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Forecasting of Electricity Demand in Malaysia with Seasonal Highly Volatile Characteristics using SARIMA – GARCH Model

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Abstract Developing an accurate forecasting model for electricity demand plays a vital role in maximising the efficiency of the planning process in the power generation industries. The time series data of electricity demand in Malaysia is highly volatile with seasonal characteristics. This study aims to evaluate the forecasting performance of the seasonal autoregressive integrated moving average (SARIMA) model with GARCH for weekly maximum electricity demand. The weekly maximum electricity demand data (in megawatt, MW) from 2005 to 2016 has been used for this study. The results show that SARIMA$(1,1,0)(0,1,0)_{52}$−GARCH$(1,2)$ with generalized error distribution (GED) is the most appropriate model for forecasting electricity demand due to its parsimonious characteristic with low values of root mean square error (RMSE), mean absolute error (MAE) and mean absolute percentage error (MAPE) which are 644.1828, 523.8380 and 3.13%, respectively. The MAPE value of the proposed model which is less than 5% indicates that the SARIMA − GARCH model is relatively good in forecasting electricity demand for the case of Malaysia data. In conclusion, the proposed model of SARIMA with GARCH has great potential and provides a promising performance in forecasting electricity demand with seasonal highly volatile characteristics.

Keywords Forecasting; Electricity Demand; SARIMA; GARCH; Seasonal Highly Volatile Data.

Mathematics Subject Classification 62M10

1 Introduction

Forecasting electricity demand is vital as electricity is a resource that is hard to store. In connection with this matter, the term peak demand, also known as peak load, is widely used by load forecasters to monitor the optimum electricity usage for a given period. The consumption of electricity depends on the change in weather and other environmental factors. For instance, according to the Department of Statistics Malaysia [1], the peak demand in Malaysia was recorded at 17,788 MW on 19 April 2016 due to the El-Nino phenomenon. During that time, due to the hot and dry conditions, consumers consumed electricity up to their highest level. Therefore, the maximum demand is considered a benchmark to measure the performance of electricity instead of the minimum demand.

Rationally, the maximum value is more reasonable compared to the minimum value, especially in forecasting electricity performance. Other than that, electricity demand forecasting is important for planning and expansion of infrastructure in the electricity sector. Accurate forecasts will significantly reduce operational and maintenance costs and improve the efficiency of the electrical power supply and distribution network. As a result, proper decisions can be made for potential developments. Thus, forecasting high-precision demand is required to prevent energy wastage and device failure. For that reason, applying the best technique to generate the most precise forecasts of electricity demand is extremely important since the prediction of electricity consumption plays a crucial role, particularly in the economy. Hence, there are several approaches that can be explored to forecast electricity demand.

Additionally, electricity represents a common and fundamental source of energy, exerting a pivotal influence on contemporary society. Its manifold advantages and contributions extend across diverse domains, encompassing transportation, manufacturing, mining, and communication sectors. Electricity stands as a cornerstone underpinning the prosperity and advancement of an economy, thus occupying a vital role in the context of socio-economic development. It serves as a versatile instrument capable of making valuable contributions to the strategic planning and future policy direction of the energy sector. The utilization of this electrical energy continues to surge progressively with each passing day. The multifaceted applications of electricity have propelled human civilization to unprecedented levels of advancement. Consequently, the demand for electricity is intrinsically intertwined with every facet of development [2].

Forecasting electricity demand and price holds paramount importance for both market participants and system operators. Accurate predictions are essential to the efficient management of power systems. Nevertheless, the task of forecasting electricity demand and prices is intricate owing to their distinctive characteristics. These include high frequency, volatility, extended trends, non-uniform mean and variance, mean reversion, numerous seasonal patterns, calendar-related effects, and the occurrence of spikes and jumps [3].

In time series modelling, it is common to consider monthly or quarterly seasonal effects. However, due to the change in weather and other environmental factors throughout the year, producing forecasts of electricity demand on a quarterly or monthly basis might not be sufficient to provide input for the efficient management of electricity supply, therefore a weekly basis can be an appropriate choice.

Therefore, viewed by highly volatile time series and seasonal characteristics in electricity demand, the good performance of SARIMA – GARCH model, and the practicality of the weekly basis data to provide input for electricity supply, this study aims to evaluate the performance of the model of SARIMA with GARCH yet providing a comprehensive procedure specifically for one-step ahead forecast for weekly maximum electricity demand produced. While previous studies such as Sigauke and Chikobvu [4] and Kim and Kim [5], have utilized the model for electricity data, this study represents a pioneering effort in Malaysia and being the first to apply the SARIMA model with GARCH for forecasting electricity demand in the country. Furthermore, previous studies lacked a comprehensive procedure tailored for one-step ahead forecasting of electricity demand, a gap that this study aims to fill. The application of this model not only addresses the unique characteristics of Malaysia's electricity demand patterns, but also establishes a potential framework for analyses that sharing similar electricity consumption patterns.

Moreover, numerous studies aim to estimate future electrical energy demand for residential and commercial purposes to enable electricity generators, distributors, and suppliers to plan effectively ahead and promote energy conservation among users. Some of the statistical models used in forecasting electricity demand are SARIMA [6], Exponential Smoothing Models such as Simple Exponential Smoothing, Holt's Exponential Smoothing, and Brown's Exponential Smoothing [7], Artificial Neural Network (ANN), Adaptive Neuro-Fuzzy Inference System (ANFIS), Least Squares Support Vector Machines (LSSVMs), and Fuzzy Time Series (FTS) [8].

The study conducted by Goswami and Kandali [6] focused on analyzing daily 24-hour electrical load data obtained from the State Load Dispatch Center (SLDC) in Assam. The dataset covered daily at 10 am load data for a period of three years, from 1 January 2016 to 31 December 2018, resulting in a total sample size of 1,095 data points. The data was split into 75% training data (822 points) and 25% testing data for model development and evaluation. The study employed the SARIMA model for time series analysis. The final results indicated that the SARIMA model that considers the seasonality of load data provided better prediction with a low MAPE value which is 10.7%.

Ishak *et al.* [7] focused on forecasting the electricity consumption of Malaysia's residential sector based on yearly data from 1997 to 2018 obtained from the Malaysia Energy Information Hub (MEIH). Three exponential smoothing models were employed in the study: simple exponential smoothing, Holt's exponential smoothing, and Brown's exponential smoothing. The study aimed to provide insights into energy trends and projections for the period from 2019 to 2032. The results show that Holt's exponential smoothing has the best performance with the lowest MAPE score of 2.299%.

Meanwhile, Lee *et al.* [8] forecasted monthly electricity consumption data for seven countries over a 10-year period (2007-2016). The data was obtained from ceicdata.com. The study employed four different models: ANN, ANFIS, LSSVMs, and FTS. The performance of these models was evaluated and compared using error metrics such as RMSE, average forecasting error (AFE), and performance parameter (PP). The study highlighted the strengths and weaknesses of each model and identified the FTS model as the best performer for most of the countries studied.

In Nyoni's research [9], the first of its kind in Zimbabwe, annual time series data spanning from 1971 to 2014 on electricity demand in Zimbabwe is employed to model and predict electricity demand. This is achieved using the Box-Jenkins ARIMA framework, marking a unique approach to this area of study in the country. The study pursues three primary objectives: firstly, to analyze the trends in electricity consumption in Zimbabwe throughout the study period; secondly, to construct a robust electricity demand forecasting model for Zimbabwe using the Box-Jenkins ARIMA technique; and lastly, to project electricity demand in Zimbabwe for the upcoming decade (2015 – 2025).

