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Forecasting Electricity Demand using Seasonal ARIMA and Asymmetric GARCH Models: A Case Study for Malaysia

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Abstract: Accurate energy load forecasting is important for enhancing functionality and reliability of strategy development within the power generation industry. Electricity systems exhibit distinct reactions to positive and negative demand shocks, making asymmetric models particularly useful for capturing these variations. Incorporating asymmetric Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models into electricity demand forecasting can enhance forecasting accuracy by capturing the responses to demand shocks. It has been demonstrated that non-seasonal Autoregressive Integrated Moving Average (ARIMA) with asymmetric GARCH-type model is promising for forecasting highly volatile data. However, Malaysia's electricity demand time series data exhibits strong seasonal fluctuations, necessitating the use of seasonal models. From this perspective, an evaluation is carried out in this study to determine the effectiveness of a seasonal ARIMA model combined with an asymmetric GARCH-type model for forecasting electricity demand in Malaysia. Additionally, it proposes a new procedure for forecasting electricity demand. This study utilized weekly peak electricity usage over the timeframe of 2005 to 2016. The results suggest the optimal combination of seasonal ARIMA with asymmetric GARCH-type model for electricity demand prediction is $\mathrm{SARIMA}(1,1,0)(0,1,0)_{52}$ integrated with $\mathrm{EGARCH}(1,2)$ structure using Student's *t*-distribution. This model was selected due to its simplicity and strong performance, reflected in its low error metrics: root mean squared error (RMSE) of 1021.6340, mean absolute error (MAE) of 867.6399, and mean absolute percentage error (MAPE) of 5.14%. The study demonstrates the model's superiority in capturing volatility and seasonality compared to traditional approaches. Given its enhanced predictive performance, the proposed seasonal ARIMA with asymmetric GARCH-type model provides critical insights for policymakers and energy sector planners in forecasting electricity demand in Malaysia.

Keywords: Forecasting Electricity Demand, ARIMA, GARCH, Asymmetric.

1. Introduction

Electricity is essential due to its feasibility, convertibility, and mobility, but since it cannot be stored economically, continuous supply and demand prediction is necessary (Keyno *et al.,* 2009). Electricity demand in a power system is largely affected by factors such as weather, socio-economic conditions, and demographic variables (Al-Alawi & Islam, 1996). In Malaysia, electricity usage is significantly affected by climate variations and economic dynamics. According to the Department of Statistics Malaysia (2018), the nation's highest recorded electricity usage, reaching 17,788 MW as observed on 19 April 2016, underscores the necessity of precise forecasting, particularly during extreme weather events. The hot and dry conditions during that period led consumers to use electricity at its highest level. Consequently, the evaluation of power system efficiency emphasizes peak load rather than lower load levels.

Furthermore, electricity is a fundamental energy source that underpins modern society, driving socio-economic development, and contributing significantly to various facets of modern infrastructure, including transportation networks, industrial production, resource extraction, and digital connectivity. It also serves as a key tool in shaping strategic planning and future energy policies. With electricity consumption steadily increasing, its diverse applications have driven human civilization to remarkable advancements. As a result, electricity demand is deeply interconnected with all aspects of development (Yasmeen & Sharif, 2014).

In competitive electricity industry, precise prediction of load requirements and electricity pricing is essential for efficient energy system management and operation, as electricity must be delivered in real time due to limited storage capability, making any imbalance between supply and demand a significant challenge for all stakeholders (Lisi & Shah, 2020). Accurate electric load forecasting and modeling are essential for efficient energy use, cost management, and economic stability, helping policymakers and organizations prevent power shortages, reduce waste, and avoid high costs (Qiu, 2013; Kavaklioglu *et al.,* 2009).

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To ensure accurate forecasting for effective power system management, various modeling techniques have been proposed including traditional statistical models such as the Seasonal Autoregressive Integrated Moving Average (SARIMA) (Zaim *et al.,* 2025; Duong *et al.,* 2023; Andoh *et al.,* 2021; Goswami & Kandali, 2020) as well as exponential smoothing methods like Simple, Holt's, and Brown's models (Ishak *et al.,* 2022). In addition, advanced machine learning techniques have been investigated (Lee *et al.,* 2022). Hybrid approaches, such as the SARIMA-GARCH model, have also been applied to capture both linear and volatility dynamics in electricity demand (Zaim *et al.,* 2023; Makobea, 2023).

However, predicting electricity demand and prices remains a challenging task because of the irregular and unpredictable patterns in the data (Shah *et al.,* 2022). Moreover, electricity demand often exhibits volatility due to several factors, including unexpected weather changes, economic disruptions, or policy shifts. These shocks may influence demand differently depending on whether they are positive (e.g., an economic boom increasing demand) or negative (e.g., a natural disaster reducing demand).

Electricity systems exhibit distinct reactions to positive and negative demand shocks. Positive shocks, such as higher-than-expected demand, often require rapid adjustments in generation, increasing system instability and operational strain. In contrast, negative shocks, such as lower-than-expected demand, may have minimal impact if the excess capacity can be effectively stored or absorbed, as seen with hydropower reservoirs or battery storage systems. Asymmetric models are particularly useful in quantifying these differing reactions, enabling more accurate forecasting and improved grid management strategies.

Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model is widely recognized as an effective tool for modeling and forecasting the volatility of time series data (Rakshit *et al.*, 2023). Despite its popularity, the GARCH model has notable limitations, particularly its assumption of symmetry, which overlooks the direction of shocks and fails to reflect how volatility may respond differently to positive and negative shocks of equal magnitude (Rakshit *et al.*, 2023).

The standard GARCH model assumes that the volatility responds equally to shocks, suggesting that shocks of equal magnitude, whether positive or negative, have an identical effect on future volatility. Positive shocks occur when higher-than-expected demand leads to increased production, potentially causing grid instability or requiring operational adjustments. These responses can, in turn, amplify volatility in the electricity system. Negative shocks, such as lower-than-expected demand, might have a smaller or delayed impact due to the presence of demand-response mechanisms or surplus generation capacity. These factors help mitigate the immediate effects of reduced demand on the electricity system. Thus, the inability of the GARCH model to distinguish between the effects of positive and negative shocks limits its applicability in accurately modeling electricity demand volatility. Incorporating asymmetric GARCH models into electricity demand forecasting can enhance forecasting accuracy by capturing the impact of demand shocks. Additionally, they support policy planning by offering insights into how certain events, such as holidays or outages, may asymmetrically affect volatility. By addressing the limitations of symmetric GARCH models and utilizing asymmetric alternatives, forecasts for electricity demand become more robust, particularly in managing volatile and shock-sensitive periods.

