forecast value for time t from the multiple linear regression model
$\hat{E}_{2,t}$	-	Forecast value of the residual from the neural network model
B	-	Backshift operator
a_t	-	White noise process
φ_p	-	Autoregressive (AR) of order p
Φ_P	-	Seasonal autoregressive (SAR) of order P
θ_q	-	Term for non-seasonal moving average (MA) of order q
Θ_Q	-	Term for seasonal moving average (SMA) of order Q
d	-	Nonseasonal differences
D	-	Seasonal differences
$\mu_{y\|x_1,x_2,\ldots,x_k}$	-	Mean value of the dependent variable y
$x_1, x_2, \ldots, x_k$	-	Independent variables
$\beta_0 + \beta_1 + \cdots + \beta_k$	-	Regression parameters relating the mean value of y

ε	-	Error term that describes the effects on y
$x_1, x_2, \ldots, x_7$	-	Dummy variables for Monday until Sunday
L_t	-	Level at time t
α	-	Weight for the level
T_t	-	Trend at time t
γ	-	Weight for the trend
S_t	-	Seasonal component at time t
δ	-	Weight for the seasonal component
P	-	Seasonal period
Y_t	-	The data value at time t
$\hat{Y}_t$	-	Fitted value, or one-period-ahead forecast, at time t
b_i	-	Bias
x_j	-	Independent variables or inputs
$w_{i,j}$	-	Weight from input x_j to i^{th} neuron in hidden layer.
γ_0	-	Bias for output
γ_i	-	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_{A_j}	-	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 $F(t)$
$W(t)$	-	Weight matrix
$w_1, w_2, \ldots, w_k$	-	Weight
$W(t) = w'_1, w'_2, \ldots, w'_k$	-	Corresponding weight for $A_{j_1}, A_{j_2}, \ldots, A_{j_k}$ in

		matrix form
L_{df}	-	Deffuzified matrix
c	-	Exponential weight
$M(t)=[m_{j_1}, m_{j_2}, \ldots, m_{j_k}]$	-	Midpoints of $A_{j_1}, A_{j_2}, \ldots, A_{j_k}$ in matrix form
n	-	Number of data
$x(t)$	-	Fractional residual
$\varphi(B)$	-	Backshift operator
ϕ_p	-	Polynomials of order p
θ_q	-	Polynomials of order q
$\nabla_7 y_t$	-	Polynomial trend of degree d after being differencing at 7
$\hat{y}_{n+1}$	-	Forecast of one step ahead for the missing value at $n+1$
$\hat{y}_{n+2}$	-	Forecast of one step ahead for the missing value at $n+2$
κ	-	Curvature of a curve y
$q'_i(x_i)$	-	Polynomial function being differentiate once
$q''_i(x_i)$	-	Polynomial function being differentiate twice

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Analysis of time series data is an important field in research. Generally, everything which is measured through time will be called time series data and the purpose as so why a data is recorded is to understand the trend and pattern of the data so that one could predict their future outcomes for consequence and make a conclusion of the product. For example, modeling a load forecasting is a very important task for electricity function in a more efficient and safe way (Soares and Medeiros, 2008). It is also important in order to give the most optimum cost for cost saving applications relying on operating reconstruction and accurate forecasts (Hahn et al., 2009). It is also important as a process of predicting the future load demands. By predicting the future load demands, power system planners and demand controllers could ensure that they would be enough supply of electricity to cope with increasing demands (Mastorocostas et al., 2000). For these reasons, load forecasting has attracted not only researchers but also organizations with the same interest to forecast energy usage by using various methods from classical methods to the advanced methods.