Sigauke and Chikobvu [4] conducted a study focused on forecasting daily peak electricity demand in South Africa. They explored different models, including a SARIMA model, a SARIMA–GARCH errors, and a regression-SARIMA–GARCH (Reg-SARIMA–GARCH) model. Among these models, the Reg-SARIMA–GARCH model emerged as the most effective, demonstrating superior forecast accuracy with MAPE of 1.42%. These results emphasize the Reg-SARIMA–GARCH model's supremacy in predicting daily peak demand, establishing it as a valuable tool for electricity demand forecasting in South Africa.

In the study conducted by Kim and Kim [5], they focused on predicting the electricity usage of an industrial manufacturing facility in Korea known as GGM over the period from January 2014 to April 2017. Various models were employed, including SARIMA, SARIMA with GARCH integration, Holt-Winters, and ARIMA with Fourier transformation. One-month-ahead electricity consumption forecasts were generated, and the predictive performance of each model was assessed by comparing the root mean square error and error rate. Given the weekly and yearly fluctuations in GGM's electricity consumption, the SARIMA-GARCH model, which accounts for both volatility and seasonality, demonstrated the best fit and prediction accuracy.

According to the prior studies, this current study is the first of its kind in the case of Malaysia where the SARIMA model with GARCH has been implemented to forecast electricity demand and potentially serve as a model for similar analyses in other regions with comparable characteristics in their electricity demand patterns. In addition, a comprehensive procedure specifically for one-step ahead forecast for weekly maximum electricity demand was not provided in the previous studies. In addition, this study initially concentrates on the standard GARCH, also known as GARCH, due to its popularity and parsimonious characteristics, in developing a basic procedure of the combination model of SARIMA and GARCH.

In the extensive body of research on electricity demand forecasting, various statistical models and methodologies have been employed to improve the precision and effectiveness of these predictions. Researchers have explored diverse datasets and applied distinct techniques to tackle the unique challenges posed by this essential aspect of energy planning. These studies, such as those discussed earlier, offer valuable insights and findings that pave the way for further advancements in the field. In summary, the studies discussed here represent a diverse spectrum of research efforts aimed at tackling the intricate challenges of electricity demand forecasting across different regions and contexts.

2 Methodology

2.1 Time Series Models

2.1.1 SARIMA Model

Electrical demand pattern shows the obvious periodic vibration resulting from seasonal changes. These seasonal changes can be dealt with the SARIMA model of Box-Jenkins. A seasonal ARIMA model is formed by including additional seasonal terms in the ARIMA models. The model can be written as $SARIMA(p,d,q)(P,D,Q)_s$, where p is non-seasonal AR order, d is non-seasonal differencing, q is non-seasonal MA order, P is seasonal AR order, D is seasonal differencing, Q is seasonal MA order, and s is the seasonal period. The mathematical model for $SARIMA(p,d,q)(P,D,Q)_s$ is given by Equation 1,

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

where

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

and y_t is 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 of degree p and q, while 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 of order P and Q, $\nabla_D^s = (1-B^s)^D$, B is the backward shift operator, and the random errors a_t are assumed to be independently and identically distributed (IID) with mean zero and constant variance σ^2.

2.1.2 GARCH Model

GARCH stands for Generalized Autoregressive Conditional Heteroscedasticity and is a statistical model commonly used in finance and economics to estimate the volatility of financial returns. The GARCH model extends the simpler ARCH (Autoregressive Conditional Heteroscedasticity) model by allowing for autoregressive terms in the conditional variance equation. The GARCH formula is typically expressed as follows,

$$s_t = \mu + a_t\ , \qquad a_t = \sigma_t \varepsilon_t\ , \qquad \sigma_t^2 = \omega + \sum_{i=1}^{r} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{s} \beta_j \sigma_{t-j}^2 \tag{2}$$

where s_t and a_t be the stationary time series data and random error at time t, μ is the conditional mean of s_t, σ_t^2 is the conditional variance of the error term at time t, ω is a constant term representing the long-term average variance of the error term, ε_t is the residual error at time t and has zero-mean IID with a continuous distribution, α_i are the coefficients for the lagged squared error terms, with $\alpha_0 = 0$, and $\alpha_i \geq 0$ for $i = 1, 2, ..., r$, β_j are the coefficients for the lagged conditional variance terms, with $\beta_0 = 0$, and $\beta_j \geq 0$ for $j = 1, 2, ..., s$.

The GARCH model specifies that the conditional variance at time t depends on the past squared errors (ε^2) and past conditional variances (σ^2) of the series. The α and β parameters represent the influence of past squared errors and past conditional variances on the current conditional variance, respectively. The ω term represents the long-run average level of variance in the series.

2.1.3 SARIMA-GARCH Model

GARCH The hybrid model combines these two models to capture both the seasonal patterns and the volatility clustering in the time series data. The SARIMA component models the mean of the time series, while the GARCH component models the volatility of the time series.

The SARIMA-GARCH model is one in which the variance of the error term of the SARIMA model follows a GARCH process. The model can be written as Equation 3,

$$\varphi_P(B)\,\emptyset_P\left(B^S\right)\left(1 - B^S\right)^D \dot{y}_t = \theta_q(B)\,\Theta_Q\left(B^S\right)a_t, \tag{3}$$

$$a_t = \ \varepsilon_t \sigma_t, \sigma_t^2 = \omega + \sum_{i=1}^{r} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{s} \beta_j \sigma_{t-j}^2$$

where the definition of the notations can be referred to in Equations 1 and 2.

2.2 Proposed Research Framework of the SARIMA - GARCH in Forecasting Electricity Demand

Figure 1 shows the proposed research framework of SARIMA - GARCH where the steps of forecasting electricity demand are properly arranged. In order to evaluate the forecast accuracy, there are four stages adopted from the Box-Jenkins modelling that need to be considered which are Model Identification, Parameter Estimation, Diagnostic Checking, and Forecasting. The framework is adopted from Yaziz [10] as the study focuses on the non-seasonal highly volatile time series data, while this study focuses on the seasonal highly volatile time series data.

2.2.1 Stage I: Model Identification

In order to identify the appropriate SARIMA and GARCH parameters, several statistical tests can be conducted.

For the SARIMA model, the following steps can be taken:

1. Stationarity Test: Check whether the time series is stationary or not using ADF test. If it is not stationary, taking differences, seasonal differences, or transformations is required to make it stationary.

2. ACF and PACF of the stationary data of the non-seasonal part: These plots are used to identify the order of the autoregressive (AR), integrated (I), and moving average (MA) terms in the SARIMA model.

3. Seasonality: Check for any seasonal patterns in the data and select the appropriate seasonal period.

4. ACF and PACF of the stationary data of the seasonal part: These plots are used to identify the order of the seasonal autoregressive (SAR), and seasonal moving average (SMA) terms in the SARIMA model.

For the GARCH model, the following steps can be taken:

1. Build a SARIMA model for the stationary data and remove any serial correlation in the data. Use the residual series of the model to check the ARCH effect. The LBQ test is used to check the conditional heteroscedasticity in the data.

2. ACF and PACF of the squared residuals of the SARIMA model: These plots are used to identify the GARCH orders, r and s, respectively.

