Jurnal
Teknologi

Full Paper

ELECTRICITY DEMAND FORECASTING IN MALAYSIA USING SEASONAL BOX-JENKINS MODEL

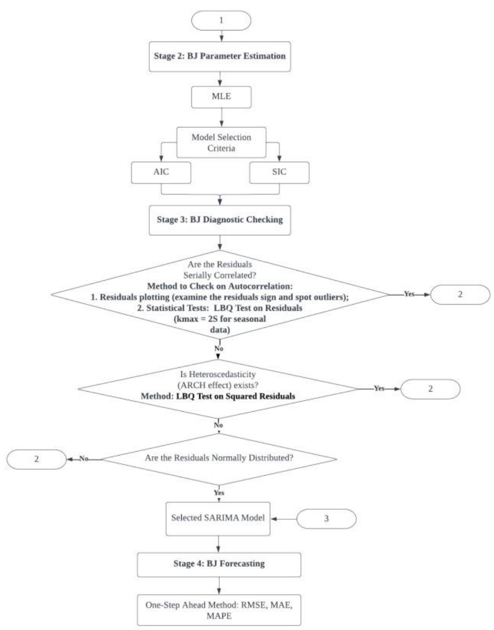
Syarranur Zaim[a], Siti Roslindar Yaziz[a]*, Roslinazairimah Zakaria[a], Nurul Najihah Mohamad[b], Noor Fadhilah Ahmad Radi[c]

[a]Centre for Mathematical Sciences, Universiti Malaysia Pahang Al-Sultan Abdullah, Kuantan, Pahang, Malaysia
[b]Department of Computational and Theoretical Sciences, Kulliyyah of Science, International Islamic University Malaysia, Kuantan, Pahang, Malaysia
[c]School of Mathematical Sciences, College of Computing Informatics and Media, UiTM Shah Alam, Shah Alam, Selangor, Malaysia

Article history
Received
28 December 2023
Received in revised form
8 May 2024
Accepted
6 June 2024
Published Online
20 February 2025

*Corresponding author
roslindar@umpsa.edu.my

Graphical abstract



Abstract

The development of a precise forecasting model for electricity demand is essential for optimizing the efficiency of planning within the power generation sector. The electricity demand data in Malaysia exhibits seasonal patterns, making it necessary to evaluate the forecasting capabilities of the Box-Jenkins model for predicting weekly peak electricity demand. The objective of this study is to assess how well the Box-Jenkins model performs in forecasting the weekly peak electricity demand. This study utilizes weekly electricity demand data, specifically the highest values recorded each week, measured in megawatts (MW), spanning from 2005 to 2016. The findings indicate that SARIMA $(4,1,0)(0,1,0)_{52}$ is the best-suited choice for predicting electricity demand. This conclusion is supported by its notably low values of Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) which stand at 623.3015, 488.5673, and 2.95%, respectively. The MAPE value of the suggested model, falling below the 5% threshold, suggests that the seasonal Box-Jenkins model performs quite effectively when it comes to predicting electricity demand in the context of Malaysian data. To summarize, the proposed seasonal Box-Jenkins model exhibits significant potential and delivers promising performance when forecasting electricity demand characterized by seasonal patterns.

Keywords: Forecasting, Electricity Demand, Box-Jenkins, Seasonal Data

Abstrak

Pembangunan model ramalan yang tepat untuk permintaan elektrik adalah penting untuk mengoptimumkan kecekapan perancangan dalam sektor penjanaan kuasa. Data permintaan elektrik di Malaysia mempamerkan corak bermusim, menjadikannya perlu untuk menilai keupayaan ramalan model *Box-Jenkins* untuk meramalkan permintaan elektrik puncak mingguan. Objektif kajian ini adalah untuk menilai sejauh mana prestasi model *Box-Jenkins* dalam meramalkan permintaan elektrik puncak mingguan. Kajian ini menggunakan data permintaan elektrik mingguan, khususnya nilai tertinggi yang dicatatkan setiap minggu, diukur dalam megawatt (MW), antara 2005 hingga 2016. Dapatan menunjukkan bahawa SARIMA $(4,1,0)(0,1,0)_{52}$ ialah pilihan yang paling sesuai untuk meramalkan permintaan elektrik. Kesimpulan ini disokong oleh nilai yang sangat rendah Punca Min Kuasa Dua Ralat (RMSE), Min Ralat Mutlak (MAE) dan Min Ralat Peratusan Mutlak (MAPE) yang masing-masing adalah 623.3015, 488.5673, dan 2.95%. Nilai MAPE model yang dicadangkan, jatuh di bawah ambang 5%, menunjukkan bahawa model Box-Jenkins bermusim menunjukkan prestasi yang agak berkesan apabila ia digunakan untuk meramalkan permintaan elektrik dalam konteks data Malaysia. Sebagai rumusan, model *Box-Jenkins* bermusim yang dicadangkan mempamerkan potensi yang ketara dan memberikan prestasi yang menjanjikan apabila meramalkan permintaan elektrik yang dicirikan oleh corak bermusim.

Kata kunci: Ramalan, Permintaan Elektrik, Box-Jenkins, Data Bermusim

1.0 INTRODUCTION

Predicting electricity consumption is crucial because electricity, being a non-storable resource, requires efficient management. In this context, load forecasters commonly refer to "peak demand" or "peak load" to analyze the optimal electricity utilization during specific time frames. The usage of electricity is influenced by shifts in weather patterns and various environmental factors. As an example, as reported by the Department of Statistics Malaysia [1], Malaysia experienced its peak electricity demand of 17,788 MW on 19 April 2016, attributed to the El-Nino phenomenon. This period saw electricity consumption soar to its highest point due to the hot and dry weather conditions. Consequently, the maximum demand is regarded as a key indicator for assessing the electricity system's performance, taking precedence over the minimum demand.

From a rational standpoint, prioritizing the maximum value over the minimum holds greater merit, especially in the context of predicting electricity demand. Additionally, in the power industry, strategic planning and infrastructure expansion depend heavily on the ability to estimate electricity demand. Therefore, the accuracy of these predictions can significantly reduce maintenance and operating expenses while improving the electrical power supply and distribution's network efficiency. This in turn makes it easier to make well-informed decisions on prospective developments. Thus, it becomes essential to achieve high-precision demand projections in order to avoid wasting energy and having equipment breakdown. Therefore, the application of the most effective techniques for generating accurate forecasts of electricity demand is of utmost importance, given the significant role that predicting electricity consumption plays, particularly in the economy. As a result, there are various approaches that can be explored for forecasting electricity demand.

Furthermore, electricity plays a crucial and widespread role as a primary source of energy, significantly shaping modern society. Its diverse benefits span various sectors such as transportation, manufacturing, mining, and communication. Serving as a foundational element, electricity plays a vital role in driving economic prosperity and development, holding a key position in socio-economic progress. It acts as a versatile tool that contributes significantly to strategic planning and future policy direction within the energy sector. The demand for electrical energy continues to rise steadily each day, and its multifaceted applications have propelled human civilization to unprecedented levels of advancement. Consequently, the need for electricity is intricately linked to all facets of development [2].

The accurate forecasting of electricity demand and prices is of paramount importance for market participants and system operators alike. Accurate forecasting is essential for effective power system management. However, because of their unique features-high frequency, volatility, extended trends, non-uniform mean and variance, mean reversion, different seasonal patterns, calendar-related effects, and the occurrence of spikes and jumps-projecting electricity demand and prices is a challenging undertaking [3].

It is essential for electricity generators, distributors, and suppliers to carry out a number of studies in order to forecast future electricity usage for both residential and commercial uses. In order to encourage consumer energy conservation efforts, this kind of proactive planning is crucial. Numerous statistical models are utilized for forecasting electricity consumption, such as the Seasonal Autoregressive Integrated Moving Average (SARIMA) [4] and the Simple, Holt's, and Brown's Exponential Smoothing Models [5]. Other methods include Fuzzy Time Series (FTS), Least Square Support Vector Machines (LSSVMs), Adaptive Neuro-Fuzzy Inference System (ANFIS), and Artificial Neural Network (ANN) [6].

Goswami and Kandali [4] focused on analyzing daily 24-hour electrical load data obtained from the State Load Dispatch Centre (SLDC) in Assam. Over a period of three years, 1095 data points from daily load data at 10 am, from 1 January 2016 to 31 December 2018, were included in the dataset. For the purposed of model creation and evaluation, the data was split into two categories which are 75% training data (822 points) and 25% testing data. The SARIMA model was utilized in the study to analyze time series data. The results showed that the SARIMA model performed better in terms of prediction, with a low MAPE value of 10.7% by integrating the seasonal patterns in the load data.

Ishak *et al.* [5] applied annual data from the Malaysia Energy Information Hub (MEIH) covering the years 1997 to 2018 to forecast the amount of power consumed in Malaysia's residential sector. Brown's Exponential Smoothing, Holt's Exponential Smoothing, and Simple Exponential Smoothing were used in the study. The principal aim was to provide an analysis of energy trends and projections for the period spanning 2019 to 2032. In results, Holt's Exponential Smoothing performed better than the others, with the lowest MAPE score of 2.3%.