In this study, we consider only the short term load forecasting (STLF). STLF covers a period of one hour to one week ahead. Some of the attractions of STLF are that it is a key role in the formulation of economic, reliable and secure operating strategies for the power system and it is also an essential element of Energy Management System (EMS) (Chatfield, 2005). STLF also delivers the input data for load flow studies and likelihood analysis to calculate the requirement of generators, to determine line flows and to ensure that the system continues to operate reliably (Taylor and McSharry, 2007). In addition, it is also useful for off-line works where a list of corrective actions can be prepared for expected faults. STLF is also beneficial to market operators, transmission owners, and other market participants because it can schedule adequate energy transactions and prepare operational plans and bidding strategies (Gross and Galiana, 1987). Because of the above advantages of STLF there has been great demand in finding a precise model. In short, many researchers are now focusing on finding a method that could model their data and provide an accurate forecast.

Other than finding a hybrid model to forecast the load data, we also propose a graphical technique to assess goodness-of-fit of a model(s). If error measurement could give information about the analysis from the value, graphs are important to show the precision for each of the value. This graph is important to identify unusual or influential observations, to measure model hypothesis and to understand the novelty of the study (Baddeley et al., 2005). Graphs should tally in a tentative manner based on specific tests of a hypothesis (Cox, 2004). Error measurements are used to give information on whether a model is good in forecasting the data. However, as mentioned by Hyndman and Koehler (2006) and Hyndman (2006), the error measurements are not generally applicable which could mislead the results of the forecasting. In assessing the goodness of fit of a model, graphical plot helps to better understand the results and make further improvements of the model used.

Addressing missing values is important in the process of getting a precise and accurate result. Missing values usually occur in load data when data is not recorded from few hours to a few months due to certain problems that may occur unexpectedly as a result of faulty equipment, lost records, or a mistake, which cannot be rectified until later. This kind of missing values could be classified as having systematic patterns. Many studies in the literature suggest how researchers can deal with the missing data as it affects model estimates and standard errors. If missing data is not treated appropriately, then the results could lead to biased estimates (Penn, 2007). In some instances, the data cannot be analyzed either at record level or for the overall database when it contains missing values. Thus, it is important to properly handle missing values in all types of analysis (Winkler and McCarthy, 2005).

1.2 Research Background

Malaysian short term load data can be classified as multiple seasonal data. Multiple seasonal data is when a time series contains more than one cycle that is repetitive in a period of a year or less. Malaysian data contains both daily and weekly cycles. Malaysia has many public holidays as the country has different ethnic groups. The cycles from Monday to Friday are similar while Saturday and Sunday are quite discrete. It is worthwhile to note that the patterns for public holidays are quite similar to weekends compared to weekdays. As stated by Gould et al. (2008), the levels of the daily cycles may change from one week to the next and yet it is still highly correlated with the prior levels of the next day.

Forecasting seasonal load demand has become increasingly challenging in the recent period. Classical methods such as regression, Holt Winter's and exponential smoothing are suitable for a large number of series especially for an analyst with limited skills and also is a norm of comparison (Chatfield, 2000). It follows a certain pattern which was determined by the parameter of the model. But as the time passed by, conventional models may no longer be a proper way to deal with seasonal data because real data never really follows a pattern of a model. As such, advanced models such as an artificial neural network (ANN) and fuzzy time series have been applied as an alternative and better forecast for a seasonal load data. Recently, hybrid models have become attractive as they improve the forecasting.

Pairwise comparison is used to determine how good a model fits a data. Despite on how many quantitative systems are used in modeling geographic data, the most important objective is to seek possible means of improving the models. Therefore, to make evaluation informative, predicted values must be compared with measured values in meaningful ways (Willmott, 1981). The most common plots that are used to help visualize the accuracy of the model in the time series analysis are time series plot and residual plot (Cox, 2004). Different kind of graphs may be used for different kind of purposes. This is mainly because each kind may have its own advantages and in the most study, a variety of models has been used with a variety of functional forms, choice of predictors and so on. Therefore, by developing more graphs, it will help more researchers to visualize their findings and understand their data better (Cox, 2004).