Overall, the process of identifying the appropriate parameters for a SARIMA-GARCH model can be iterative, and several models may need to be tested before selecting the best-fitting model.

2.2.2 Stage II: Parameter Estimation

Parameter estimation in the SARIMA-GARCH model involves estimating the parameters of both the SARIMA and the GARCH components separately. The steps involved in parameter estimation in the SARIMA-GARCH model are as follows:

1. Stationarity and Seasonality Analysis: Check whether the time series is stationary and has any seasonal patterns using statistical tests such as the ADF test and the Seasonal Decomposition of Time Series (STL) method, respectively.

2. SARIMA Parameter Estimation: Estimate the parameters of the SARIMA component of the model using MLE. This involves selecting the appropriate orders for AR, MA, SAR, and SMA components of the model.

3. GARCH Parameter Estimation: Estimate the parameters of the GARCH component of the model using MLE. This involves selecting the appropriate orders for ARCH and GARCH components of the model.

4. Model Selection: Select the appropriate SARIMA-GARCH model based on the AIC and BIC as proposed by Akaike [11] and Schwarz [12], respectively. The AIC or BIC with the lowest value is preferred in the model selection criteria.

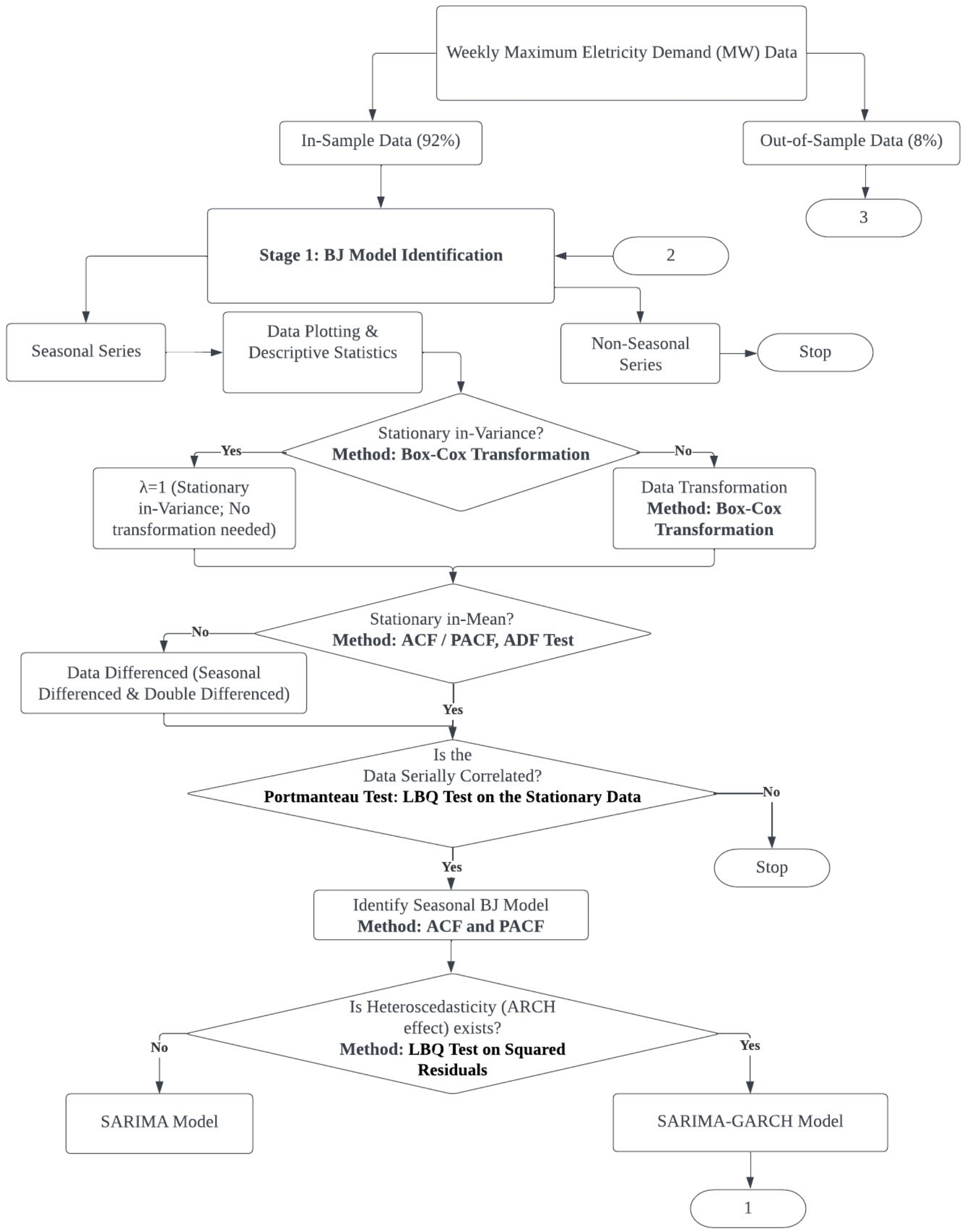

Figure 1: Research Framework of SARIMA - GARCH in Forecasting

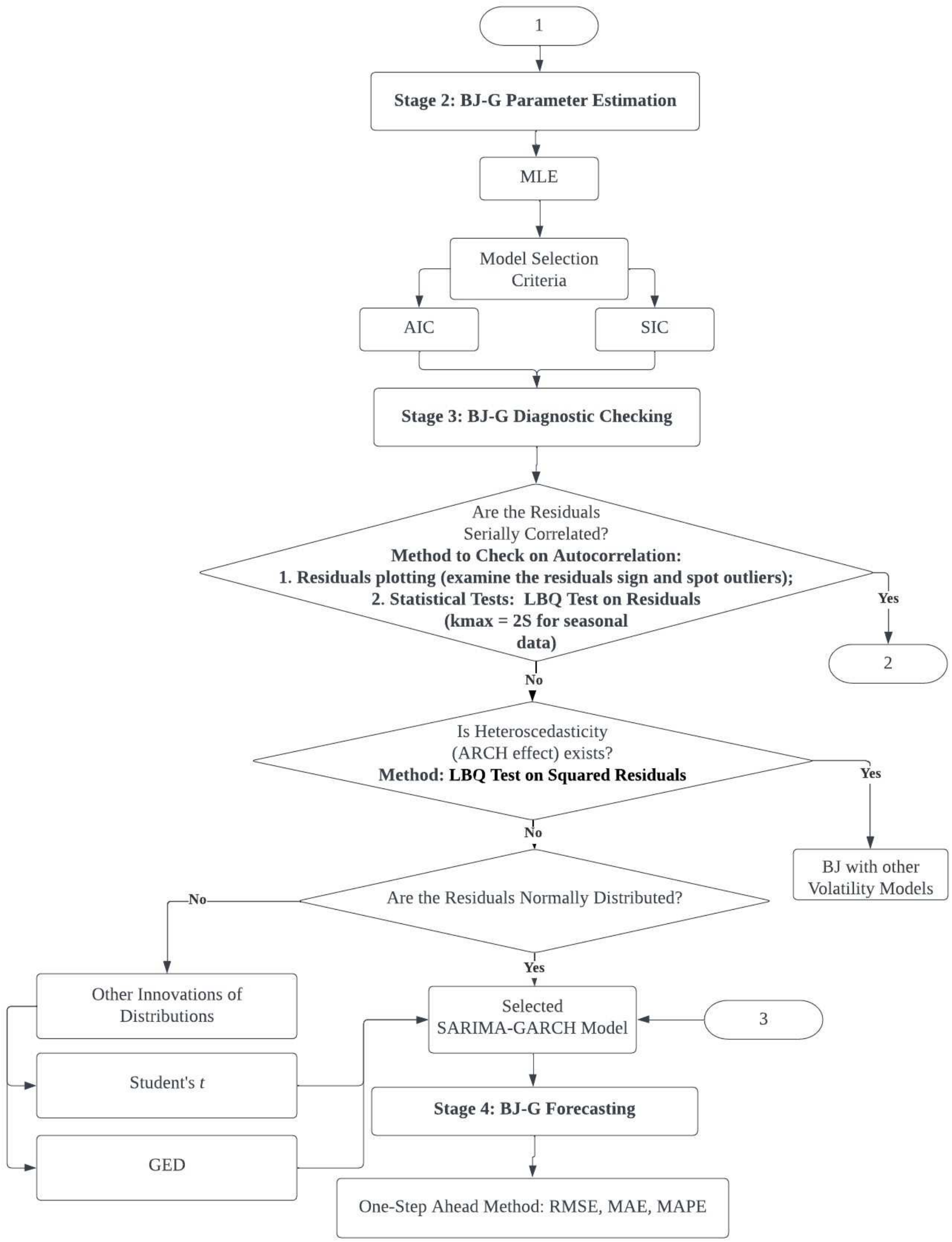

Figure 1: Continued

2.2.3 Stage III: Diagnostic Checking

Diagnostic checking is an important step in the modeling process, as it allows us to evaluate the adequacy of the model and identify any potential shortcomings. When it comes to SARIMA-GARCH models, diagnostic checking is particularly important as it can help us ensure that both the time series and the volatility components of the model are adequately captured. If the model is adequate, then the residual series should behave as a white noise [13]. In the diagnostic checking stage, the tests considered are serial correlation test, heteroscedasticity test and normality test to assure that the errors behave like white noise.

One way to check the serial correlation in the model residuals is to plot the ACF and PACF of the model residuals and perform an LBQ test on the residuals. If there is evidence of autocorrelation, it may be necessary to revise the model. Meanwhile, to detect the existence of heteroscedasticity in the residuals, the LBQ test on the squared residuals is used. The residuals of the model should be normally distributed and exhibit no autocorrelation or ARCH/GARCH effects. For normality test, Jarque-Bera test (JB test) has been utilized. However, when the residuals are not normally distributed, another innovation of distributions such as Student's t and GED needs to be considered.

2.2.4 Stage IV: Forecasting

Forecast accuracy refers to the degree to which the actual outcomes of a future event match the predictions made by a forecast model. It is a measure of the effectiveness of the model in predicting future outcomes, and it is typically expressed as a percentage or a numerical score. Additionally, it is important to continually evaluate and update forecast models to ensure their accuracy and relevance over time.
Some common measures of forecast accuracy include the MAE, RMSE, and MAPE, as given by Equation 4, 5, and 6, respectively,