Meanwhile, monthly electricity consumption data for seven nations over a ten-year period (2007-2016) was projected by Lee *et al.* [6]. Four different models were used in the study which are Fuzzy Time Series (FTS), Least Squares Support Vector Machines (LSSVMs), Adaptive Neuro-Fuzzy Inference System (ANFIS), and Artificial Neural Network (ANN) and the data source from ceicdata.com has been implemented. Metrics including RMSE, average forecasting error (AFE), and performance parameter (PP) were utilized to evaluate and compare the performance of these models. In conclusion, after highlighting the advantages and disadvantages of each model, for the majority of the countries under examination, the FTS model performed best.

The electricity demand, particularly in Malaysia, is a seasonal time series. In the field of time series data analysis, the Box-Jenkins modelling approach stands out as a very powerful forecasting technique. The Box-Jenkins model is a reliable option for forecasting and is frequently used as the standard or a crucial part of modern research due to its practicality and steady high performance in time series data analysis. The adoption of the seasonal Box-Jenkins model to anticipate the electricity demand data is justified by its seasonal aspect.

Andoh *et al.* [7] investigated the potential time series models for predicting energy consumption in Ghana's Western Regions. Forecasting was done using historical data, which included the monthly electricity usage by three client categories from January 2008 to December 2013. Therefore, the purpose of this research is to evaluate SARIMA's predictive power. In order to confirm the parameter values of of *p, q, P,* and *Q,* Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) were examined. The Sum of Squared Estimate of Error (SSE) values, which yield the least squares regression line of the data, have been used to evaluate the forecast's accuracy. The Box-Jenkins methodology was employed in the construction of the model for each of the three-monthly time series related to load tariffs. The aim of this approach is to fit a SARIMA model to the given series. It has been demonstrated that the time series models can reveal and amplify the region's electricity consumption in upcoming months or years.

Furthermore, Duong *et al.* [8] investigated how the SARIMA model could be used to forecast Hanoi's short-term load. Finding appropriate methods and models for forecasting energy consumption, especially electricity load, is the aim of their study. The dataset used for assessing and forecasting the power load in Hanoi encompassed the period from 1 January 2019 to 23 December 2021 which included hourly data every day. According to Box-Jenkins methodology, there is a structured four-step process, and it has been implemented in this research. Firstly, they focused on model recognition, which involved preparing the data and choosing suitable models. They also evaluated the stationarity of the data series and determined which model most closely matched the data. Subsequently, the authors estimated model parameters to select the most suitable model based on appropriate criteria, utilizing EVIEWS software. The third step involved assessing the suitability of the models by conducting residual tests. In the final step, the authors forecasted three SARIMA models which are SARIMA$(0,1,1)(0,1,1)_{24}$, SARIMA$(0,1,6)(0,1,1)_{24}$, SARIMA$(0,1,7)(0,1,1)_{24}$, for comparison purposes. After considering various factors, including the conditions of random residuals and forecasting accuracy, they concluded that SARIMA$(0,1,7)(0,1,1)_{24}$ was the most appropriate choice for hourly load forecasting on regular days in Hanoi.

Additionally, forecasting electricity prices and demand is essential to the smooth operation and management of energy markets. To improve the accuracy of these projections, researchers have been using more complex modelling techniques in recent years. Functional data analysis is one of these techniques that has shown promise since it can identify intricate patterns present in time series data.

Shah *et al.* [9] utilized data from the Nord Pool energy market and various forecasting accuracy metrics have been implemented to assess the one-day-ahead out-of-sample that was achieved for an entire year. The purpose of this study was to examine how well models based on functional data analysis forecasted. First, the extreme values in the demand time series are processed. Next, the filtered series is split into components that are stochastic and deterministic. The deterministic component is modeled using the generalized additive modelling technique, while the stochastic component is modeled and forecasted using functional autoregressive (FAR), FAR with exogenous variable (FARX), and classical univariate AR models. The findings show that the functional modelling technique yields better predicting outcomes than FAR and classical AR models where FARX generates a MAPE value of 2.74%, while the MAPE values for FAR and AR models are 6.27% and 9.73%, respectively.

Shah *et al.* [3] proposed models that can efficiently forecast electricity demand and prices. The demand and prices datasets of Nord Pool electricity market from 1 January 2013 to 31 December 2017 are considered. There are two parts of the time series. A trend, weekly, seasonal, and yearly periodicities, calendar effects, and lagged exogenous data are all included in the first component, which is regarded as deterministic and is modelled using both parametric and nonparametric techniques. The univariate autoregressive (AR) and multivariate vector autoregressive (VAR) models are used to estimate the second component, which is referred to as a stochastic component. Four distinct estimation techniques are used to carry out the estimate of these models: Elastic-net (E), Lasso (L), Ridge (R), and Ordinary Least Squares (O). The findings imply that the suggested methodology successfully predicts the cost and demand for electricity.

Jan *et al.* [10] suggested a functional forecasting technique based on a two-component estimate strategy for the precise forecasting of power prices. Italian Electricity Market (IPEX) provided the "Prezzo Unico Nazionale (PUN)" dataset for this empirical study, which was gathered between 1 January 2012 to 31 December 2017. The additive modelling method is used to calculate the first component, also referred to as the deterministic component. On the other side, a functional AR of order P, FAR (P) model is used to represent the stochastic component, and the dimension and lags are chosen automatically. Lastly, a full year of testing is done on the model to determine how well it forecasts. Based on the empirical data, it can be concluded that the suggested FAR(P) model outperformed the rival model with significantly less predicting mistakes. In addition, the component estimating process works quite well for predicting the cost of power.

Shah *et al.* [11] implemented a forecasting procedure based on components estimation technique to forecast medium-term electricity consumption. They utilized the dataset of Pakistan electricity consumption ranging from January 1990 to December 2015. The electricity consumption series is divided into two major components: deterministic and stochastic. For the estimation of deterministic component, parametric and nonparametric models have been used. The stochastic component is modeled by using four different univariate time series models including parametric AR, nonparametric AR (NPAR), Smooth Transition autoregressive (STAR), and Autoregressive Moving Average (ARMA) models. To evaluate the forecasting accuracy, three standard error measures, namely MAE, MAPE, and RMSE, were calculated. The results show that the proposed component-based estimation procedure is very effective at predicting electricity consumption.

Shah *et al.* [12] forecasted one-day-ahead electricity prices by using different forecasting techniques and models. The electricity price data, ranges from 1 January 2012 to 31 December 2017, is used from the Italian electricity market (IPEX). They considered linear and nonlinear models for one-day-ahead forecast of electricity prices using components estimation techniques where the price time series is divided into two major components: deterministic and stochastic. The deterministic component consists of long-run dynamics, multiple periodicities (yearly and weekly cycles) and calendar effects whereas the stochastic component accounts for the short-run dynamics of the process. Deterministic as well as stochastic components are modelled through parametric and nonparametric approaches. The results indicate that the component estimation approach is efficient in forecasting electricity prices series. The parametric estimation of deterministic component performs better forecasting results.

Shah *et al.* [13] took into account demand data from the Italian electricity market (IPEX) for the period 1 January 2005 to 31 December 2010 as well as from the British market (APX Power UK) for the period 1 April 2005 to 31 December 2010. This study compares the forecasting performances of parametric and nonparametric models based on the functional approach with other standard models, such as multivariate AR models, univariate AR models, and univariate kernel-based nonparametric models. The demand projections for the Italian (IPEX) and British (APX Power UK) electricity markets. Descriptive indicators are used to analyze predictive performances, followed by conducting a test to determine the significance of the discrepancies, According to the analysis, functional nonparametric models are the most accurate within the multivariate framework, with VAR being a competitive model. The multivariate approach yields better results than the univariate one.

Overall, the results point to the potential of functional data analysis to enhance the accuracy and dependability of forecasts of power demand and price in energy markets. The potential for applying these methods to other domains and the creation of advanced functional models to further improve predictive performance could be investigated in this field of study.

In the realm of time series modelling, it is a common practice to account for monthly or quarterly seasonal effects. Nevertheless, given the fluctuations in weather and various environmental factors over the course of a year, generating electricity demand forecasts solely on a quarterly or monthly basis may not adequately support effective electricity supply management. Hence, opting for a weekly basis can be a more suitable approach.

The current research landscape on electricity demand forecasting has extensively covered various models, including SARIMA, Exponential Smoothing Models, and Artificial Neural Networks. However, a significant gap exists in the exploration of weekly peak electricity demand forecasting, as most studies have focused on daily, monthly, or yearly predictions. Furthermore, previous studies lacked a comprehensive procedure tailored for one-step ahead forecasting of electricity demand specifically using seasonal Box-Jenkins model, a gap that this study aims to fill. There is a need for a dedicated investigation into the efficacy of the seasonal Box-Jenkins model for one-step-ahead forecasting of weekly peak demand in the Malaysian context yet providing a comprehensive procedure for weekly maximum electricity demand produced using the proposed model. This study would fill a crucial void by providing insights into the model's performance in addressing the unique challenges posed by weekly variations, ultimately contributing to more effective forecasting practices in the field of electricity demand prediction.