Several studies have demonstrated the importance of using asymmetric GARCH models in overcoming the shortcomings of symmetric GARCH models in effectively capturing the effects of positive and negative shocks on volatility. Ndege *et al.* (2023) examined the application of asymmetric GARCH-type models to address the limitations of symmetric GARCH models in forecasting volatility in the Kenyan exchange rate market. The study compared various asymmetric Conditional Heteroscedasticity models, including Exponential GARCH (EGARCH), Threshold GARCH (TGARCH), and Asymmetric Power Autoregressive Conditional Heteroscedastic (APARCH). Using secondary data on exchange rates obtained from the Central Bank of Kenya, spanning from January 1993 to June 2021, the authors identified the most representative model according to the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Log-Likelihood criterion, and error minimization metrics such as mean error (ME) and root mean absolute error (RMAE). Their findings revealed that the ARMA (3,0) - APARCH (1,1) model with a skewed normal distribution is the best fit for the exchange rate data (AIC = -4.6871, BIC = -4.5860). While Rakshit *et al.* (2023) investigated price volatility in the potato markets of major Indian cities, emphasizing the role of seasonal production, weather abnormalities, and perishability in creating volatility. They highlighted that GARCH models cannot capture asymmetric price volatility, where positive and negative shocks of similar magnitude have different effects. To address this, EGARCH, APARCH, and Glosten-Jagannathan-Runkle GARCH (GJR-GARCH) models were employed to analyze weekly wholesale potato prices in Agra, Ahmedabad, Bengaluru, Delhi, Kolkata, and Mumbai. The study confirmed the presence of asymmetry using News Impact Curves (NICs), which quantified the degree of volatility asymmetry across different markets.

Chen *et al.* (2019) employed various GARCH-type models, including GJR-GARCH, APARCH, and EGARCH, in wind power forecasting to account for asymmetry in volatility, observing that negative shocks exert a milder effect compared to positive ones. While, Lim and Sek (2013) examined volatility in the Malaysian stock market by applying both symmetric and asymmetric GARCH models, assessing their performance through error metrics such as mean squared error (MSE), root mean squared error (RMSE), and mean absolute percentage error (MAPE) on data from January 1990 to December 2010, divided into pre-crisis, crisis, and post-crisis periods. Their findings showed that symmetric GARCH models performed better during stable periods (pre- and post-crisis), while asymmetric GARCH models were more effective during volatile periods like the 1997 financial crisis. This research highlights the importance of using different GARCH models depending on market conditions, offering valuable insights for improving volatility modeling in various applications, such as electricity demand forecasting.

These studies underscore the effectiveness of asymmetric GARCH models in capturing complex volatility dynamics, highlighting their importance in capturing the volatility dynamics

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of time series data. By addressing the asymmetry in volatility caused by positive and negative shocks, such models demonstrate improved forecasting accuracy compared to their symmetric counterparts. These findings are particularly relevant to electricity demand forecasting, where volatility and shock asymmetry are critical factors, emphasizing the need for similar modeling techniques. By capturing complex volatility dynamics, these asymmetric GARCH-type models provide strong foundation for enhancing electricity demand forecasting.

Through a systematic review, Chalissery *et al.* (2022) found that most highly cited studies in the field used the EGARCH model to capture asymmetric volatility, and many authors considered EGARCH to be the best-performing among asymmetric GARCH models. They also noted a significant contribution in the literature from researchers comparing GARCH model variants and advancing their theoretical foundations. However, Tehrani *et al.* (2022) showed that in the case of European electricity markets, asymmetric GARCH models like SGARCH, GJR-GARCH, and APARCH offered only minor improvements over the simpler symmetric GARCH (SGARCH) model. Their findings suggest that including an asymmetric parameter is not always necessary, as the SGARCH model can effectively capture volatility in practice.

While these studies highlight the significance of asymmetric GARCH models across various domains, there remains a gap in applying these advanced models to electricity demand forecasting, particularly in Malaysia, where electricity demand exhibits unique characteristics such as strong seasonality, volatility, and asymmetric shock responses. Additionally, there is lack of a detailed framework designed for one-step-ahead electricity demand forecasting that accounts for the distinct characteristics of Malaysia's electricity load trends. In line with previous studies on time series data with significant volatility, the present study will utilize asymmetric variants of the GARCH model, specifically EGARCH, APARCH, and TGARCH (also known as GJR-GARCH) in order to explore asymmetries in electricity demand volatility.

Furthermore, previous studies have not provided a thorough approach designed for one-step-ahead electricity demand forecasting. This study addresses these gaps by not only applying asymmetric GARCH models to forecast weekly maximum electricity demand but also developing a tailored framework for one-step ahead forecasting. The framework is designed to account for the distinct patterns of Malaysia's electricity demand while serving as a potential template for analyzing regions with similar electricity load patterns. Therefore, this study aims to bridge these gaps by applying asymmetric GARCH models to weekly maximum electricity demand data, identifying the best-fitting model, and using it to improve forecasting accuracy.

The study is guided by the following specific objectives:

1. To utilize SARIMA with asymmetric GARCH-type models to fit the weekly maximum electricity demand data.
2. To determine the optimal SARIMA with an asymmetric GARCH-type model that best fits the weekly maximum electricity demand data.
3. To forecast weekly maximum electricity demand using the best-performing SARIMA with asymmetric GARCH-type model.

By achieving these objectives, the study not only aims to enhance the understanding of electricity demand volatility but also introduces a robust framework for modeling and forecasting electricity demand. This framework accommodates the particular challenges of Malaysia's power load and offers a practical tool for energy management and planning in regions with similar load patterns.

2. Modelling Framework and Procedures

2.1 Model Specification and Descriptions

2.1.1 SARIMA

Analysis of electrical requirement data highlights periodic trends resulting from seasonal influences. To model and forecast these recurring seasonal effects, the Box-Jenkins SARIMA model, is widely used. A SARIMA model is developed through the inclusion of seasonal elements in the ARIMA model. It can be represented as $SARIMA(p,d,q)(P,D,Q)_s$, where *p* stands for the non-seasonal AR order, *d* is the degree of non-seasonal differencing, and *q* refers to the non-seasonal MA order. The parameters *P, D,* and *Q* represent the seasonal AR order, seasonal differencing, and seasonal MA order, while *s* indicates the length of the seasonal period. The formulation for $SARIMA(p,d,q)(P,D,Q)_s$ is expressed mathematically, as shown in 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

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

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 EGARCH

To address certain limitations of the GARCH model in modeling financial time series, Nelson (1991) introduced the $EGARCH(r,s)$ model. Specifically, to capture the asymmetric impact of positive and negative asset returns, he incorporated a weighted innovation term. In this context, let s_t denotes the stationary time series data, a_t represents the random error at

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time t, μ_t is the conditional mean of s_t, and σ_t^2 is the conditional variance of the error term at time t,

$$s_t = \mu_t + a_t, \quad a_t = \sigma_t \varepsilon_t, \quad ln(\sigma_t^2) = \alpha_0 + \sum_{i=1}^{r} \alpha_i [|\varepsilon_{t-i}| + \gamma_i \varepsilon_{t-i}] + \sum_{j=1}^{s} \beta_j \, ln(\sigma_{t-j}^2) \quad (2)$$

where, a positive a_{t-i} contributes $\alpha_i(1+\gamma_i)\,|\varepsilon_{t-i}|$ to the log volatility, whereas a negative a_{t-i} gives $\alpha_i(1-\gamma_i)\,|\varepsilon_{t-i}|$, where $\varepsilon_{t-i} = \frac{a_{t-i}}{\sigma_{t-i}}$. The parameter γ_i thus signifies the leverage effect, controlling the asymmetric impact of positive and negative shocks on volatility, enabling the model to capture this effect, with γ_i usually negative in financial data (Tsay, 2013).