$$MAE = \frac{1}{n}\sum_{t=1}^{n}\left|y_t - \widehat{y_t}\right| \tag{4}$$

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(y_t - \widehat{y_t})^2}{n}} \tag{5}$$

$$MAPE = \frac{100\%}{n}\sum_{t=1}^{n}\left|\frac{y_t - \widehat{y_t}}{y_t}\right| \tag{6}$$

where y_t and $\widehat{y_t}$ are the observed and forecast values at time t, respectively, and n is the number of out-of-sample data. The best forecasting model is the one that generates the lowest prediction error. However, if the results are not consistent among the forecast evaluations, it is suggested to choose MAPE since it is relatively more stable than others [14]. According to Girish [15], the ability of forecasting is considered relatively good if the model has a MAPE value of around 5%.

3 Results and Discussion

3.1 Dataset

This study uses weekly maximum electricity demand data (in MW) in the year range of 2005 to 2016 from Single Buyer Department (SB) website (https://www.singlebuyer.com.my/). SB is the entity authorised by Suruhanjaya Tenaga (Energy Commission) to be responsible for the management of electricity procurement and related services. This data is considered secondary data. Table 1 shows the weekly maximum electricity demand data. The input data has been split into two groups of training and testing data to build the forecasting model with the typical ratio of 90:10. However, since the data is weekly and seasonal, the ratio of estimate to forecast used is 92:8 for better cycle. There are 624 observations in the in-sample data and 52 observations in the out-of-sample data. Meaning that, 52 weeks represent one whole year 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

3.2 Modelling and Forecasting using SARIMA Model with GARCH

The modelling and forecasting of the dataset of electricity demand are conducted based on the proposed framework of SARIMA - GARCH as illustrated in Figure 1. Figure 2 shows the trend increases in in-sample data of weekly maximum electricity demand from 2005 to 2016. However, within the increasing trend, there can be periods of fluctuation. These fluctuations represent short-term variations, often caused by various factors such as seasonal effects, economic cycles, or other external events. Graphically, Figure 2 shows that electricity demand data exhibits strong seasonality and has a positive upward trend. Hence, this study utilizes the peak electricity demand from 2005 to 2016 to forecast electricity demand in 2017.

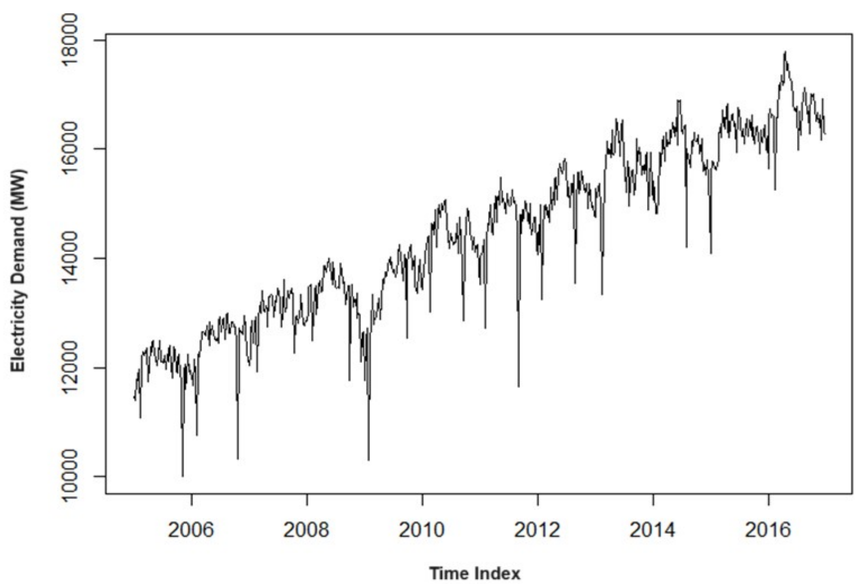

Figure 2: In-Sample Data of Weekly Maximum Electricity Demand from 2005 to 2016

Figure 3 shows the decomposed data of weekly maximum electricity demand from 2005 to 2016. The seasonal variation looked to be about the same magnitude across time, so an additive decomposition might be good. The additive model is useful when the seasonal variation is relatively constant over time. The plot shows the data, the seasonal pattern, the smoothed trend line, and the remaining part of the series. The seasonal pattern is a regularly repeating pattern. These components can be added together to reconstruct the data shown in the top panel. Notice that the seasonal component changes slowly over time, so that any two consecutive years have similar patterns, but years far apart may have different seasonal patterns. The remainder component shown in the bottom panel is what is left over when the seasonal and trend-cycle components have been subtracted from the data.