2.0 METHODOLOGY

Seasonal Box-Jenkins Model

The electrical demand pattern exhibits evident periodic fluctuations attributed to seasonal changes. Addressing these seasonal variations can be achieved through the SARIMA model proposed by Box-Jenkins. This model incorporates additional seasonal terms into the ARIMA framework, resulting in a seasonal ARIMA model denoted as SARIMA(p,d,q)(P,D,Q)$_s$. Here, *p* represents the non-seasonal autoregressive (AR) order, *d* is the non-seasonal differencing, *q* signifies the non-seasonal moving average (MA) order, *P* denotes the seasonal AR order, *D* represents the seasonal differencing, *Q* stands for the seasonal MA order, and s represents the seasonal period. The mathematical expression for the SARIMA(p,d,q)(P,D,Q)$_s$ model is expressed by Equation 1:

$$\Phi_P(B^s)\varphi_p(B)(1-B)^d(1-B^s)^D\dot{y}_t = \Theta_Q(B^s)\theta_q(B)a_t \quad (1)$$

where

$$\dot{y}_t = \begin{cases} y_t - \mu, & if\ d = D = 0 \\ y_t, & otherwise \end{cases}$$

The model in Equation 2 is formulated to forecast the next observation (y_t) based on the historical data and error term (a_t). Besides, *C*, represents the constant term.

$$\Phi_P(B^s)\varphi_p(B)(1-B)^d(1-B^s)^D y_t = \Theta_Q(B^s)\theta_q(B)a_t + C \quad (2)$$

Let y_t represents the observed time series data at time *t*. The operator of

$\varphi_p(B) = 1 - \sum_{i=1}^{p}\varphi_i B^i$ and

$\theta_q(B) = 1 - \sum_{j=1}^{q}\theta_j B^j$ are polynomials in terms of B with degrees *p* and *q*, respectively. Similarly, the operator of

$\Phi_P(B^s) = 1 - \sum_{I=1}^{P}\Phi_I\,(B^s)^I$

and

$\Theta_Q(B^s) = 1 - \sum_{J=1}^{Q}\Theta_J\,(B^s)^J$

are polynomials in terms of B^s with orders *P* and Q. The term

$\nabla_D^s = (1-B^s)^D$

is defined, where B is the backward shift operator, and the random errors a_t are assumed to be independently and identically distributed (IID) with a mean of zero and constant variance σ^2.

Proposed Research Framework of The Seasonal Box-Jenkins in Forecasting Electricity Demand

The general Box-Jenkins framework includes four iterative stages namely Stage I: Model identification, Stage II: Parameter estimation, Stage III: Diagnostic checking and Stage IV: Forecasting [14].

Figure 1 illustrates the proposed research framework inspired by Box-Jenkins, outlining the systematically organized steps for forecasting electricity demand. To assess forecast accuracy, it is crucial to consider four stages adopted from Box-Jenkins modelling: Model Identification, Parameter Estimation, Diagnostic Checking, and Forecasting. This framework is adapted from Yaziz [15], with a modification for this study, which centers on seasonal highly volatile time series data, in contrast to Yaziz's emphasis on non-seasonal highly volatile time series data.

Stages in Modelling and Forecasting using Box-Jenkins Models

Stage I: Model Identification

To determine the suitable SARIMA parameters, various statistical tests can be conducted. The steps for constructing a SARIMA model involve the following:

1. Stationarity Test: Utilize the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test to assess whether the time series is stationary. If it is not, adjustments such as differencing, seasonal differences, or transformations are necessary to induce stationarity.
2. ACF and PACF of the Stationary Data (Non-seasonal part): To determine the ordering of AR, Integrated (I), and MA components in the SARIMA model, look at the ACF and PACF plots of the stationary data.
3. Seasonality: Look for any seasonal trends in the data and identify the appropriate seasonal timeframe.
4. ACF and PACF of the Stationary Data (Seasonal part): To determine the ordering of the Seasonal Autoregressive (SAR) and Seasonal Moving Average (SMA) terms in the SARIMA model, examine the ACF and PACF plots of the stationary data.

Iteration may be required to find the right parameters for a SARIMA model and evaluating multiple models may be required to determine which model best matches the data.

Stage II: Parameter Estimation

Determining the values for the various SARIMA components is the process of estimating parameters in the SARIMA model. The following is a list of the steps that go into parameter estimate in the SARIMA model:

1. Stationarity and Seasonality Analysis: Use statistical tests like the ADF test and the Seasonal Decomposition of Time Series (STL) approach to determine whether the time series is stationary and to look for any seasonal trends, respectively.
2. SARIMA Parameter Estimation: To estimate the parameters related to the SARIMA component of the model, use Maximum Likelihood Estimation (MLE). This entails determining the proper orders for AR, MA, SAR, and SMA components of the model.
3. Model Selection: Based on the recommendations of Akaike [16] and Schwarz [17], determine the most suitable SARIMA model by evaluating the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). In the model selection procedure, the model with the lowest AIC or BIC value is preferred.

Stage III: Diagnostic Checking

Stage III is a crucial step in the modelling process within the diagnostic checking phase, which makes it possible to evaluate the suitability of the model and spot any possible flaws. In diagnostic checking, the residual series is expected to behave like white noise after the model is judged adequate [18]. Therefore, examinations for serial correlation, heteroscedasticity, and normalcy are part of the diagnostic evaluation during this stage. Additionally, careful consideration of residual plots is necessary to confirm that errors behave as white noise.

To examine serial correlation in model residuals, plotting the ACF and PACF of the residuals and conducting the Ljung-Box Q-test (LBQ test) on them is recommended. If autocorrelation evidence surfaces, model revision may be required. Furthermore, to detect potential heteroscedasticity within residuals, the LBQ test is applied to the squared residuals. Model residuals are expected to conform to white noise characteristics with no autocorrelation. For the normality test, the Jarque-Bera (JB) test has been employed.

Stage IV: Forecasting

Forecast accuracy pertains to the extent to which the actual results of a forthcoming event align with the forecasts generated by a predictive model. It serves as an indicator of the model's efficacy in foreseeing future outcomes and is often quantified as a percentage or a numerical score. Continuous evaluation and updating of forecast models are crucial to maintaining their accuracy and applicability over time.

Equations 3, 4, and 5 provide common metrics for forecast accuracy, namely the MAE, RMSE, and MAPE, respectively,

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|y_t - \hat{y}_t| \tag{3}$$

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(y_t - \hat{y}_t)^2}{n}} \tag{4}$$

$$MAPE = \frac{100\%}{n}\sum_{t=1}^{n}\left|\frac{y_t - \hat{y}_t}{y_t}\right| \tag{5}$$

where y_t and $\hat{y}_t$ represent the observed and forecast values at time t, respectively, and n is the count of out-of-sample data. The most favourable forecasting model is the one that minimizes prediction error. However, in cases where discrepancies emerge among different forecast evaluations, it is recommended to MAPE, as it tends to display greater stability compared to alternative metrics [19]. Girish [20] suggested that a MAPE value of approximately 5% indicates a relatively good forecasting ability for the model.

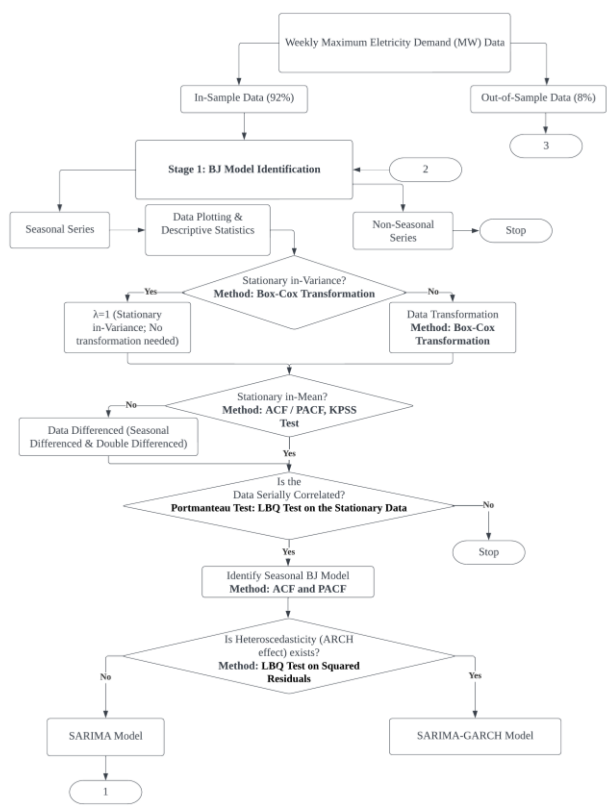


Figure 1 Research Framework of Seasonal Box-Jenkins in Forecasting

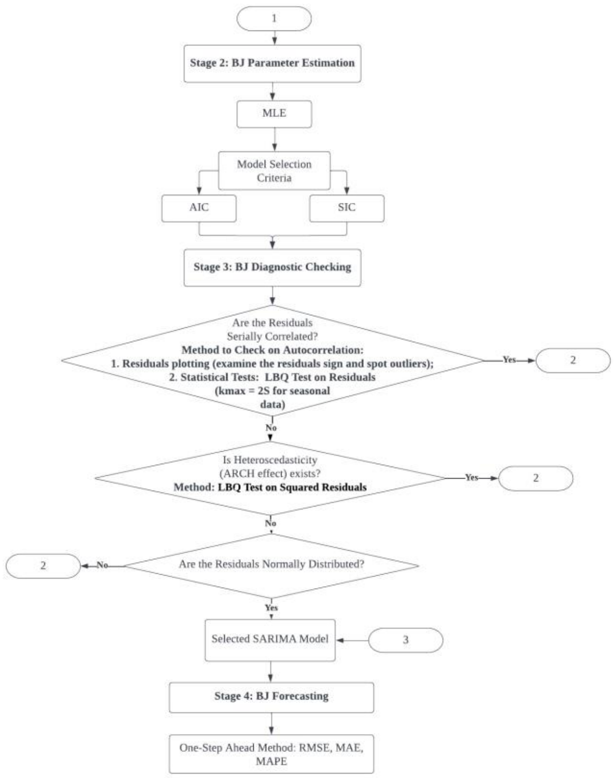


Figure 1 Research Framework of Seasonal Box-Jenkins in Forecasting (Continued)