2.1.3 APARCH

The APARCH model, proposed by Ding *et al.* (1993), is expressed as follows:

$$s_t = \mu_t + a_t, \quad a_t = \sigma_t \varepsilon_t, \quad \sigma_t^{\delta} = \alpha_0 + \sum_{i=1}^{r} \alpha_i (|a_{t-i}| + \gamma_i a_{t-i})^{\delta} + \sum_{j=1}^{s} \beta_j \, \sigma_{t-j}^{\delta} \quad (3)$$

where s_t and a_t represent the stationary component of the series and the random error at time t, μ_t is the conditional mean of s_t, σ_t^2 is the conditional variance of the error term, and ε_t is independently and identically distributed (IID) with zero mean and unit variance. The positive real number δ, together with coefficients $\alpha_0 > 0, \alpha_i \geq 0, |\gamma_i| < 1$, and $\beta_j \geq 0$, satisfy regularity conditions to ensure positive volatility.

The parameter γ_i controls the leverage effect, where the asymmetric response of volatility to positive and negative shocks. Three special cases of the APARCH model are of interest, for $\delta = 1$ and γ_i = 0, the model reduces to the standard GARCH model, while if $\delta = 2$, it becomes the GJR-GARCH or TGARCH model. The $APARCH\ (1,1)$ model is often used in practice (Tsay, 2013).

2.1.4 TGARCH

Another volatility model commonly used to handle leverage effects is the TGARCH model (Glosten *et al.*, 1993; Zakoian, 1994), also known as GJR-GARCH model. The $TGARCH(r,s)$ model is defined as,

$$s_t = \mu_t + a_t, \quad a_t = \sigma_t \varepsilon_t, \quad \sigma_t^2 = \alpha_0 + \sum_{i=1}^{r} (\alpha_i + \gamma_i N_{t-i}) a_{t-i}^2 + \sum_{j=1}^{s} \beta_j \, \sigma_{t-j}^2 \quad (4)$$

where $N_{t-i} = 1$ if $a_{t-i} < 0$, and 0 otherwise. Here, s_t is the stationary series, μ_t is the conditional mean, a_t is the innovation, and ε_t is independently and identically distributed (IID) with zero mean and unit variance. The parameters $\alpha_0 > 0, \alpha_i \geq 0, \gamma_i \geq 0$, and $\beta_j \geq 0$ ensure positive variance. The parameter γ_i captures the leverage effect, as negative shocks, $a_{t-i} < 0$ contribute $(\alpha_i + \gamma_i) a_{t-i}^2$ to volatility, while positive shocks, $a_{t-i} \geq 0$ contribute only $\alpha_i a_{t-i}^2$.

2.2 Proposed Framework for Forecasting Electricity Demand using SARIMA with Asymmetric GARCH-Type Models

Figure 1 presents the proposed research framework incorporating SARIMA with asymmetric GARCH-type models, detailing the systematic steps used for forecasting electricity demand. The framework adopts the four fundamental stages of the Box-Jenkins methodology which follows three primary steps: identifying a suitable model, estimating its parameters, conducting diagnostic evaluations, and forecasting to evaluate forecast accuracy. While the original framework proposed by Yaziz (2019) focused on non-seasonal, highly volatile time series data, this study extends its application to encompass seasonal characteristics within similarly volatile series.

2.2.1 Stage I: Identification

To determine the suitable parameters for the SARIMA and asymmetric GARCH-type models, various statistical tests can be performed. The process begins with assessing the stationarity of the time series using the Augmented Dickey-Fuller (ADF) test. If the series is found to be non-stationary, apply differencing, seasonal differencing, or transformations to achieve stationarity. Once stationarity is achieved, the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots of the non-seasonal component are analyzed to identify the optimal orders for the autoregressive (AR), integrated (I), and moving average (MA) terms. Additionally, the presence of seasonal patterns in the data is examined to determine the appropriate seasonal cycle length. Following this, ACF and PACF plots of the seasonal component are used to estimate the seasonal AR (SAR) and seasonal MA (SMA) parameters. These steps form the foundation for developing a well-specified SARIMA model before incorporating the volatility structure through an asymmetric GARCH-type model.

The process of specifying the asymmetric GARCH-type model begins with constructing a SARIMA model for the stationary time series data to remove any serial correlation. Once the SARIMA model is fitted, the residuals are examined for the presence of conditional heteroscedasticity using the Ljung-Box Q (LBQ) test, which helps identify ARCH effects in the residual series. If such effects are detected, the next step involves analyzing the ACF and PACF plots of the squared residuals. These plots are used to determine the appropriate lag orders, denoted as r and s, for configuring the asymmetric GARCH-type model.

In general, identifying the optimal parameters for a SARIMA model combined with an asymmetric GARCH-type structure is an iterative process, often requiring the evaluation of multiple candidate models to determine the best fit.

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2.2.2 Stage II: Estimation Phase

The process of statistical estimation in a SARIMA model integrated with an asymmetric GARCH-type component requires estimating the parameters for both components separately. The first step entails examining the stationarity and seasonal characteristics of the time series, typically through tests such as the ADF test and seasonal decomposition methods like STL. Once these properties are identified, the SARIMA parameters are estimated using Maximum Likelihood Estimation (MLE), focusing on selecting the most suitable orders for the AR, MA, SAR, and SMA components. Subsequently, parameters for the GARCH structure are also estimated via MLE, which includes determining the optimal lag orders for the ARCH and GARCH terms. To finalize the model, selection criteria such as the AIC and BIC, introduced by Akaike (1974) and Schwarz (1978), respectively, are employed to identify the best-fitting SARIMA-GARCH configuration based on the lowest information criterion values.

2.2.3 Stage III: Model Validation

Diagnostic evaluation is a vital part of model development, as it assesses the adequacy of the model and helps identify any potential limitations. For SARIMA models combined with asymmetric GARCH-type models, diagnostic checking is especially important to adequately capture both the time series dynamics and the volatility aspects. A well-fitted model should produce residuals that exhibit white noise behavior (Tsay, 2013). During the diagnostic checking stage, tests for serial correlation, heteroscedasticity, and normality are conducted to ensure that the errors exhibit white noise behavior.

To detect correlation across residual lags, one approach is to assess serial dependence through residual correlation plots and confirm findings with an LBQ test. If autocorrelation is detected, model adjustments may be necessary. Heteroscedasticity, on the other hand, is assessed by subjecting the squared residuals to the LBQ test. Ideally, the model's residuals should yield a normal distribution and free from serial dependence or ARCH/GARCH effects. The Jarque-Bera (JB) test is employed to evaluate the normality of the residual distribution. However, if the residuals deviate from normality, alternative distributional assumptions, such as Student's *t* or Generalized Error Distribution (GED), should be considered. Student's t distribution is selected for its robustness in handling heavy-tailed data.