Therefore, the numerical output is shown in Table 2 where the seasonal effect values are repeated each year for 52 weeks. This requires estimating the impact for each week of the year for weekly data. According to R statistical software, seasonality in a time series was evaluated where there is a regular pattern of changes that repeats over seasonal periods of 52 weeks, until the pattern consistently repeats again at the same frequency.

The seasonally differenced data is shown in Figure 4. Based on the data series in Figure 4, the data is clearly non-stationary, with strong seasonality and a nonlinear trend, so seasonal difference is required. These also appear to be non-stationary, therefore additional first differenced is required as shown in Figure 5. Figure 5 shows the stationary data as the differencing has been utilized to the seasonal series.

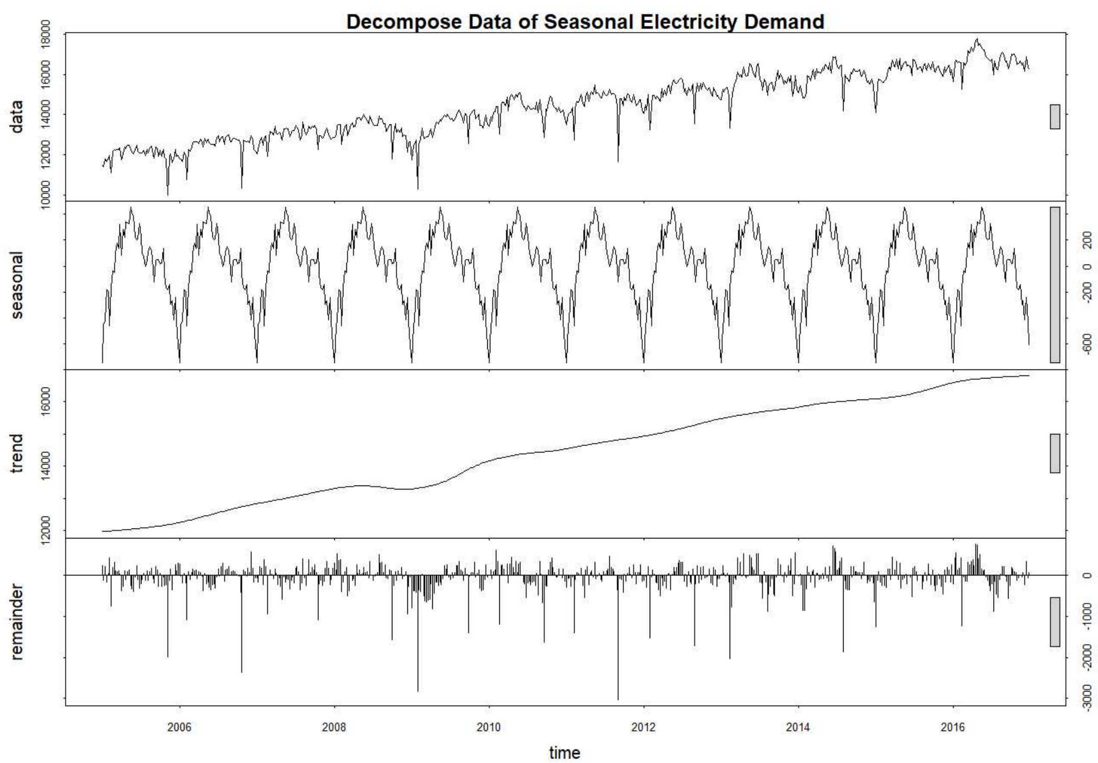

Figure 3: Decompose Data of Weekly Maximum Electricity Demand from 2005 to 2016

Table 2: Additive Seasonal Effects on Weekly Maximum Electricity Demand Data

Week	Seasonal	Week	Seasonal	Week	Seasonal	Week	Seasonal
1	-746.10643	14	83.279955	27	229.641055	40	17.940921
2	-453.570003	15	277.813744	28	94.930048	41	24.395311
3	-421.14846	16	218.915386	29	75.914597	42	136.866413
4	-182.889025	17	342.976185	30	-4.364496	43	-71.787237
5	-195.218038	18	334.228121	31	40.950543	44	-168.380759
6	-458.885644	19	327.723248	32	108.12446	45	-182.14976
7	-165.18635	20	452.649327	33	151.965315	46	-139.350252
8	-39.000477	21	411.627251	34	123.208896	47	-295.65627
9	-49.501256	22	386.41597	35	-24.998705	48	-264.466928
10	103.707071	23	220.04397	36	-122.37355	49	-414.021955
11	176.26278	24	199.505319	37	42.100497	50	-242.904177
12	133.870152	25	208.052205	38	47.489786	51	-424.704133
13	-424.704133	26	330.178137	39	49.495172	52	-602.442584