3.0 RESULTS AND DISCUSSION

Dataset

In this investigation, weekly maximum electricity demand data (measured in MW) spanning from 2005 to 2016 is utilised, obtained from the Single Buyer Department (SB) website (https://www.singlebuyer.com.my/). SB, authorized by the Suruhanjaya Tenaga (Energy Commission), oversees electricity procurement and related services. The data is classified as secondary data, and Table 1 presents the weekly maximum electricity demand information. To construct the forecasting model, the input data is divided into training and testing sets with a standard ratio of 90:10 [21].

The preceding techniques for dividing data can be applied by defining a splitting ratio. A frequently employed ratio is 80:20, signifying that 80% of the data is designated for training, and 20% is allocated for testing. Alternative ratios like 70:30, 60:40, and even 50:50 are also commonly utilized. Determining the optimal ratio for a specific dataset lacks clear guidance. The justification for the 80:20 split is often linked to the familiar Pareto principle, but it is essentially a rule of thumb employed by practitioners [22].

However, given the weekly and seasonal nature of the data, a ratio of 92:8 for estimation to forecast is employed to enhance cycle accuracy. The in-sample data comprises 624 observations, while the out-of-sample data consists of 52 observations, equivalent to one full year, serving as the testing data.

Table 1 Weekly Maximum Electricity Demand Data

Duration	Number of Data	In-Sample Data	Out-of-Sample Data
2005 - 2016	676	1 - 624	625 - 676

Modelling and Forecasting using Box-Jenkins Model

The modelling and forecasting of electricity demand in this study are carried out based on the proposed SARIMA framework depicted in Figure 1. A discernible upward trend in in-sample data for weekly maximum electricity demand from 2005 to 2016 is illustrated in Figure 2. Despite the overall increasing trend, there are periods of fluctuation within, signifying short-term variations influenced by factors such as seasonal effects, economic cycles, or external events. Graphically, Figure 2 highlights the pronounced seasonality and a positive upward trend in electricity demand data. Consequently, this study leverages the historical peak electricity demand data spanning from 2005 to 2016 to forecast electricity demand for the year 2017.

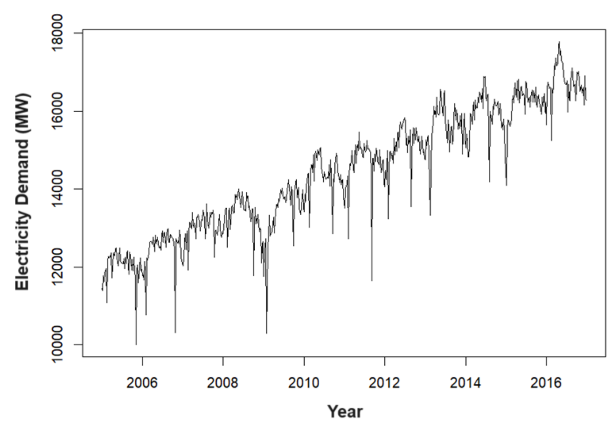


Figure 2 In-Sample Data of Weekly Maximum Electricity Demand from 2005 to 2016

Figure 3 displays the decomposed data for weekly maximum electricity demand spanning from 2005 to 2016. The observed seasonal variation appears relatively consistent over time, suggesting the suitability of an additive decomposition. The additive model is particularly effective when the seasonal variation remains relatively constant. The plot depicts the original data, the seasonal pattern, a smoothed trend line, and the residual part of the series. The seasonal pattern exhibits regular, repeating trends, and combining these components reconstructs the data showcased in the top panel.

Notably, the seasonal component evolves gradually over time, resulting in similar patterns for consecutive years but potential differences for years far apart. The residual component in the bottom panel represents the portion remaining after subtracting the seasonal and trend-cycle components.

The corresponding numerical output is presented in Table 2, where seasonal effect values are repeated for each of the 52 weeks, necessitating estimation for weekly data impact. Utilizing R statistical software, the evaluation of seasonality in the time series identifies a regular pattern of changes repeating over 52-week seasonal periods until consistent repetition at the same frequency is observed.

Figure 4 depicts the seasonally differenced data, revealing clear non-stationarity with pronounced seasonality and a nonlinear trend. Consequently, seasonal differencing is applied. However, as these differentials also appear non-stationary, an additional first difference is applied, as shown in Figure 5. The resulting stationary data in Figure 5 reflects the successful application of differencing to the seasonal series.

The KPSS test has been used in this analysis to test for data stationarity [23]. The null hypothesis for this test is that the data is stationary. According to the analysis, at 5% significance level, the value of test statistic is 3.1053 at lag 19, which is larger than the critical value of 0.4630. This indicates that the null hypothesis is rejected, suggesting that differencing is required since the data is not stationary.

Therefore, the KPSS test has been applied again and the results show that the value of test statistic is 0.0976 at lag 19, which is smaller than the critical value of 0.4630 at 5% significance level. Consequently, the differenced data is stationary.

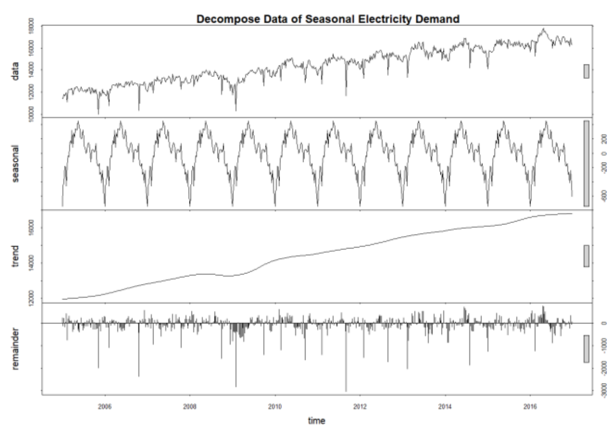


Figure 3 Decompose Data of Weekly Maximum Electricity Demand from 2005 to 2016

Table 2 Additive Seasonal Effects on Weekly Maximum Electricity Demand Data

Week	Seasonal	Week	Seasonal
1	-746.10643	14	83.279955
2	-453.570003	15	277.813744
3	-421.14846	16	218.915386
4	-182.889025	17	342.976185
5	-195.218038	18	334.228121
6	-458.885644	19	327.723248
7	-165.18635	20	452.649327
8	-39.000477	21	411.627251
9	-49.501256	22	386.41597
10	103.707071	23	220.04397
11	176.26278	24	199.505319
12	133.870152	25	208.052205
13	318.834652	26	330.178137

Week	Seasonal	Week	Seasonal
27	229.641055	40	17.940921
28	94.930048	41	24.395311
29	75.914597	42	136.866413
30	-4.364496	43	-71.787237
31	40.950543	44	-168.380759
32	108.12446	45	-182.14976
33	151.965315	46	-139.350252
34	123.208896	47	-295.65627
35	-24.998705	48	-264.466928
36	-122.37355	49	-414.021955
37	42.100497	50	-242.904177
38	47.489786	51	-424.704133
39	49.495172	52	-602.442584