2.2.4 Stage IV: Forecasting

Forecast accuracy measures the degree to which a model's predictions match the actual results of future events. It serves as a key indicator of how well the model performs in forecasting, typically represented as a percentage or numerical value. Additionally, it is important to continually evaluate and refine forecasting models to ensure they remain accurate and relevant over time. The forecasting accuracy is evaluated using MAE, RMSE, and MAPE scores, as shown in Equations (5), (6), and (7), respectively,

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|y_t - \hat{y}_t| \quad (5)$$

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(y_t-\hat{y}_t)^2}{n}} \quad (6)$$

$$MAPE = \frac{100\%}{n}\sum_{t=1}^{n}\left|\frac{y_t-\hat{y}_t}{y_t}\right| \quad (7)$$

where y_t and $\hat{y}_t$ represent the actual and predicted values at time t, respectively, and n indicates the number of out-of-sample observations. The best forecasting model is identified as the one with the smallest prediction error. Nevertheless, when the evaluation outcomes differ depending on the metric used, MAPE is preferred, as it generally offers greater stability than other performance measures (Wang *et al.,* 2012). According to Girish

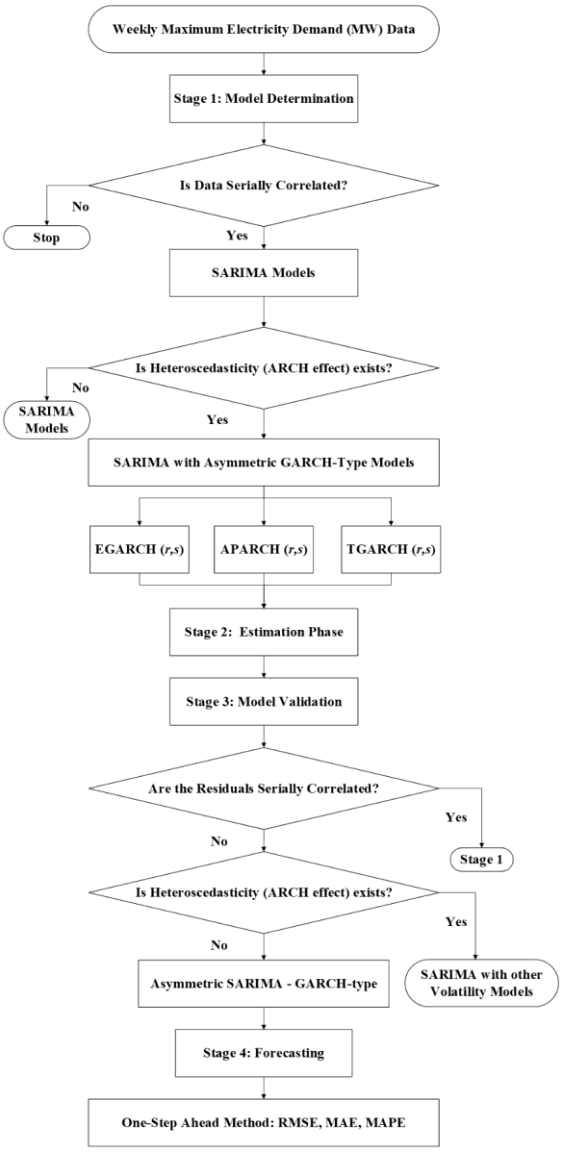


Figure 1. Proposed framework for forecasting electricity demand using SARIMA with Asymmetric GARCH-Type models.

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(2016), a forecasting model is generally regarded as fairly accurate when its MAPE value is around 5%.

3. Findings and Analysis

3.1 Data Overview

The study retrieved weekly peak electricity usage data from Single Buyer (SB) official website (https://www.singlebuyer.com.my/) covering the period from 2005 to 2016 and is classified as secondary data. SB operates under the authority of the Energy Commission and is responsible for electricity supply management and operational functions. A summary of the weekly demand figures is shown in Table 1. The dataset is divided into training and testing subsets based on the conventional 90:10 ratio, which is commonly applied for developing forecasting models (Yaziz, 2019; Chatfield, 2001). However, since the dataset follows weekly and seasonal characteristics, the dataset is divided into 92:8 ratio for the estimate to forecast, ensuring a better cycle. This results in 624 observations used for training and 52 observations for testing, corresponding to a full year of weekly data.

Although monthly or quarterly seasonality is commonly used in time series analysis, these broader intervals may fail to capture subtle fluctuations influenced by weather changes and environmental factors. Weekly forecasting offers higher temporal resolution, enabling a more precise understanding of short-term demand variations, which is valuable for effective electricity supply planning (Taylor, 2010). According to Hor *et al.* (2005), the monthly demand shows a strong cyclic pattern due to yearly temperature changes. However, the authors noted that these variations are clearer in daily demand. This suggests that weekly forecasts may be more effective than monthly or quarterly ones for managing electricity supply.

Table 1. Weekly Maximum Electricity Demand Dataset Overview.

Time Period	Total Data Points	Training Set (In-Sample)	Testing Set (Out-of-Sample)
2005 - 2016	676	Weeks 1 to 624	Weeks 625 to 676

3.2 Time Series Modeling using SARIMA and Asymmetric GARCH-Type Models

Forecasting was done using a hybrid of SARIMA and asymmetric GARCH-type models (Figure 1). Meanwhile, Figure 2 presents the pattern of in-sample weekly peak electricity load, revealing a clear upward trend over the 2005–2016 period. Despite the overall growth, short-term fluctuations are present, which likely result from seasonal factors, economic conditions, and other external influences.

The data displays both a strong seasonal structure and a consistent upward trajectory. Consequently, weekly peak electricity demand from 2005 to 2016 is used as the basis for projecting electricity usage for the subsequent year.

Outcome of the decomposition process for weekly peak electricity load data is illustrated in Figure 3. The data has been broken down into four key elements which are raw data, extracted periodic component, trend line with smoothing, and residuals. The consistency of seasonal fluctuations justifies the additive decomposition model. The seasonal component reveals a distinct and regular pattern, repeating in a predictable cycle. These components, when summed, reconstruct the original series shown in the top panel. Residuals, depicted in the bottom panel, quantify the unexplained variation post-detrending and deseasonalizing.

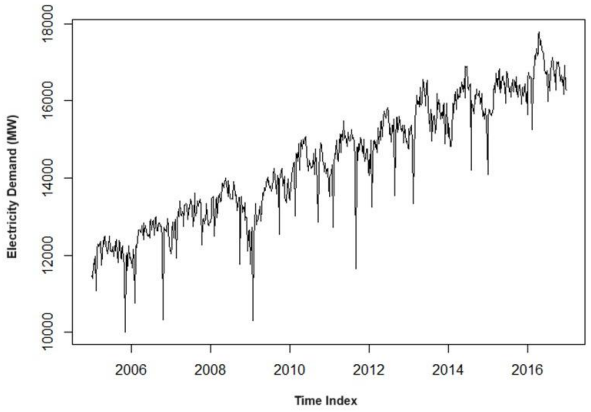


Figure 2. Weekly peak electricity load observations.

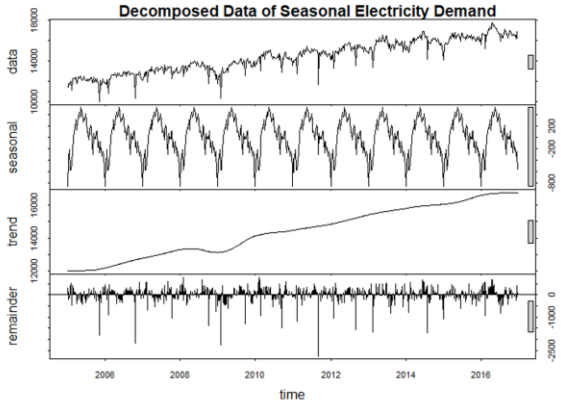


Figure 3. Time series decomposition of weekly maximum electricity load.