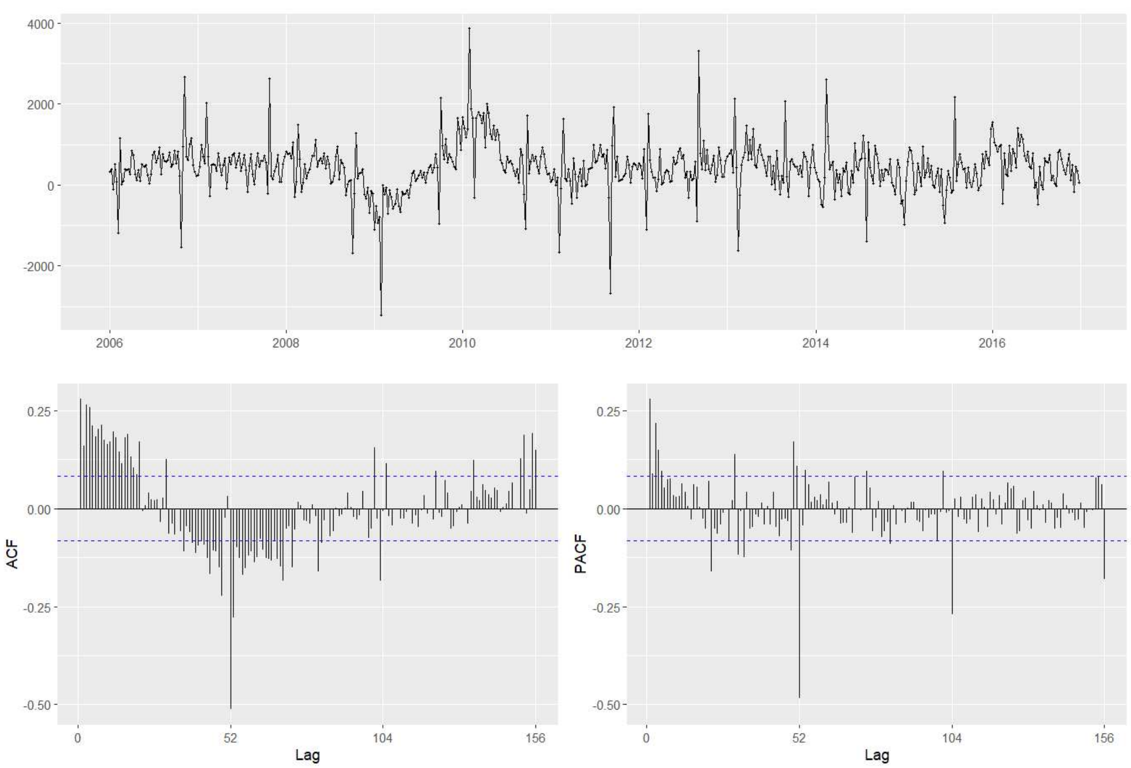

Figure 4: Seasonally Differenced Weekly Maximum Electricity Demand Data

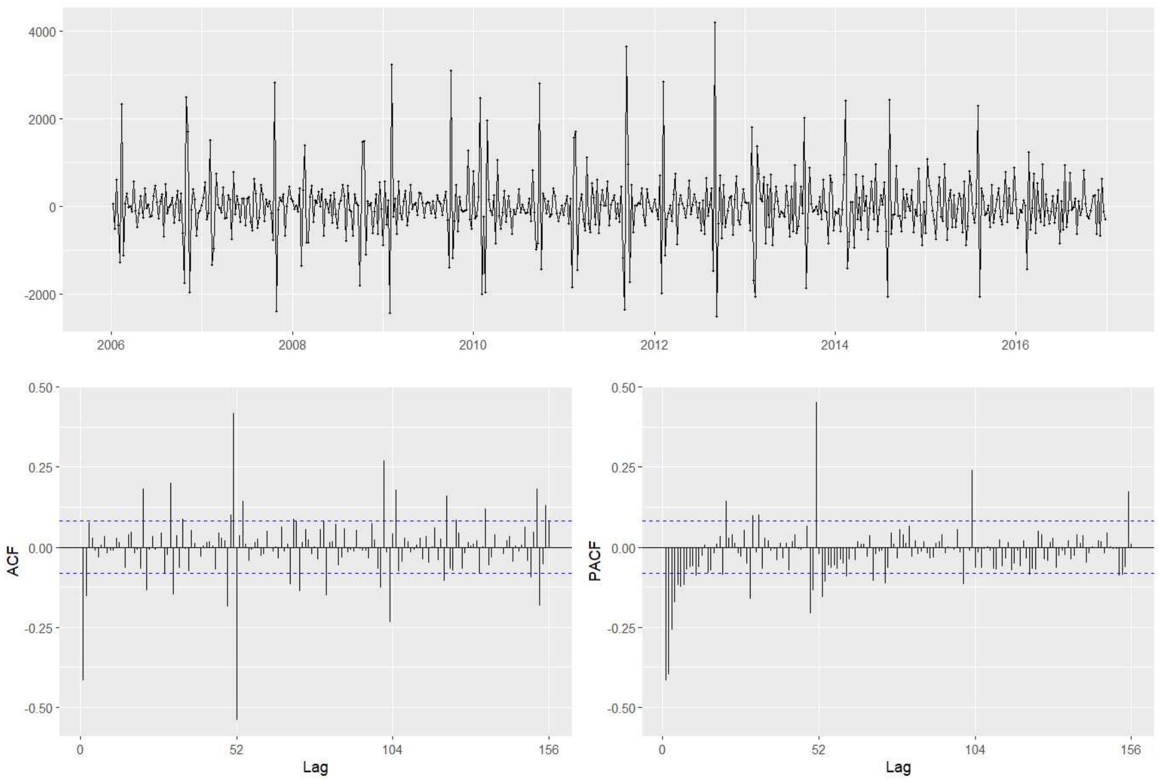

Figure 5: Double Differenced Weekly Maximum Electricity Demand Data

LBQ test has been utilized to ensure that there is no serial correlation in the series. In this test, the null hypothesis is 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 rejected at 5% significance level. It indicates that the first differenced series is serially correlated and SARIMA model is justified to be considered in this time series data. It turns out that there are seven significant SARIMA models out of 10 possible models at 5% significance level, which the specific models are presented in Table 3.

Table 3: Heteroscedasticity Checking on the Significant SARIMA Models

	SARIMA Model	Remarks on Model Significance	Heteroscedasticity
1.	$\mathbf{SARIMA(1,1,0)(0,1,0)_{52}}$	Significant	Exists
2.	$\mathbf{SARIMA(2,1,0)(0,1,0)_{52}}$	Significant	Exists
3.	$\mathbf{SARIMA(3,1,0)(0,1,0)_{52}}$	Significant	Exists
4.	$\mathbf{SARIMA(4,1,0)(0,1,0)_{52}}$	Significant	Exists
5.	$\mathbf{SARIMA(5,1,0)(0,1,0)_{52}}$	Significant	Exists
6.	$\mathbf{SARIMA(6,1,0)(0,1,0)_{52}}$	Significant	Exists
7.	$\mathbf{SARIMA(7,1,0)(0,1,0)_{52}}$	Significant	Exists

In checking whether the data series is highly volatile and exists an ARCH effect, the squared residuals of the significant SARIMA model 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 exists in all the significant SARIMA models. Therefore, all the significant SARIMA models need to be combined with the GARCH model to handle the volatility that exists in the data series.

JB test is a frequently used statistical test to determine whether a dataset or the errors within the dataset exhibit a normal distribution. This test statistic quantifies the disparity between the skewness and kurtosis of the dataset and those of a standard normal distribution. In this study, a significance level of α=0.05 was employed for the normality test. The decision-making process regarding normality is informed by the probability results obtained from the JB test. If the p-value is greater than 0.05, it is considered that the assumption of normality is satisfied. Conversely, if the p-value is less than 0.05, it is deemed that the assumption of normality is not met. Looking at Table 6 below, the JB statistic yields probability values of 613.3802, 429.3995, 472.1505, 867.6595, and 1153.183. Notably, each of these p-value is 0.000 for all SARIMA-GARCH models, which is lower than the specified significance level of 0.05. Consequently, it can be concluded that the assumption of normality is not satisfied.

According to the ACF and PACF plot for the seven significant SARIMA models, the possible ARCH and GARCH orders are 0,1 and 2, respectively. Therefore, there are 52 possible models from the combination of SARIMA and GARCH with the consideration of distribution errors of student's *t* and GED. Table 6 presents the five significant SARIMA – GARCH models out of the 52 possible models where GED has been selected as the most appropriate distribution of errors.

Table 4: Results of the Possible SARIMA Models

Parameter	SARIMA(4,1,0)(0,1,0)[52]	SARIMA(5,1,0)(0,1,0)[52]	SARIMA(6,1,0)(0,1,0)[52]	SARIMA(7,1,0)(0,1,0)[52]
C	-0.0808 (0.9929)	0.0164 (0.9984)	0.0565 (0.9938)	0.1125 (0.9862)
φ_1	-0.7312 (0.0000)	-0.7521 (0.0000)	-0.7671 (0.0000)	-0.7824 (0.0000)
φ_2	-0.6443 (0.0000)	-0.6900 (0.0000)	-0.7226 (0.0000)	-0.7485 (0.0000)
φ_3	-0.3771 (0.0000)	-0.4543 (0.0000)	-0.5118 (0.0000)	-0.5535 (0.0000)
φ_4	-0.1734 (0.0001)	-0.2609 (0.0000)	-0.3475 (0.0000)	-0.4094 (0.0000)
φ_5	-	-0.1194 (0.0172)	-0.2136 (0.0000)	-0.3003 (0.0000)
φ_6	-	-	-0.1265 (0.0188)	-0.2180 (0.0013)
φ_7	-	-	-	-0.1207 (0.0133)
AIC	15.6480	15.6372	15.6247	15.6137
SIC	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

Based on the information presented in Table 4, the model SARIMA$(4, 1, 0)(0, 1, 0)_{52}$ has been chosen as the preferred model during the model estimation stage. This decision is based on the observation that its values for AIC and BIC, as well as its log-likelihood, exhibit only slight differences compared to other significant models, while adhering to the principle of parsimony. Furthermore, the selection of the SARIMA$(4,1,0)(0,1,0)_{52}$ model for forecasting weekly maximum electricity demand is further validated by the results of the forecasting evaluation, as demonstrated in Table 5.