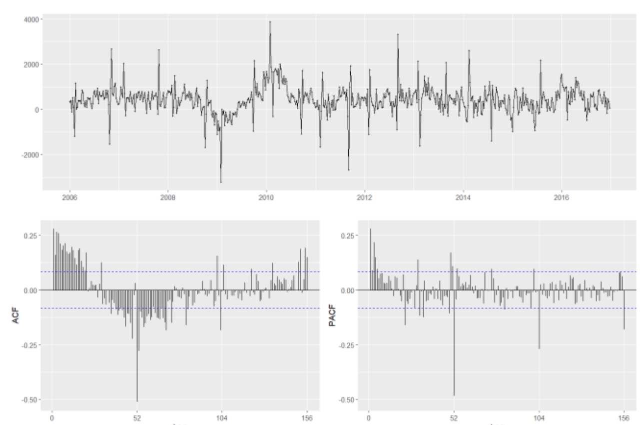


Figure 4 Seasonally Differenced Weekly Maximum Electricity Demand Data

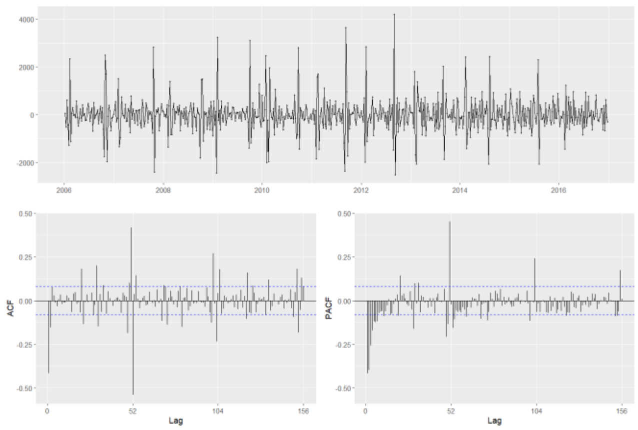


Figure 5 Double Differenced Weekly Maximum Electricity Demand Data

The LBQ test has been utilized to ensure the absence of serial correlation within the series. In this testing procedure, the null hypothesis recommends that the series is not serially correlated. Consequently, the p-value of 2.2 x 10^{-16} which is less than 0.05 suggests that the null hypothesis is disproven at a significance level of 5%. It indicates that the series is serially correlated and the Box-Jenkins model is justified to be considered in this time series data. According to Figure 5, ACF and PACF plots of the double differenced weekly maximum electricity demand data show that there are seven possible significant SARIMA models out of 10 at 5% significance level, which the specific models are presented in Table 3. The other three models, which are not significant and thus not included in the table are SARIMA(0,1,1)(0,1,1)$_{52}$, SARIMA(0,1,2)(0,1,1)$_{52}$, and SARIMA(0,1,2)(0,1,0)$_{52}$.

In checking whether the data series is highly volatile and exist an ARCH effect, the squared residuals of the identified SARIMA models have been examined. The LBQ test has been utilized on the squared residuals of the SARIMA models. Based on the results in Table 3, heteroscedasticity does not exist in four SARIMA models. Therefore, there are no ARCH effects and volatility does not exist in these four SARIMA models.

During the diagnostic assessment phase, it is crucial to include tests for serial correlation and heteroscedasticity, alongside the examination of residual plots, to ensure that the errors demonstrate white noise-like behaviour. According to Table 3, all of the identified SARIMA models are not serially correlated, however, four SARIMA models out of seven have no heteroscedasticity with zero mean residuals and they literally pass the diagnostic checking. The residual plots of the considered models support the randomness and no serial correlation in the residuals of the SARIMA models as shown in Table 3.

According to Table 3, the mean of the residuals for all SARIMA models are close to zero and there is no significant correlation in the residuals series. Moreover, residuals play a vital role in assessing the effectiveness of a model in encapsulating the information present in the data. An effective forecasting method is characterized by residuals exhibiting specific properties. Firstly, the residuals should demonstrate uncorrelated behaviour. The presence of correlations among residuals suggests untapped information that should be incorporated into forecast computations. Secondly, an ideal scenario involves residuals possessing a mean of zero. If the residuals deviate from this, carrying a mean other than zero, it implies a bias in the forecasts. These criteria serve as benchmarks to gauge the performance and reliability of a forecasting model.

The JB test is a commonly utilized statistical measure to assess whether a dataset or the errors within it adhere to a normal distribution. This test statistic gauges the dissimilarity between the skewness and kurtosis of the dataset and those expected in a standard normal distribution. In this study, a significance level of 0.05 was employed for the normality test. The determination of normality is based on the probability results derived from the JB test. If the p-value exceeds 0.05, it indicates that the assumption of normality holds. Conversely, if the p-value is below 0.05, it suggests that the assumption of normality is not met. Examining Table 3, the JB test statistics values are 715.1444, 963.0602, 966.8753, 1022.2090, 1105.5060, 1110.8090, and 1143.2470. Significantly, each of p-values for the JB test statistic is 0.000 for all SARIMA models, falling below the specified significance level of 0.05. Consequently, it can be inferred that the assumption of normality is not satisfied.

Table 3 Diagnostic Checking on Identified SARIMA Models

SARIMA Model	Serially Correlated	Heteros-cedasticity
$\mathbf{SARIMA(1,1,0)(0,1,0)_{52}}$	Not serially correlated up to lag 1	Exists
$\mathbf{SARIMA(2,1,0)(0,1,0)_{52}}$	Not serially correlated up to lag 2	Exists
$\mathbf{SARIMA(3,1,0)(0,1,0)_{52}}$	Not serially correlated up to lag 3	Exists
$\mathbf{SARIMA(4,1,0)(0,1,0)_{52}}$	Not serially correlated up to lag 4	Not exist at Lag 4 up to lag 42, then continue to not exist at lag 45 up to lag 49

SARIMA Model	Serially Correlated	Heteros-cedasticity
$\mathbf{SARIMA(5,1,0)(0,1,0)_{52}}$	Not serially correlated up to lag 5	Not exist at Lag 3 up to lag 49
$\mathbf{SARIMA(6,1,0)(0,1,0)_{52}}$	Not serially correlated up to lag 6	Not exist up to lag 49
$\mathbf{SARIMA(7,1,0)(0,1,0)_{52}}$	Not serially correlated up to lag 7	Not exist up to lag 49

Table 3 Continued

SARIMA Model	Mean of the Residuals	Normality Test
$\mathbf{SARIMA(1,1,0)(0,1,0)_{52}}$	-0.5432	Yes JB: 715.1444 p-value: 0.0000
$\mathbf{SARIMA(2,1,0)(0,1,0)_{52}}$	-0.4194	Yes JB: 963.0602 p-value: 0.0000
$\mathbf{SARIMA(3,1,0)(0,1,0)_{52}}$	-0.5329	Yes JB: 966.8753 p-value: 0.0000
$\mathbf{SARIMA(4,1,0)(0,1,0)_{52}}$	-0.5126	Yes JB: 1022.2090 p-value: 0.0000
$\mathbf{SARIMA(5,1,0)(0,1,0)_{52}}$	-0.5218	Yes JB: 1105.5060 p-value: 0.0000
$\mathbf{SARIMA(6,1,0)(0,1,0)_{52}}$	-0.3944	Yes JB: 1110.8090 p-value: 0.000
$\mathbf{SARIMA(7,1,0)(0,1,0)_{52}}$	-0.2388	Yes JB: 1143.2470 p-value: 0.0000

Additionally, Table 4 shows the estimation results of the possible SARIMA models. Utilizing the information provided in Table 4, the model SARIMA(4,1,0)(0,1,0)$_{52}$ has been designated as the preferred model during the model estimation phase, as it consists of fewer parameters and does not violate the constant variance assumption of the Box-Jenkins model. This choice is grounded in the observation that its values for AIC and BIC, along with its log-likelihood, display only marginal differences in comparison to other notable models, all while adhering to the principle of parsimony. As outlined by McLeod [24], the principle of parsimony means that the simplest possible model should be chosen. Moreover, the endorsement of the SARIMA(4,1,0)(0,1,0)$_{52}$ model for forecasting weekly maximum electricity demand finds additional support in the results of the forecasting evaluation, as depicted in Table 5.

According to Table 4, SARIMA(4,1,0)(0,1,0)$_{52}$, SARIMA(6,1,0)(0,1,0)$_{52}$, SARIMA(7,1,0)(0,1,0)$_{52}$ are denoted as Model 1, Model 2, Model 3, and Model 4, respectively.

Table 4 Results of the Possible SARIMA Models

Para-meter	Model 1	Model 2	Model 3	Model 4
$\boldsymbol{C}$	-0.0808 (0.9929)	0.0164 (0.9984)	0.0565 (0.9938)	0.1125 (0.9862)
$\boldsymbol{\varphi_1}$	-0.7312 (0.0000)	-0.7521 (0.0000)	-0.7671 (0.0000)	-0.7824 (0.0000)
$\boldsymbol{\varphi_2}$	-0.6443 (0.0000)	-0.6900 (0.0000)	-0.7226 (0.0000)	-0.7485 (0.0000)
$\boldsymbol{\varphi_3}$	-0.3771 (0.0000)	-0.4543 (0.0000)	-0.5118 (0.0000)	-0.5535 (0.0000)
$\boldsymbol{\varphi_4}$	-0.1734 (0.0001)	-0.2609 (0.0000)	-0.3475 (0.0000)	-0.4094 (0.0000)
$\boldsymbol{\varphi_5}$	-	-0.1194 (0.0172)	-0.2136 (0.0000)	-0.3003 (0.0000)
$\boldsymbol{\varphi_6}$	-	-	-0.1265 (0.0188)	-0.2180 (0.0013)
$\boldsymbol{\varphi_7}$	-	-	-	-0.1207 (0.0133)
AIC	15.6480	15.6372	15.6247	15.6137
BIC	15.6936	15.6905	15.6856	15.6822
Log-l	-4461.4890	-4457.4100	-4452.8580	-4448.7170

* values in parenthesis denote p-value and Log-l is abbreviated for log-likelihood

The widely recognized criteria, AIC and BIC, are employed in this proposed methodology to identify the most relevant SARIMA model. These criteria penalize models with an excess of parameters, emphasizing the selection of the model with the lowest AIC or BIC value that still effectively captures the essential time series components. In instances where models differ in the number of parameters, the principle of parsimony guides the preference for a simpler model that remains adequate and exhibits comparable performance. Therefore, referring to Table 4, the model SARIMA(4,1,0)(0,1,0)$_{52}$ is designated as the preferred model during the model estimation phase. This choice is justified by its AIC and BIC values, as well as its log-likelihood, which exhibit marginal differences compared to other noteworthy models while adhering to the principle of parsimony.