Table 2 presents the numerical results, which demonstrate seasonal effects that recur annually over 52 weeks. The analysis estimates the impact for each week using weekly data. Employing R statistical software, seasonality was evaluated in the time series, revealing a consistent pattern that repeats every 52 weeks.

As illustrated in Figure 4, after regular differencing, the series still exhibits clear seasonal patterns and nonstationarity, indicating that regular differencing alone is insufficient to achieve

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Table 2. Periodic Variation Effects on Weekly Electricity Demand Peaks.

Period (Week)	Estimated Seasonal Coefficient
1	-746.1064
2	-453.5700
3	-421.1485
4	-182.8890
5	-195.2180
6	-458.8856
7	-165.1864
8	-39.0005
9	-49.5013
10	103.7071
11	176.2628
12	133.8702
13	318.8347
14	83.2800
15	277.8137
16	218.9154
17	342.9762
18	334.2281
19	327.7232
20	452.6493
21	411.6273
22	386.4160
23	220.0440
24	199.5053
25	208.0522
26	330.1781
27	229.6411
28	94.9300
29	75.9146
30	-4.3645
31	40.9505
32	108.1245
33	151.9653
34	123.2089
35	-24.9987
36	-122.3736
37	42.1005
38	47.4898
39	49.4952
40	17.9409
41	24.3953
42	136.8664
43	-71.7872
44	-168.3808
45	-182.1498
46	-139.3503
47	-295.6563
48	-264.4669
49	-414.0220
50	-242.9042
51	-424.7041
52	-602.4426

stationarity. To address the remaining seasonality, a seasonal differencing operation is performed, as illustrated in Figure 5. After both regular and seasonal differencing, the series in Figure 5 appears stationary, with the trend and seasonality largely removed. This transformation makes the series suitable for further modeling, such as with the SARIMA framework.

To ensure the appropriateness of SARIMA modeling, LBQ test is conducted on the first-differenced series to check for serial correlation. With *p*-value of 2.2×10^{-16}, which is less than 0.05, the null hypothesis can be rejected with confidence, indicating the presence of serial correlation at the 5% significance level which supports the application of the Box-Jenkins methodology.

From ten SARIMA models initially considered, seven models are found to be statistically significant, as shown in Table 3. Three models, specifically, one with a single non-seasonal and seasonal MA term, another with two non-seasonal and single seasonal MA terms, and the third model with two non-seasonal MA terms. Although these models are theoretically parsimonious, they did not appear among the significant models and thus are excluded based on model diagnostics.

Additionally, heteroscedasticity checks are performed on the error terms of the significant Seasonal Box-Jenkins models through the application of LBQ test to their squared values. Only three models exhibit signs of ARCH effects, indicating the presence of volatility and making them suitable for extension with GARCH models.

Based on the diagnostic checking results, the $\mathrm{SARIMA}(1,1,0)(0,1,0)_{52}$ model is statistically significant, with no evidence of serial correlation in the residuals, but it exhibits heteroscedasticity and non-normal residuals. These characteristics indicate that this model is the most suitable candidate for integration with a GARCH-type model to better capture volatility and improve the distributional assumptions of the residuals.

To ensure the appropriateness of SARIMA modeling, LBQ test is conducted on the first-differenced series to check for serial correlation. With p-value of 2.2 × 10-16, which is less than 0.05, the null hypothesis can be rejected with confidence, indicating the presence of serial correlation at the 5% significance level which supports the application of the Box-Jenkins methodology.

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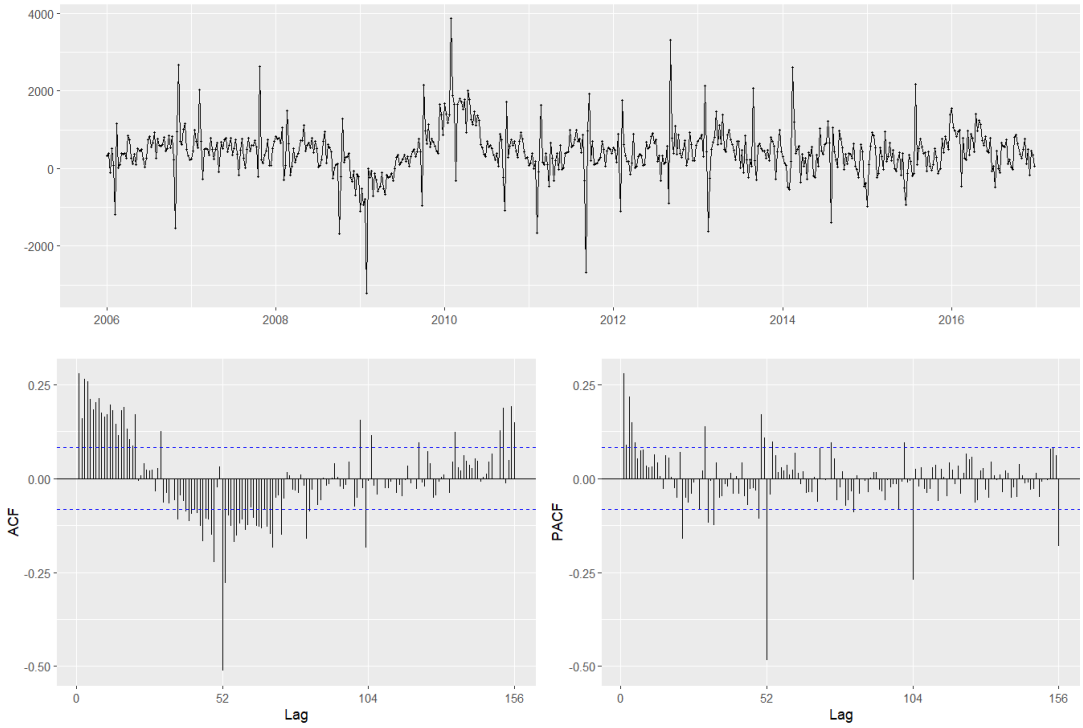


Figure 4. Regular differenced time series of weekly maximum electricity load.