Table 5. Forecast Accuracy of Significant SARIMA Models

	SARIMA Model	Forecast Accuracy (Test Set Evaluation)		
		RMSE	MAE	MAPE (%)
1.	**SARIMA$(1,1,0)(0,1,0)_{52}$**	606.4686	477.2099	2.88
2.	**SARIMA$(2,1,0)(0,1,0)_{52}$**	627.2976	492.4028	2.97
3.	**SARIMA$(3,1,0)(0,1,0)_{52}$**	622.4103	486.3534	2.94
4.	**SARIMA$(4,1,0)(0,1,0)_{52}$**	623.4419	488.5009	2.95
5.	**SARIMA$(5,1,0)(0,1,0)_{52}$**	624.5307	489.3780	2.95
6.	**SARIMA$(6,1,0)(0,1,0)_{52}$**	632.1847	493.3851	2.98
7.	**SARIMA$(7,1,0)(0,1,0)_{52}$**	637.3993	496.5803	3.00

Table 6: The Significant SARIMA-GARCH Models

SARIMA-GARCH Model	Serially Correlated	Heteroscedasticity	Normality Test	Distribution
SARIMA$(1,1,0)(0,1,0$ $-$GARCH$(1,2)$	Not serially correlated up to lag 1	Not exists up to Lag 51	Not normal JB: 613.3802 *P*-value: 0.000	GED
SARIMA$(1,1,0)(0,1,0$ $-$GARCH$(2,1)$	Not serially correlated up to lag 1	Not exists up to Lag 50	Not normal JB: 429.3995 *P*-value: 0.000	GED
SARIMA$(1,1,0)(0,1,0)$ $-$GARCH$(2,2)$	Not serially correlated up to lag 1	Not exists up to Lag 51	Not normal JB: 472.1505 *P*-value: 0.000	GED
SARIMA$(3,1,0)(0,1,0)$ $-$GARCH$(1,1)$	Not serially correlated up to lag 3	Not exists up to Lag 51	Not normal JB: 867.6595 *P*-value: 0.000	GED
SARIMA$(6,1,0)(0,1,0)$ $-$GARCH$(0,1)$	Not serially correlated up to lag 6	Not exists up to Lag 1	Not normal JB: 1153.183 *P*-value: 0.000	GED

According to Table 6, all of the significant SARIMA-GARCH models are not serially correlated, no heteroscedasticity exists and they literally pass the diagnostic checking for GED error distribution. The residuals plot of the considered models supports the randomness and no serial correlation in the residuals of the SARIMA-GARCH models. Table 7 shows the estimation results of the five significant SARIMA-GARCH models with GED distribution.

The well-known AIC and BIC are implemented in this proposed procedure to determine the most significant SARIMA-GARCH model. These criteria penalise models with too many parameters, so the model with the lowest AIC or BIC value that still adequately captures the time series and volatility components should be selected. If the number of parameters of the models are different, then the parsimony principle is applied by selecting the simpler model that is adequate and has similar performance. Therefore, based on Table 7, the model of SARIMA$(1,1,0)(0,1,0)_{52}$−GARCH$(1,2)$ is chosen as the preferred model in the model estimation stage since its values of AIC and BIC, as well as its log-likelihood are marginally difference to other significant models, yet apply the parsimony principle. The selection of SARIMA$(1,1,0)(0,1,0)_{52}$−GARCH$(1,2)$ as the best model in forecasting weekly maximum electricity demand is supported as well by the forecasting evaluation results, which as shown in Table 8.

Table 7: Estimation Results of the Significant SARIMA-GARCH Models with GED Distribution

Parameter	**SARIMA (1,1,0) (0,1,0) [52]-GARCH (1,2)**	**SARIMA (1,1,0) (0,1,0) [52]-GARCH (2,1)**	**SARIMA (1,1,0) (0,1,0) [52]-GARCH (2,2)**	**SARIMA (3,1,0) (0,1,0) [52]-GARCH (1,1)**	**SARIMA (6,1,0) (0,1,0) [52]-GARCH (0,1)**
C	-5.8942 (0.6910)	-10.6981 (0.5129)	-6.8661 (0.6470)	-2.8861 (0.7658)	1.0485 (0.8733)
φ_1	-0.3531 (0.0000)	-0.2674 (0.0000)	-0.3113 (0.0000)	-0.5518 (0.0000)	-0.7484 (0.0000)
φ_2	-	-	-	-0.3954 (0.0000)	-0.6463 (0.0000)
φ_3	-	-	-	-0.1546 (0.0003)	-0.4305 (0.0000)
φ_4	-	-	-	-	-0.2936 (0.0000)
φ_5	-	-	-	-	-0.1718 (0.0003)
φ_6	-	-	-	-	-0.1083 (0.0064)
ω	173432.6000 (0.0000)	23474.1000 (0.1347)	51789.5100 (0.0432)	157315.2000 (0.0000)	8877.6710 (0.0009)
α_1	0.4156 (0.0000)	0.4946 (0.0000)	0.4215 (0.0000)	0.3398 (0.0000)	-
α_2	-	-0.4622 (0.0000)	-0.3300 (0.0000)	-	-
β_1	0.3100 (0.0032)	0.9131 (0.0000)	0.9420 (0.0000)	0.1818 (0.0146)	0.9708 (0.0000)
β_2	-0.1355 (0.0167)	-	-0.1629 (0.0041)	-	-
AIC	15.5254	15.5241	15.5123	15.3954	15.4038
BIC	15.5712	15.5699	15.5656	15.4489	15.4729
Log-l	-4418.7440	-4418.3750	-4413.9980	-4365.2810	-4342.5800

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

Table 8: Forecast Accuracy of Significant SARIMA-GARCH Models

	SARIMA-GARCH Model	Forecast Accuracy (Test Set Evaluation)		
		RMSE	**MAE**	**MAPE (%)**
1.	$\mathbf{SARIMA(1,1,0)(0,1,0)_{52}-GARCH(1,2)}$	644.1828	523.8380	3.13
2.	$\mathbf{SARIMA(1,1,0)(0,1,0)_{52}-GARCH(2,1)}$	713.4813	606.6723	3.62
3.	$\mathbf{SARIMA(1,1,0)(0,1,0)_{52}-GARCH(2,2)}$	656.2296	538.7854	3.22
4.	$\mathbf{SARIMA(3,1,0)(0,1,0)_{52}-GARCH(1,1)}$	623.5834	491.5818	2.96
5.	$\mathbf{SARIMA(6,1,0)(0,1,0)_{52}-GARCH(0,1)}$	634.8374	493.1797	2.98

The one-step ahead forecast of weekly maximum electricity demand from $SARIMA(1,1,0)(0,1,0)_{52}-GARCH(1,2)$ model with GED for the next 52 weeks is shown in Figure 6. According to the plot, the solid line in blue colour presents the forecasted values whereas the solid line in green colour shows the actual value of electricity demand. The forecasted values are estimated to fall within a range of ±2 standard errors which is in red colour of dashed line. Graphically, the plot shows a fluctuating trend between 17815 and 15337 MW for 52 weeks of out-sample period and the trend of forecast values closely follows the actual data within that period which suggests that the forecasting model is performing well in terms of capturing the underlying trend in the data. The comparison between actual weekly maximum electricity demand and its one-step ahead forecast value using the proposed SARIMA – GARCH model for 52 weeks of out-of-sample simulation period is given by Table 10. In this study, 52 weeks represent one whole year as the testing data and it is adequate to capture a comprehensive trend as 52 weeks would provide a year's worth of information.