During diagnostic checking, the fit adequacy of the models is assessed by scrutinizing the residuals from the fitted model. In this context, autocorrelation checks have been undertaken, presenting the standardized residuals derived from the fitted model alongside the estimated autocorrelations of these residuals in Figure 6. The residual autocorrelations exhibit no indications of lack of fit, as none of the values significantly deviate beyond the approximate two-standard-error limits, with the exception of lag 0. The ACF of the residuals displays no noteworthy autocorrelations, marking a positive outcome.

Furthermore, the p-values for the LBQ statistics reveal that the first two lags surpass the dashed line denoting the significance level of 0.05. Consequently, non-significant values of the residuals for this statistic indicate that the residuals are not serially correlated. Additionally, the mean of the residuals for the SARIMA(4,1,0)(0,1,0)$_{52}$ model is -0.5126. This proximity to zero suggests that the mean of the residuals is negligible, signifying the absence of significant correlation in the residual series.

The examination of the standardized residuals graph and the normal Q-Q plot reveal the continued presence of outliers. However, if a majority of the residuals cluster around the linear line in the normal Q-Q plot, as depicted in Figure 7, it indicates adherence to a normal distribution. Despite this, the JB test results indicate a departure from normality, likely influenced by the presence of outlier data. Graphically, in a Q-Q plot, normally distributed data typically appears as a roughly straight line, although deviations from this line may occur at the ends. As per Brys *et al.* [25], the rejection by the JB test does not stem from an overall departure from normal distribution but is instead attributed to a few outliers originating from a different distribution. Similarly, Brys *et al.* [26] argued that the Jarque-Bera test of normality is unable to detect normality in the presence of outlying values.

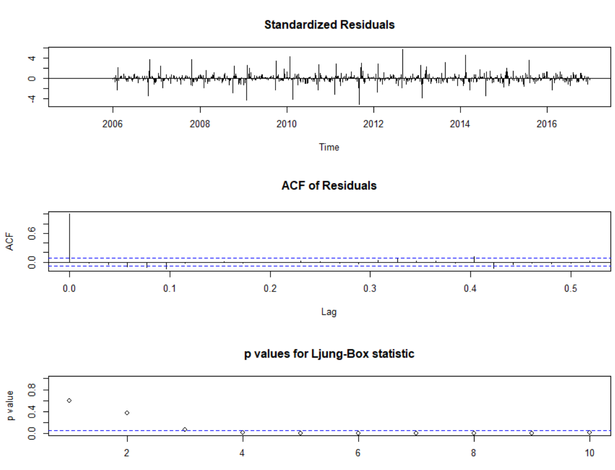


Figure 6 Plot of Standardized Residuals, ACF of Residuals, and the p-values for Ljung–Box statistics for SARIMA(4,1,0)(0,1,0)$_{52}$

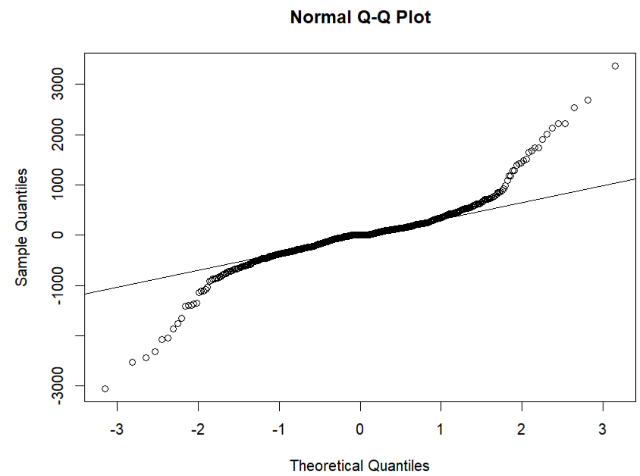


Figure 7 The Normal Q-Q Plot of Standardised Residuals of SARIMA(4,1,0)(0,1,0)$_{52}$

Table 5 Forecast Accuracy of Significant SARIMA Models

SARIMA Model	Forecast Accuracy (Test Set Evaluation)		
	RMSE	MAE	MAPE (%)
$\mathbf{SARIMA(1,1,0)(0,1,0)_{52}}$	607.2617	477.8067	2.88
$\mathbf{SARIMA(2,1,0)(0,1,0)_{52}}$	627.1651	492.4845	2.97
$\mathbf{SARIMA(3,1,0)(0,1,0)_{52}}$	622.2790	486.4788	2.94
$\mathbf{SARIMA(4,1,0)(0,1,0)_{52}}$	623.3015	488.5673	2.95
$\mathbf{SARIMA(5,1,0)(0,1,0)_{52}}$	624.5603	489.3622	2.95
$\mathbf{SARIMA(6,1,0)(0,1,0)_{52}}$	632.3441	493.3443	2.98
$\mathbf{SARIMA(7,1,0)(0,1,0)_{52}}$	637.8275	496.6446	3.00

The one-step-ahead forecast for weekly maximum electricity demand from the SARIMA(4,1,0)(0,1,0)$_{52}$ model for the upcoming 52 weeks is visually represented in Figure 8. In the graphical representation, the blue solid line denotes the predicted values, while the green solid line corresponds to the actual electricity demand values. The forecasted values are bounded within a range of ±2 standard errors, indicated by the red dashed line. The plot reveals a fluctuating trend spanning from 15,471 MW to 18,000 MW over the 52-week out-sample period, with the predicted values closely aligning with the observed trend in the actual data. This alignment suggests that the forecasting model performs well in capturing the underlying trend in the data. Table 6 presents a comparison between the real weekly peak electricity demand and the one-step-ahead forecast values generated by the suggested seasonal Box-Jenkins model over the 52-week out-of-sample simulation period. In this study, the chosen 52-week duration adequately represents a full year as the testing data, ensuring a comprehensive capture of the underlying trend with a year's worth of information.

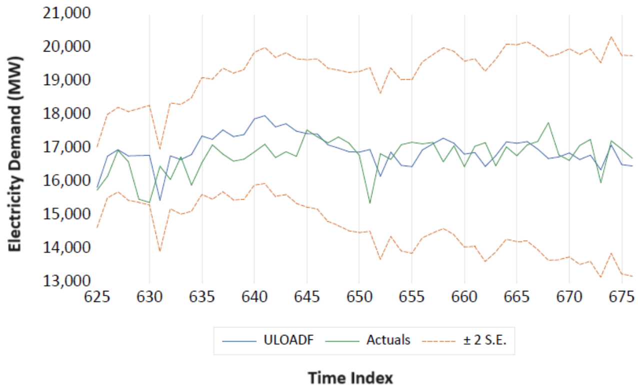


Figure 8 Forecast Values of SARIMA(4,1,0)(0,1,0)$_{52}$

Table 6 The Actual and Forecast Values of SARIMA(4,1,0)(0,1,0)$_{52}$

Week (Out-of-Sample Data)	Actual	Forecast	Difference
625	15773.00	15860.76	-87.76
626	16186.00	16786.80	-600.80
627	16964.00	16980.21	-16.21
628	16621.00	16794.07	-173.07
629	15501.00	16807.48	-1306.48
630	15407.00	16816.11	-1409.11
631	16492.00	15471.23	1020.77
632	16094.00	16794.86	-700.86
633	16767.00	16690.06	76.94
634	15926.00	16835.64	-909.64
635	16600.00	17389.09	-789.09
636	17126.00	17289.32	-163.32
637	16849.00	17569.87	-720.87
638	16641.00	17371.79	-730.79
639	16701.00	17435.24	-734.24
640	16914.00	17901.40	-987.40
641	17144.00	18000.04	-856.04
642	16749.00	17659.81	-910.81
643	16922.00	17757.83	-835.83
644	16782.00	17534.84	-752.84
645	17571.00	17461.73	109.27
646	17364.00	17452.60	-88.60
647	17184.00	17123.52	60.48
648	17360.00	17032.47	327.53
649	17180.00	16921.39	258.61
650	16814.00	16908.30	-94.30
651	15391.00	16985.21	-1594.21
652	16862.00	16190.13	671.87
653	16693.00	16907.06	-214.06
654	17130.00	16512.97	617.03
655	17202.00	16475.89	726.11
656	17157.00	16974.81	182.19
657	17197.00	17155.73	41.27
658	16623.00	17324.65	-701.65
659	17095.00	17176.57	-81.57
660	16479.00	16851.49	-372.49
661	17087.00	16895.41	191.59
662	17190.00	16483.33	706.67
663	16504.00	16800.25	-296.25
664	17069.00	17217.17	-148.17
665	16800.00	17174.08	-374.08
666	17124.00	17223.00	-99.00
667	17227.00	17000.92	226.08
668	17790.00	16715.84	1074.16
669	16827.00	16766.76	60.24
670	16662.00	16886.68	-224.68
671	17108.00	16688.60	419.40
672	17286.00	16821.52	464.48
673	15998.00	16378.44	-380.44
674	17244.00	17118.36	125.64
675	17000.00	16535.28	464.72
676	16721.00	16495.19	225.81