There have been many methods developed to handle missing values in the literature. Cokluk et al. classified it into three methods on how a missing value is being handled (Cokluk and Kayri, 2011). The first method is known as *defining one or more value(s) instead of the missing value and excluding these missing data from analysis*. This type of handling is usually a computer program to identify the missing value and the computer will just ignore the missing datum from the analysis. The second method is known as *deleting subjects and variables including missing value*. This method just deletes the missing values with its pairing variables and assumes that it does not affect the analysis of the data. The third method is *predictions of missing values/imputation*. This method predicts the missing values and uses this value in basic analysis. However, predictions and imputation processes can only be applied for quantitative variables.

By considering these three methods above, predictions and imputations are the most appropriate approach to handle the missing values because the deletion leads to a prejudiced estimation and can decrease or exaggerate statistical power. According to Mertler and Vannatta (2002) and Tabachnick and Fidell (2001) three most common methods of predictions and imputations are by using prior knowledge, average (mean) and regression. In prior knowledge, the missing values are being imputed with previous values. Mean imputation is the most basic and common imputation being used especially if there is no other information available. While in regression, one or more independent variables will be taken into the process which will be used later to impute the dependent variable value (Cokluk and Kayri, 2011). But as mentioned by Kihoro and Athiany (2013), it is important to identify appropriate model as it depends on the type and nature of the data in order to obtain the best possible estimates.

1.3 Problem Statement

The 24 hours load usage is often treated as one series instead of a set of independent points. As mentioned by Soares and Medeiros (2008), 24 hours load should be treated as an independent series since each hour has their own dynamics and structures. Fay et al. (2003) also noted that when separating the 24 hours series, it has a dual nature that each hour has independent pattern and different from one another (Fay et al., 2003). Thus, Malaysian 24 hours load data contains a multiple seasonal cycle and this technique should be considered during forecasting.

Another major concern when forecasting a load data is whether to consider the linearity of the data. A real data may not consist of pure linear or nonlinear but may contain both linear and nonlinear (Zhang, 2003). In order to check the linearity of data, residual plot is often used. Residuals are important in order to check whether a model is able to fit with a data. Although there is no general statistical diagnostic on how to detect nonlinear autocorrelation relationship, residuals can be utilised in a diagnosis step to ensure that both linear and nonlinear part are considered (Zhang, 2003). In this study, 24 hours load usage will be treated as a set of independent points and a hybrid model consists of both the linear and nonlinear parts will be developed to forecast the load usage in Malaysia.

Basically, time series plot is a graph that was used to evaluate the pattern of the data over time. This plot is commonly used by many to show the difference between the actual and forecast data (Baharudin and Kamel, 2007, Gould et al., 2008, Soares and Medeiros, 2008, Zhang, 2003). The problem with time series plot is that there is not much information that can be gained from the plot. Residual plot is a plot that is used to show the difference between the actual and forecasted values. The problem with residual plot is that it is dependent to the scale. If the data has a large value such as in load usage or arrival of tourists per year where the figure is in hundred thousand units where the difference might reach to thousands, one could think that it is a bad forecast although it is actually a good forecast. Moreover, it is also hard to set a benchmark on the residual plot to decide whether a model is good or bad.

The presence of missing values in the underlying time series is a persistent problem when dealing with databases. Therefore, it is important to handle the missing values problem appropriately. Often time series data contain certain patterns such as trend, seasonality and stationarity. Because of complexity of data, missing data in time series can be quite challenging and can be handled by using imputation from regression model, Box-Jenkins model, Kalman-filtering model and so forth (Kihoro and Athiany, 2013, Gómez et al., 1992, Sorjamaa and Lendasse, 2007). The most common model used to deal with this problem is the Box-Jenkins model.

1.4 Research Question

This research will focus on statistical modeling with the problems as follow:

i. How to enhance the forecasting of short term load data?
ii. What is an appropriate approach to forecast a multiple seasonal load data amongst conventional models, advanced models and a hybrid model?
iii. How can the performance of a model be visualized and making it happen by using a graphical plot?
iv. How to deal with missing values problem in a seasonal load data?