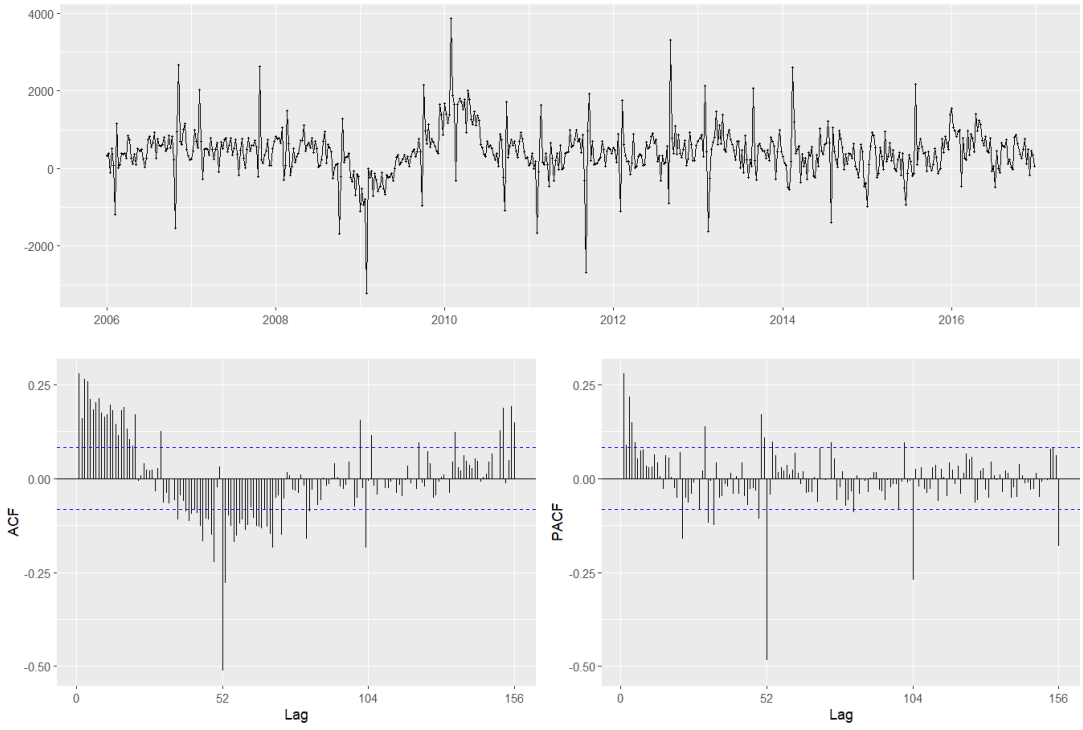


Figure 5. Seasonally differenced time series of weekly maximum electricity load.

From ten SARIMA models initially considered, seven models are found to be statistically significant, as shown in Table 3. Three models, specifically, one with a single non-seasonal and seasonal MA term, another with two non-seasonal and single seasonal MA terms, and the third model with two non-seasonal MA terms. Although these models are theoretically parsimonious, they did not appear among the significant models and thus are excluded based on model diagnostics.

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Table 3. Diagnostic Checking on Selected SARIMA Models.

SARIMA Model	Significance Check	Autocorrelation Check	Heteroscedasticity Status	Normality Check
$\text{SARIMA}(1,1,0)(0,1,0)_{52}$	Significant	No correlation up to lag 1	Present	Not normal JB: 715.1444 *p*-value: 0.0000
$\text{SARIMA}(2,1,0)(0,1,0)_{52}$	Significant	No correlation up to lag 2	Present	Not normal JB: 963.0602 *p*-value: 0.0000
$\text{SARIMA}(3,1,0)(0,1,0)_{52}$	Significant	No correlation up to lag 3	Present	Not normal JB: 966.8753 *p*-value: 0.0000
$\text{SARIMA}(4,1,0)(0,1,0)_{52}$	Significant	No correlation up to lag 4	Absent (Lag 4-42, Lag 45-49)	Not normal JB: 1022.2090 *p*-value: 0.0000
$\text{SARIMA}(5,1,0)(0,1,0)_{52}$	Significant	No correlation up to lag 5	Absent (Lag 3-49)	Not normal JB: 1105.5060 *p*-value: 0.0000
$\text{SARIMA}(6,1,0)(0,1,0)_{52}$	Significant	No correlation up to lag 6	Absent (Lag 1-49)	Not normal JB: 1110.8090 *p*-value: 0.000
$\text{SARIMA}(7,1,0)(0,1,0)_{52}$	Significant	No correlation up to lag 7	Absent (Lag 1-49)	Not normal JB: 1143.2470 *p*-value: 0.0000

Additionally, heteroscedasticity checks are performed on the error terms of the significant Seasonal Box-Jenkins models through the application of LBQ test to their squared values. Only three models exhibit signs of ARCH effects, indicating the presence of volatility and making them suitable for extension with GARCH models.

Based on the diagnostic checking results, the $\text{SARIMA}(1,1,0)(0,1,0)_{52}$ model is statistically significant, with no evidence of serial correlation in the residuals, but it exhibits heteroscedasticity and non-normal residuals. These characteristics indicate that this model is the most suitable candidate for integration with a GARCH-type model to better capture volatility and improve the distributional assumptions of the residuals.

Among these, a SARIMA model with a single non-seasonal AR term, is selected not only for its parsimonious structure but also due to its superior forecasting performance. As presented in Table 4, it achieves the lowest MAPE of 2.88%, along with the lowest RMSE and MAE among the significant models. Thus, the selection is based on a combination of statistical significance, presence of heteroscedasticity for GARCH modeling, and better forecasting accuracy with fewer parameters, aligning with the principle of parsimony.

Table 5 shows the diagnostic results for the selected SARIMA-GARCH-type models. All models are statistically significant and show no serial correlation in their residuals, which means the models have captured the time series patterns well. When looking at volatility (heteroscedasticity), the EGARCH and TGARCH models perform better. They successfully remove the volatility effects in the data up to lag 51. In contrast, both APARCH models still show signs of remaining heteroscedasticity, meaning they may not handle changing variance as effectively. For normality, all models fail the test where JB values are very high with *p*-values of 0.0000. This shows that the residuals are not normally distributed, likely because of heavy tails or skewed data. Because of this, using distributions like Student's *t* or GED is important when estimating the models. In summary, the EGARCH and TGARCH models are better at handling volatility, but none of the models meet the normality assumption which is expected for real-world electricity demand data.

The proposed procedure utilizes the widely adopted AIC and BIC criteria to determine the most suitable SARIMA model combined with a GARCH-type specification. These criteria impose penalties for model complexity, favoring models that balance goodness of fit with simplicity. Accordingly, the preferred model is the one that achieves the lowest AIC or BIC score while accurately representing both the underlying time series pattern and the volatility behavior. When comparing models with differing numbers of parameters, the parsimony principle promotes choosing the less complex model if it provides comparable performance. According to McLeod (1993), the principle of parsimony suggests selecting the simplest model available.

Table 6 and Table 7 present the best performing model, which is the $\text{SARIMA}(1,1,0)(0,1,0)_{52} - \text{EGARCH}(1,2)$ with Student's *t* distribution, as it minimizes both AIC and BIC while achieving the highest log-likelihood, yet adheres to the parsimony principle. This model effectively captures heteroscedasticity and adapts well to heavy-tailed data, making it a robust choice. Close second is the TGARCH(1,2) model with Student's *t* distribution,

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Table 4. Evaluation of Forecasting Accuracy for Selected SARIMA Models.

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

Table 5. Diagnostic Tests for Selected SARIMA-GARCH-type Models.