Modelling and Forecasting using SARIMA(4,1,0)(0,1,0)$_{52}$ Model

The expressions in Equation 6, 7, and 8 describe a SARIMA model with autoregressive, differencing, and seasonal components, respectively. The coefficients of φ_1, φ_2, φ_3, and φ_4 determine the influence of previous observations on the current observation. In addition, the backshift operator (*B*) indicates the lagged values of the time series. For the differencing part, $(1-B)^d$ is used to make the time series stationary. Since this study used a seasonal data, there exists a seasonal differencing part where $(1-B^s)^D$ is applied to address seasonality.

$$ARIMA\ \underbrace{(p,d,q)}_{\boxed{\text{Non-seasonal part of the model}}}\underbrace{(P,D,Q)_s}_{\boxed{\text{Seasonal part of the model}}}$$

$$AR\ for\ non-seasonal = \varphi_4(B) = 1 - \varphi_1 B - \varphi_2 B^2 - \varphi_3 B^3 - \varphi_4 B^4 \quad (6)$$

$$Difference\ operator\ for\ non-seasonal = \nabla^d = (1-B)^d = (1-B) \quad (7)$$

$$Difference\ operator\ for\ seasonal = \nabla_s^D = (1-B^s)^D = (1-B^{52}) \quad (8)$$

Equation 9 shows the mathematical expression of SARIMA model with a constant term, *C*,

$$\varphi_p(B)(1-B)^d(1-B^s)^D y_t = a_t + C \quad (9)$$

From Equation 9, the terms have been expanded and rearranged, as can be seen in Equation 10 to Equation 18.

$$(1-\varphi_1 B-\varphi_2 B^2-\varphi_3 B^3-\varphi_4 B^4)(1-B)(1-B^{52})y_t=a_t+C \tag{10}$$

$$\begin{gathered}(1-B-B^{52}+B^{53}-\varphi_1 B+\varphi_1 B^2+\varphi_1 B^{53}-\varphi_1 B^{54}-\varphi_2 B^2\\+\varphi_2 B^3+\varphi_2 B^{52}+\varphi_2 B^{55}-\varphi_3 B^3+\varphi_3 B^4+\varphi_3 B^{55}+\varphi_3 B^{56}-\varphi_4 B^4\\+\varphi_4 B^5+\varphi_4 B^6-\varphi_4 B^7)\,y_t=a_t+C\end{gathered} \tag{11}$$

$$\begin{gathered}y_t-By_t-B^{52}y_t+B^{53}y_t-\varphi_1 By_t+\varphi_1 B^2 y_t+\varphi_1 B^{53}y_t\\-\varphi_1 B^{54}y_t-\varphi_2 B^2 y_t+\varphi_2 B^3 y_t+\varphi_2 B^{52}y_t+\varphi_2 B^{55}y_t-\varphi_3 B^3 y_t\\+\varphi_3 B^4 y_t+\varphi_3 B^{55}y_t+\varphi_3 B^{56}y_t-\varphi_4 B^4 y_t+\varphi_4 B^5 y_t\\+\varphi_4 B^6 y_t-\varphi_4 B^7 y_t=a_t+C\end{gathered} \tag{12}$$

$$\begin{gathered}y_t-By_t-B^{52}y_t+B^{53}y_t\\-\varphi_1(By_t-B^2y_t-B^{53}y_t+B^{54}y_t)-\varphi_2(B^2y_t-B^3y_t-B^{52}y_t-B^{55}y_t)\\-\varphi_3(B^3y_t-B^4y_t-B^{55}y_t-B^{56}y_t)-\varphi_4(B^4y_t-B^5y_t-B^6y_t+B^7y_t)\\=a_t+C\end{gathered} \tag{13}$$

$$\text{Since Backshift Operator}, B: B^k y_t = y_{t-k}$$

$$\begin{gathered}y_t-y_{t-1}-y_{t-52}+y_{t-53}-\varphi_1(y_{t-1}-y_{t-2}-y_{t-53}+y_{t-54})\\-\varphi_2(y_{t-2}-y_{t-3}-y_{t-52}-y_{t-55})-\varphi_3(y_{t-3}-y_{t-4}-y_{t-55}-y_{t-56})\\-\varphi_4(y_{t-4}-y_{t-5}-y_{t-6}+y_{t-7})=a_t+C\end{gathered} \tag{14}$$

$$\begin{gathered}y_t-By_t-B^{52}y_t+B^{53}y_t-\varphi_1 By_t+\varphi_1 B^2 y_t+\varphi_1 B^{53}y_t\\-\varphi_1 B^{54}y_t-\varphi_2 B^2 y_t+\varphi_2 B^3 y_t+\varphi_2 B^{52}y_t+\varphi_2 B^{55}y_t-\varphi_3 B^3 y_t\\+\varphi_3 B^4 y_t+\varphi_3 B^{55}y_t+\varphi_3 B^{56}y_t-\varphi_4 B^4 y_t\\+\varphi_4 B^5 y_t+\varphi_4 B^6 y_t-\varphi_4 B^7 y_t=a_t+C\end{gathered} \tag{15}$$

$$\begin{gathered}y_t-y_{t-1}-y_{t-52}+y_{t-53}-\varphi_1 y_{t-1}+\varphi_1 y_{t-2}+\varphi_1 y_{t-53}-\varphi_1 y_{t-54}\\-\varphi_2 y_{t-2}+\varphi_2 y_{t-3}+\varphi_2 y_{t-52}+\varphi_2 y_{t-55}-\varphi_3 y_{t-3}+\varphi_3 y_{t-4}+\varphi_3 y_{t-55}\\+\varphi_3 y_{t-56}-\varphi_4 y_{t-4}+\varphi_4 y_{t-5}+\varphi_4 y_{t-6}-\varphi_4 y_{t-7}=a_t+C\end{gathered} \tag{16}$$

$$\begin{gathered}y_t-y_{t-1}-\varphi_1 y_{t-1}+\varphi_1 y_{t-2}-\varphi_2 y_{t-2}+\varphi_2 y_{t-3}-\varphi_3 y_{t-3}+\varphi_3 y_{t-4}\\-\varphi_4 y_{t-4}+\varphi_4 y_{t-5}+\varphi_4 y_{t-6}-\varphi_4 y_{t-7}-y_{t-52}+\varphi_2 y_{t-52}+y_{t-53}\\+\varphi_1 y_{t-53}-\varphi_1 y_{t-54}+\varphi_2 y_{t-55}+\varphi_3 y_{t-55}+\varphi_3 y_{t-56}=a_t+C\end{gathered} \tag{17}$$

$$\begin{gathered}y_t-(1+\varphi_1)y_{t-1}+(\varphi_1-\varphi_2)y_{t-2}+(\varphi_2-\varphi_3)y_{t-3}+(\varphi_3-\varphi_4)y_{t-4}\\+\varphi_4 y_{t-5}+\varphi_4 y_{t-6}-\varphi_4 y_{t-7}-(1-\varphi_2)y_{t-52}+(1+\varphi_1)y_{t-53}\\-\varphi_1 y_{t-54}+(\varphi_2+\varphi_3)y_{t-55}+\varphi_3 y_{t-56}=a_t+C\end{gathered} \tag{18}$$

The substitution of the terms with all the estimated values of coefficients has been done in order to get the mathematical model of SARIMA, as shown in Equation 19 to Equation 21.

$$\begin{gathered}y_t-(1-0.7312)y_{t-1}+(-0.7312+0.6443)y_{t-2}\\+(-0.6443+0.3771)y_{t-3}+(-0.3771+0.1734)y_{t-4}-0.1734\,y_{t-5}\\-0.1734\,y_{t-6}+0.1734\,y_{t-7}-(1+0.6443)y_{t-52}+(1-0.7312)y_{t-53}\\+0.7312\,y_{t-54}+(-0.6443-0.3771)y_{t-55}-0.3771\,y_{t-56}=a_t+C\end{gathered} \tag{19}$$

$$\begin{gathered}y_t=(1-0.7312)y_{t-1}-(-0.7312+0.6443)y_{t-2}\\-(-0.6443+0.3771)y_{t-3}-(-0.3771+0.1734)y_{t-4}+0.1734\,y_{t-5}\\+0.1734\,y_{t-6}-0.1734\,y_{t-7}+(1+0.6443)y_{t-52}\\-(1-0.7312)y_{t-53}-0.7312\,y_{t-54}-(-0.6443-0.3771)y_{t-55}\\+0.3771\,y_{t-56}+a_t-0.0808\end{gathered} \tag{20}$$

$$\begin{gathered}y_t=0.2688y_{t-1}+0.0869y_{t-2}+0.2672y_{t-3}+0.2037y_{t-4}\\+0.1734\,y_{t-5}+0.1734\,y_{t-6}-0.1734\,y_{t-7}+1.6443y_{t-52}\\-0.2688y_{t-53}-0.7312\,y_{t-54}+1.0214y_{t-55}+0.3771\,y_{t-56}\\+a_t-0.0808;\end{gathered} \tag{21}$$

$$a_t\sim N(0,357731.2)$$

The last expression, Equation 21 provides the specific coefficients and structure of the SARIMA model, including the autoregressive and lagged terms. The normal distribution $a_t\sim N(0{,}357731.2)$ indicates that the error term follows a normal distribution with mean 0 and variance 357731.2.