1.5 Objective of the study

The main interest of this study is to propose a feasible model to forecast the short term load data. The main objectives of this study are:

i. To propose a hybrid method to enhance the forecasting of short term load data.
ii. To evaluate the forecasting performance between the classical, advanced and the proposed model for short term load data.

iii. To propose an alternative graphical approach to evaluate performance of a model(s) and to manipulate the practice of the plot.

iv. To propose a feasible method of dealing with missing values in a seasonal time series data.

1.6 Significance of the Study

In the literature, researchers developed new method in forecasting time series data to improve and get a better forecast. A good forecast is important as they help to better understand and make predictions based on data available. This also applies in load forecasting. Not only will it help the energy provider company to manage the power supply, it also helps consumers pay at the optimum cost.

It can be difficult to identify a data as a pure linear or nonlinear. Often a few models are selected for comparison and the most precise result is selected to be the best model in modeling the data. Thus, developing a hybrid model that combines different models can be a good option to address this. Hybrid model also has the advantage of embracing other model weaknesses. For example if one model is good in forecasting a linear data, another model would be good in forecasting the nonlinear data. Hence, by combining these two models will create a hybrid model that could deal with both linear and nonlinear pattern in a data. In particular, this study aims to develop a hybrid model that fits the Malaysian load data that could improve the forecasting.

A statistical graph is a common purpose to observe the various aspects of residual and predicted values after fitting a model. Unlike the regression algorithms and analysis of variance, statistical graph shows a set of individual residuals. There are many studies on how to examine the fit by using this value graphically in order to seek possible means and improvise the method. In this study, a residual plot is proposed to help understand the modeling better by standardizing the value of the residuals and to expand the usage of the plot.

In certain practice, missing values can affect the behaviour of the data or the result of the forecasting. A lot of techniques were developed in order to tackle the missing value problem. Load data are not exempted from this problem. But time series data usually contains certain trend and seasonality. Thus it requires a specific method to deal with it by considering the pattern of the data. By gaining the information from the forecasting, the load contains daily cycle which is repetitive and predictable. Therefore, this information will benefit in solving the missing values problem. And since it is common for load to have a particular cycle, we will benefit from the information in this study. A comparison with other few techniques will give beneficial information guideline on how one could deal with missing values when they have a seasonal data.

1.7 Scope and Limitation of the Study

After considering the data's pattern and appropriateness of the models with the data, the only time series models that will be considered in this study are the Holt Winter's, multiple linear regressions, SARIMA, fuzzy time series and neural networks models. Meanwhile, performance indicators that will be used to compare the results are the mean absolute error (MAE), mean absolute percentage error (MAPE) and root mean square error (RMSE). These three measurements are chosen because they are the most common and widely applied in measuring forecast accuracy as it is simple to be used and scale-free.

Malaysian load are not really affected by other effects such as temperature or seasons because Malaysia does not has a dramatic climate changes such as at a four seasons countries therefore we only consider the weekdays and weekend effects. The load data used in this study is only from Johor Bahru. The data consists of a daily record documented at every hour from 1st January 2008 until 31st January 2011 respectively. For the missing values problem, only hour 1200 is considered because it shows obvious pattern between the weekdays and the weekends. The limitation of this study is that the proposed hybrid model is only suitable for a seasonal data.

This study only deals with the common missing values faced by load data, which is the univariate type. Other types of missing values are not considered since they are not related to load data. Plus, the percentage of missing values that were used is only up to 25% because it is uncommon to have a load data that contains more than 10% of missing values and by considering larger percentage of missingness, we hope this study could cover if there is a missing values problem larger than 10% involve in the future. Therefore by choosing 25% as the maximum missing percentage is sufficient for this study.

1.8 Outline of Thesis

The organization of the thesis is given as follows. Chapter 2 provides the literature review and background study of the methodology used. This is followed by Chapter 3 where the theory of the models and techniques used in this study are discussed. In chapter 4, the results from the proposed technique and comparison with other models and techniques are discussed thoroughly. Chapter 5 will present the conclusion of the study and further work that can be expanded from this study.

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