SARIMA-GARCH-type Model	Significance Check	Autocorrelation Check	Heteroscedasticity Status	Normality Check
$SARIMA(1,1,0)(0,1,0)_{52} - EGARCH(1,1)$	Significant	No correlation up to lag 1	Absent (Lag 1-51)	Not normal JB: 731.7946 *p*-value: 0.0000
$SARIMA(1,1,0)(0,1,0)_{52} - APARCH(1,1)$	Significant	No correlation up to lag 1	Present	Not normal JB: 940.6238 *p*-value: 0.0000
$SARIMA(1,1,0)(0,1,0)_{52} - TGARCH(1,1)$	Significant	No correlation up to lag 1	Absent (Lag 1-51)	Not normal JB: 737.9878 *p*-value: 0.0000
$SARIMA(1,1,0)(0,1,0)_{52} - EGARCH(1,2)$	Significant	No correlation up to lag 1	Absent (Lag 1-51)	Not normal JB: 835.9982 *p*-value: 0.0000
$SARIMA(1,1,0)(0,1,0)_{52} - APARCH(1,2)$	Significant	No correlation up to lag 1	Present	Not normal JB: 467.8978 *p*-value: 0.0000
$SARIMA(1,1,0)(0,1,0)_{52} - TGARCH(1,2)$	Significant	No correlation up to lag 1	Absent (Lag 1-51)	Not normal JB: 738.6357 *p*-value: 0.000

which performs nearly as well as EGARCH(1,2) but is slightly less favorable due to marginally higher values of model selection criteria (AIC and BIC). PARCH models, on the other hand, are the least effective, likely due to parameter instability and higher AIC and BIC values.

Table 8 presents the comparison of different SARIMA-GARCH-type models in capturing the volatility dynamics of the dataset. Among the models evaluated, $SARIMA(1,1,0)(0,1,0)_{52} - EGARCH(1,2)$ demonstrates the best fit and forecasting performance, making it the preferred selection as it effectively addresses the heteroscedasticity detected in the SARIMA residuals. Diagnostic checks confirm that the residuals of the fitted model no longer exhibit heteroscedasticity, indicating the EGARCH model's strength in capturing the volatility pattern. It also exhibits the lowest AIC and BIC values, indicating superior model fit. Additionally, it uses Student's *t* distribution, which effectively captures the heavy-tailed nature of the data. These findings confirm that the $SARIMA(1,1,0)(0,1,0)_{52} - EGARCH(1,2)$ model provides the best fit for the dataset, making it the most reliable choice for volatility forecasting.

Table 9 compares forecasting accuracy of two models: $SARIMA(1,1,0)(0,1,0)_{52} - EGARCH(1,1)$ and $SARIMA(1,1,0)(0,1,0)_{52} - EGARCH(1,2)$. The results show that the $SARIMA(1,1,0)(0,1,0)_{52} - EGARCH(1,2)$ model performs slightly better, with lower values for RMSE (1021.6340), MAE (867.6399), and MAPE (5.14%) highlights the model's utility for operational forecasting compared to $SARIMA(1,1,0)(0,1,0)_{52} - EGARCH(1,1)$ model. This indicates that $SARIMA(1,1,0)(0,1,0)_{52} - EGARCH(1,2)$ model provides more accurate forecasts for electricity demand in Malaysia.

Figure 7 shows the $SARIMA(1,1,0)(0,1,0)_{52} - EGARCH(1,2)$ model (based on Student's *t* assumptions) one-step-ahead predictions for weekly peak electricity load for the next 52 weeks. The plot shows the forecasted values as a solid blue line, while the solid green line represents the recorded electricity usage. The values obtained from the forecast, shown with a margin of ±2 standard errors by the dotted lines, fluctuate between 17,788 MW and 10,005 MW throughout the 52-week validation period, closely following actual data and indicating the model effectively captures the underlying trend. In this study, the 52 weeks represent a full year of testing data, which is sufficient to capture a comprehensive trend, as it encompasses an entire year's worth of information.

4. Conclusion

In conclusion, the proposed SARIMA model with the asymmetric EGARCH model shows promising performance for forecasting electricity demand based on Malaysian data. Utilizing Student's *t* distribution, the $SARIMA(1,1,0)(0,1,0)_{52} -$

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Table 6. Estimation Results for SARIMA-GARCH-type Models.

SARIMA-GARCH-type Model	Parameter Estimation	Innovations of Distributions		
		Normal	**Student's *t***	**GED**
$\mathrm{SARIMA}(1,1,0)(0,1,0)_{52} - \mathrm{EGARCH}(1,1)$	C	-39.3657 (0.0046)	-26.1627 (0.0442)	-23.0548 (0.0594)
	φ_1	-0.3361 (0.0000)	-0.3463 (0.0000)	-0.3105 (0.0000)
	α_0	5.5135 (0.0000)	4.8090 (0.0001)	5.2714 (0.0002)
	α_1	0.5917 (0.0000)	0.7686 (0.0000)	0.6900 (0.0000)
	γ_1	-0.3399 (0.0000)	-0.2775 (0.0045)	-0.2692 (0.0035)
	β_1	0.5369 (0.0000)	0.5872 (0.0000)	0.5470 (0.0000)
	T-DIST. DOF	-	3.2125 (0.0000)	-
	GED PARAMETER	-	-	1.0333 (0.0000)
	AIC	15.6360	**15.4284**	15.4600
	BIC	15.6818	**15.4818**	15.5134
	Log-l	-4450.262	-4390.095	-4399.095
$\mathrm{SARIMA}(1,1,0)(0,1,0)_{52} - \mathrm{APARCH}(1,1)$	C	-2088.547 (0.0000)	-21.1864 (0.0055)	-4889.562 (0.0087)
	φ_1	-1.0748 (0.0000)	-2.6982 (0.0000)	-16.4900 (0.3330)
	α_0	10898.72 (0.0000)	489238.3 (0.4069)	449543.5 (0.4935)
	α_1	-1.8605 (0.0000)	-2.6402 (0.8720)	-2.5944 (0.7999)
	γ_1	-0.1793 (0.0003)	-0.3892 (0.9541)	-0.4335 (0.9271)
	β_1	0.8217 (0.0000)	0.4670 (0.4689)	0.4253 (0.4296)
	T-DIST. DOF	-	2.0000 (0.0000)	-
	GED PARAMETER	-	-	0.9288 (0.5948)
	AIC	21.7735	17.8080	26.4637
	BIC	21.8193	17.8613	26.5170
	Log-l	-6199.460	-5068.271	-7535.141
$\mathrm{SARIMA}(1,1,0)(0,1,0)_{52} - \mathrm{TGARCH}(1,1)$	C	-36.4173 (0.0406)	-26.6810 (0.0442)	-22.7238 (0.0731)
	φ_1	-0.3087 (0.0000)	-0.3464 (0.0000)	-0.3099 (0.0000)
	α_0	199967.6 (0.0000)	183751.8 (0.0001)	172128.2 (0.0000)
	α_1	0.1197 (0.0079)	0.2181 (0.1338)	0.1741 (0.1285)
	γ_1	0.8071 (0.0000)	0.9425 (0.0157)	0.7677 (0.0100)
	β_1	0.1358 (0.0290)	0.1753 (0.1150)	0.1446 (0.2127)
	T-DIST. DOF	-	3.2270 (0.0000)	-
	GED PARAMETER	-	-	1.0384 (0.0000)
	AIC	15.6297	15.4215	15.4539
	BIC	15.6754	15.4749	15.5073
	Log-l	-4448.458	-4388.135	-4397.357

* Values in parentheses represent *p*-values, and Log-l refers to log-likelihood.

$\mathrm{EGARCH}(1,2)$ model demonstrates superior effectiveness in forecasting electricity demand in the Malaysian context with its low MAPE value of 5.14%.