Table 9 provides a comparison between two types of models which are SARIMA model and SARIMA-GARCH model. This comparison could relate to evaluation metrics like RMSE, MAE, and MAPE for forecasting. In this case, a lower MAPE value which is 2.95% for $SARIMA(4,1,0)(0,1,0)_{52}$ suggests that it has a smaller average percentage error in its predictions compared to $SARIMA(1,1,0)(0,1,0)_{52}-GARCH(1,2)$ which produced MAPE value of 3.13%. In summary, based on all the evaluation metrics (RMSE, MAE, and MAPE), $SARIMA(4,1,0)(0,1,0)_{52}$ appears to perform better in forecasting electricity demand compared to $SARIMA(1,1,0)(0,1,0)_{52}-GARCH(1,2)$. Note that, the SARIMA model fails to handle the heteroscedasticity that exist in the data series, as well as violating the assumption on the constant variance in the errors of the Box-Jenkins model. Therefore, it can solely be concluded that SARIMA-GARCH with GED innovations is appropriate and preferred in forecasting weekly maximum electricity demand since it reflects its pattern without violating the errors assumptions of the Box-Jenkins model.

Table 9: Comparison of Forecast Accuracy between SARIMA and SARIMA-GARCH Models

Model	Forecast Accuracy (Test Set Evaluation)		
	RMSE	MAE	MAPE (%)
1. SARIMA$(4,1,0)(0,1,0)_{52}$	623.4419	488.5009	2.95
2. SARIMA$(1,1,0)(0,1,0)_{52}$−GARCH$(1,2)$	644.1828	523.8380	3.13

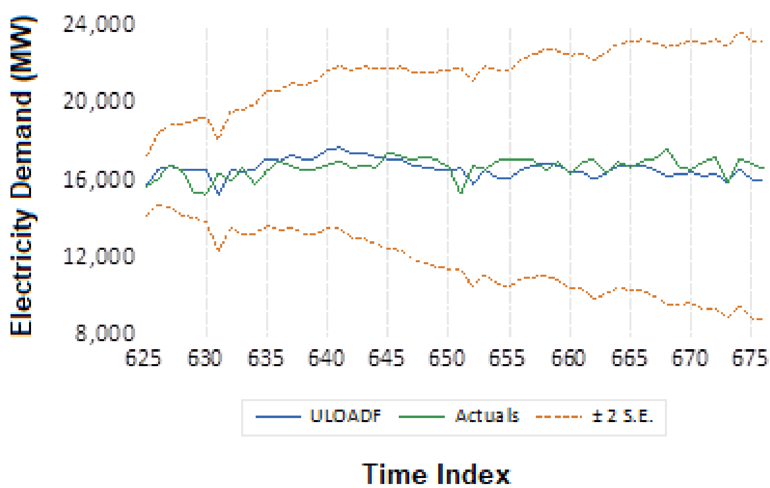

Figure 6: Forecasted Results of SARIMA$(1,1,0)(0,1,0)_{52}$−GARCH$(1,2)$

Table 10: The Actual and Forecast Values of SARIMA$(1,1,0)(0,1,0)_{52}$−GARCH$(1,2)$

Week (Out-of-Sample Data)	Actual	Forecast	Difference
625	15773.00	15789.53	-16.53
626	16186.00	16671.47	-485.47
627	16964.00	16850.35	113.65
628	16621.00	16682.95	-61.95
629	15501.00	16714.64	-1213.64
630	15407.00	16690.19	-1283.19
631	16492.00	15337.49	1154.51
632	16094.00	16660.53	-566.53
633	16767.00	16553.66	213.34
634	15926.00	16692.76	-766.76
635	16600.00	17236.86	-636.86
636	17126.00	17131.97	-5.97
637	16849.00	17408.08	-559.08
638	16641.00	17204.18	-563.18

Table 10: Continued

639	16701.00	17261.29	-560.29
640	16914.00	17721.39	-807.39
641	17144.00	17814.50	-670.50
642	16749.00	17468.60	-719.60
643	16922.00	17560.71	-638.71
644	16782.00	17331.82	-549.82
645	17571.00	17252.92	318.08
646	17364.00	17238.03	125.97
647	17184.00	16903.13	280.87
648	17360.00	16806.24	553.76
649	17180.00	16689.34	490.66
650	16814.00	16670.45	143.55
651	15391.00	16741.56	-1350.56
652	16862.00	15940.66	921.34
653	16693.00	16651.77	41.23
654	17130.00	16251.87	878.13
655	17202.00	16208.98	993.02
656	17157.00	16702.09	454.91
657	17197.00	16877.19	319.81
658	16623.00	17040.30	-417.30
659	17095.00	16886.40	208.60
660	16479.00	16555.51	-76.51
661	17087.00	16593.61	493.39
662	17190.00	16175.72	1014.28
663	16504.00	16486.83	17.17
664	17069.00	16897.93	171.07
665	16800.00	16849.04	-49.04
666	17124.00	16892.14	231.86
667	17227.00	16664.25	562.75
668	17790.00	16373.35	1416.65
669	16827.00	16418.46	408.54
670	16662.00	16532.57	129.43
671	17108.00	16328.67	779.33
672	17286.00	16455.78	830.22
673	15998.00	16006.88	-8.88
674	17244.00	16740.99	503.01
675	17000.00	16152.10	847.90
676	16721.00	16106.20	614.80

4 Conclusion

This study indicates that SARIMA$(1,1,0)(0,1,0)_{52}$−GARCH$(1,2)$ with GED is the most appropriate model for forecasting electricity demand in the Malaysia data due to its parsimonious characteristic with a low value of MAPE which is 3.13% as compared to other considered models. Yet, it can be said that electricity demand in Malaysia can be forecasted accurately using SARIMA$(1,1,0)(0,1,0)_{52}$−GARCH$(1,2)$ with GED model since its MAPE statistic value of less than 5% which is considered to be relatively good [15]. This concludes that the proposed model of SARIMA - GARCH is able to produce a promising performance for electricity demand for the case of Malaysia data. In conclusion, the proposed model of SARIMA with GARCH has great potential and yet provides a comprehensive procedure specifically for one-step ahead forecast in forecasting electricity demand and would be a good start for multistep forecasting by considering other GARCH-type models as well in handling heteroscedasticity in the data for further study.

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