4.0 CONCLUSION

This study suggests that the SARIMA(4,1,0)(0,1,0)$_{52}$ model stands out as the most suitable choice for forecasting electricity demand in Malaysia. Its parsimonious nature, which does not violate the constant variance assumption of the Box-Jenkins model, coupled with a low MAPE value of 2.95%, sets it apart from other considered models. The accuracy achieved, as reflected in the MAPE statistic of less than 5%, falls within the range deemed relatively good [12], affirming the effectiveness of SARIMA(4,1,0)(0,1,0)$_{52}$ in accurately forecasting electricity demand in Malaysia. In conclusion, the proposed seasonal Box-Jenkins model demonstrates promising performance in the context of Malaysia's electricity demand forecasting. With notable potential, this model offers a comprehensive procedure, particularly for one-step ahead forecasting, making it a favourable starting point for multistep forecasting considerations, taking into account the time series data's period length. The methods of prediction using a seasonal component of the time series can improve the forecast accuracy by leveraging historical seasonal trends. In conclusion, using SARIMA(4,1,0)(0,1,0)$_{52}$ to predict future electricity demand has proven to be beneficial and, in some cases, effective.

However, the study is constrained by the fact that there is insufficient updated data source of the actual electricity demand data from 2017 to 2023 while implementing the chosen SARIMA model. A more compelling presentation of the Box-Jenkins technique and the SARIMA model created for electricity demand forecast in Malaysia would require an improved updating of the electricity demand data. Therefore, further investigations in this field will concentrate on the application of multistep forecasting and consider the updated data.

In order to enhance the performance, comparing the results of Box-Jenkins model with other statistical model like generalized autoregressive conditional heteroskedasticity (GARCH) can also be considered for further improvement. With that, the most accurate model for forecasting electricity demand will be analysed.

Acknowledgement

The authors are grateful to the UMP Research Grant (RDU240306) and Doctorate Research Scheme (Zaim, S.) for sponsorship of the research work.

Conflicts of Interest

The author(s) declare(s) that there is no conflict of interest regarding the publication of this paper.

References

[1] Department of Statistics Malaysia. 2018. Malaysia's Economic Performance Report (DOSM/BPPIB/1.2018/Series 10(Electricity Sector in Malaysia)). Retrieved from

https://www.dosm.gov.my/v1/uploads/files/6_Newsletter/newsletter%202018/Series%2010_Electricity%20Sector.pdf.

[2] Yasmeen, F., & Sharif, M. 2014. Forecasting Electricity Consumption for Pakistan. *International Journal of Emerging Technology and Advanced Engineering*. 4(4): 496–503.

[3] Shah, I., Iftikhar, H., & Ali, S. 2022. Modeling and Forecasting Electricity Demand and Prices: A Comparison of Alternative Approaches. *Journal of Mathematics*. 2022. Doi: https://doi.org/10.1155/2022/3581037

[4] Goswami, K., & Kandali, A. B. 2020. Electricity Demand Prediction using Data Driven Forecasting Scheme: ARIMA and SARIMA for Real-time load Data of Assam. In *2020 International Conference on Computational Performance Evaluation (ComPE), IEEE*. 570–574. Doi: https://doi.org/10.1109/ComPE49325.2020.9200031.

[5] Ishak, I., Othman, N. S., & Harun, N. H. 2022. Forecasting Electricity Consumption of Malaysia's Residential Sector: Evidence from an Exponential Smoothing Model. *F1000Research*. 11(54): 54. Doi: https://doi.org/10.12688/f1000research.74877.1.

[6] Lee, M. H. L., Ser, Y. C., Selvachandran, G., Thong, P. H., Cuong, L., Son, L. H., ... & Gerogiannis, V. C. 2022. A Comparative Study of Forecasting Electricity Consumption using Machine Learning Models. *Mathematics.* 10(8): 1329. Doi: https://doi.org/10.3390/math10081329.

[7] Andoh, P. Y. A., Sekyere, C. K. K., Mensah, L. D., & Dzebre, D. E. K. 2021. Forecasting Electricity Demand in Ghana with the SARIMA Model. *Journal of Applied Engineering and Technological Science (JAETS)*. 3(1): 1–9. Doi: https://doi.org/10.37385/jaets.v3i1.288.

[8] Duong, T. K., Phan, D. H., & Nguyen, D. M. 2023. Application of Sarima Model in Load Forecasting in Hanoi City. *International Journal of Energy Economics and Policy*. 13(3): 164–170. Doi: https://doi.org/10.32479/ijeep.14121.

[9] Shah, I., Jan, F., & Ali, S. 2022. Functional Data Approach for Short-term Electricity Demand Forecasting. *Mathematical Problems in Engineering*. 2022. Doi: https://doi.org/10.1155/2022/6709779.

[10] Jan, F., Shah, I., & Ali, S. 2022. Short-term Electricity Prices Forecasting using Functional Time Series analysis. *Energies*. 15(9): 3423. Doi: https://doi.org/10.3390/en15093423.

[11] Shah, I., Iftikhar, H., & Ali, S. 2020. Modeling and Forecasting Medium-term Electricity Consumption using Component Estimation Technique. *Forecasting*. 2(2): 163–179. Doi: https://doi.org/10.3390/forecast2020009.

[12] Shah, I., Bibi, H., Ali, S., Wang, L., & Yue, Z. 2020. Forecasting One-day-ahead Electricity Prices for Italian Electricity Market using Parametric and Nonparametric Approaches. *IEEE Access*. 8: 123104–123113. Doi: https://doi.org/10.1109/ACCESS.2020.3007189.

[13] Shah, I., & Lisi, F. 2015. Day-ahead Electricity Demand Forecasting with Nonparametric Functional Models. *2015 12th International Conference on the European Energy Market (EEM)* (pp. 1–5). IEEE. Doi: https://doi.org/10.1109/EEM.2015.7216741.

[14] Box, G. E., Jenkins, G. M., Reinsel, G. C., & Ljung, G. M. 2015. *Time Series Analysis: Forecasting and Control*. John Wiley & Sons.

[15] Yaziz, S. R. 2019. Modified Box-Jenkins and GARCH for Forecasting Highly Volatile Time Series Data. PhD Thesis. Universiti Malaysia Pahang.

[16] Akaike, H. 1974. A New Look at the Statistical Model Identification. *IEEE Transactions on Automatic Control.* 19(6): 716–723. Doi: https://doi.org/10.1109/TAC.1974.1100705.

[17] Schwarz, G. 1978. Estimating the Dimension of a Model. *The Annals of Statistics.* 6(2): 461–464. Doi: https://doi.org/10.1214/aos/1176344136.

[18] Tsay, R. S. 2013. An Introduction to Analysis of Financial Data with R. Hoboken, N.J: Wiley.

[19] Wang, B., Huang, H., & Wang, X. 2012. A Novel Text Mining Approach to Financial Time Series Forecasting. *Neurocomputing.* 83: 136–145. Doi: https://doi.org/10.1016/j.neucom.2011.12.013.

[20] Girish, G. P. 2016. Spot Electricity Price Forecasting in Indian Electricity Market using Autoregressive-GARCH Models. *Energy Strategy Reviews.* 11(12): 52–57. Doi: https://doi.org/10.1016/j.esr.2016.06.005.

[21] Chatfield, C. 2001. Time-series Forecasting. Retrieved from http://www.crcnetbase.com/isbn/9781584880639. Doi: https://doi.org/10.1201/9781420036206.

[22] Joseph, V. R. 2022. Optimal Ratio for Data Splitting. *Statistical Analysis and Data Mining: The ASA Data Science Journal*. 15(4): 531–538. Doi: https://doi.org/10.1002/sam.11583.

[23] Kwiatkowski, D., Phillips, P. C., Schmidt, P., & Shin, Y. 1992. Testing the Null Hypothesis of Stationarity against the Alternative of a Unit Root: How Sure Are We That Economic Time Series Have a Unit Root? *Journal of Econometrics*. 54(1–3): 159–178. Doi: https://doi.org/10.1016/0304-4076(92)90104-Y.

[24] McLeod, A. I. 1993. Parsimony, Model Adequacy and Periodic Correlation in Time Series Forecasting. *International Statistical Review/Revue Internationale de Statistique*. 387–393. Doi: https://doi.org/10.2307/1403750.

[25] Brys, G., Hubert, M., & Struyf, A. 2008. Goodness-of-fit Tests based on a Robust Measure of Skewness. *Computational Statistics.* 23: 429–442. Doi: https://doi.org/10.1007/s00180-007-0083-7.

[26] Brys, G., Hubert, M., & Struyf, A. 2004. A Robustification of the Jarque-Bera Test of Normality. In *COMPSTAT 2004 Symposium, Section: Robustness.*