However, this study is limited by the lack of updated electricity demand data, utilizing data from 2017 to 2023. A more robust demonstration of SARIMA with asymmetric GARCH-type model for forecasting electricity demand in Malaysia would require more recent data updates. Additionally, the study employs weekly maximum electricity demand, which may not capture more granular variations, such as daily or intraday fluctuations, that are critical for real-time energy management. Future research in this area should focus on applying multistep forecasting while incorporating updated data.

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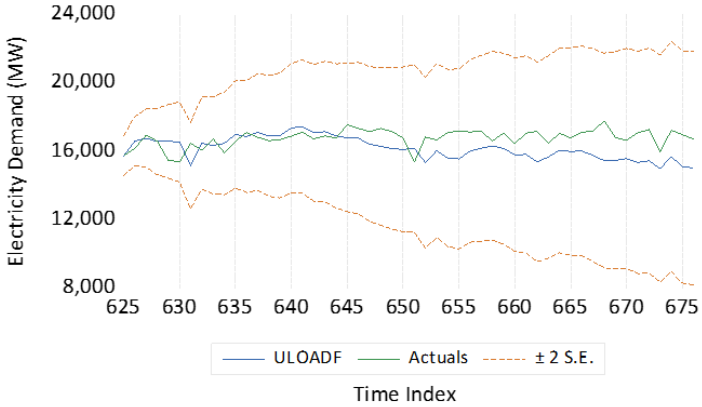


Figure 6. Weekly electricity demand forecast using $\mathrm{SARIMA}(1,1,0)(0,1,0)_{52} - \mathrm{EGARCH}(1,1)$.

Table 7. Estimation Results for SARIMA-GARCH-type Models.

SARIMA-GARCH-type Model	Parameter Estimation	Innovations of Distributions		
		Normal	**Student's *t***	**GED**
$\mathrm{SARIMA}(1,1,0)(0,1,0)_{52} - \mathrm{EGARCH}(1,2)$	C	-37.1886 (0.0094)	-25.5287 (0.0371)	-24.7191 (0.0392)
	φ_1	-0.3608 (0.0000)	-0.3913 (0.0000)	-0.3504 (0.0000)
	α_0	6.2604 (0.0000)	5.2072 (0.0000)	5.6656 (0.0000)
	α_1	0.4786 (0.0000)	0.6321 (0.0000)	0.5546 (0.0000)
	γ_1	-0.2652 (0.0000)	-0.2129 (0.0057)	-0.2216 (0.0031)
	β_1	0.9667 (0.0000)	1.0187 (0.0000)	0.9750 (0.0000)
	β_2	-0.4831 (0.0000)	-0.4571 (0.0000)	-0.4523 (0.0005)
	T-DIST. DOF	-	3.2852 (0.0000)	-
	GED PARAMETER	-	-	1.0595 (0.0000)
	AIC	15.6223	**15.4143**	15.4528
	BIC	15.6757	**15.4753**	15.5138
	Log-l	-4445.349	-4385.068	-4396.036
$\mathrm{SARIMA}(1,1,0)(0,1,0)_{52} - \mathrm{APARCH}(1,2)$	C	-28.5307 (0.2417)	-16.6803 (0.0333)	-4704.133 (0.0080)
	φ_1	-0.3850 (0.0000)	-2.0846 (0.0000)	-18.0671 (0.3474)
	α_0	1231.358 (0.0000)	491143.4 (0.8507)	489108.2 (0.5315)
	α_1	-0.0059 (0.5705)	-2.3778 (0.9069)	-2.3331 (0.8302)
	γ_1	-1.0000 (0.5941)	-0.5770 (0.9483)	-0.5944 (0.9234)
	β_1	0.1693 (0.0000)	0.4128 (0.9307)	0.4461 (0.3411)
	β_2	-0.9883 (0.0000)	-0.1068 (0.9500)	-0.0748 (0.8931)
	T-DIST. DOF	-	2.0000 (0.0000)	-
	GED PARAMETER	-	-	0.9304 (0.5927)
	AIC	15.8846	17.2301	26.5867
	BIC	15.9380	17.2911	26.6477
	Log-l	-4520.114	-4902.580	-7569.215

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Table 7. Continued.

SARIMA-GARCH-type Model	Parameter Estimation	Innovations of Distributions		
		Normal	Student's *t*	GED
$\mathrm{SARIMA}(1,1,0)(0,1,0)_{52} - \mathrm{TGARCH}(1,2)$	C	-37.8297 (0.0385)	-26.4966 (0.0446)	-23.3647 (0.0663)
	φ_1	-0.2955 (0.0000)	-0.3524 (0.0000)	-0.3099 (0.0000)
	α_0	222391.5 (0.0000)	187752.7 (0.0001)	184096.4 (0.0000)
	α_1	0.1523 (0.0015)	0.2400 (0.1184)	0.1847 (0.1092)
	γ_1	0.7531 (0.0000)	0.8227 (0.0204)	0.7334 (0.0095)
	β_1	0.1534 (0.0250)	0.2613 (0.0781)	0.1863 (0.1728)
	β_2	-0.0795 (0.0081)	-0.0788 (0.1668)	-0.0675 (0.1579)
	T-DIST. DOF	-	3.2342 (0.0000)	-
	GED PARAMETER	-	-	1.0453 (0.0000)
	AIC	15.6222	15.4196	15.4526
	BIC	15.6756	15.4805	15.5136
	Log-l	-4445.332	-4386.571	-4395.999

* Values in parentheses represent *p*-values, and Log-l refers to log-likelihood.

Table 8. Selected SARIMA with GARCH-type Models.

SARIMA-GARCH-type Model	Distribution Type	AIC	BIC
$\mathrm{SARIMA}(1,1,0)(0,1,0)_{52} - \mathrm{EGARCH}(1,1)$	Student's *t*	15.4284	15.4818
$\mathrm{SARIMA}(1,1,0)(0,1,0)_{52} - \mathrm{APARCH}(1,1)$	Student's *t*	17.8080	17.8613
$\mathrm{SARIMA}(1,1,0)(0,1,0)_{52} - \mathrm{TGARCH}(1,1)$	Student's *t*	15.4215	15.4749
$\mathrm{SARIMA}(1,1,0)(0,1,0)_{52} - \mathrm{EGARCH}(1,2)$	Student's *t*	**15.4143**	**15.4753**
$\mathrm{SARIMA}(1,1,0)(0,1,0)_{52} - \mathrm{APARCH}(1,2)$	Normal	15.8846	15.9380
$\mathrm{SARIMA}(1,1,0)(0,1,0)_{52} - \mathrm{TGARCH}(1,2)$	Student's *t*	15.4196	15.4805

Table 9. Evaluation of Forecasting Performance of SARIMA-EGARCH Models.

SARIMA-EGARCH Model	Forecast Performance on Test Data		
	RMSE	MAE	MAPE (%)
$\mathrm{SARIMA}(1,1,0)(0,1,0)_{52} - \mathrm{EGARCH}(1,1)$	1041.1700	882.5311	5.23
$\mathrm{SARIMA}(1,1,0)(0,1,0)_{52} - \mathrm{EGARCH}(1,2)$	**1021.6340**	**867.6399**	**5.14**

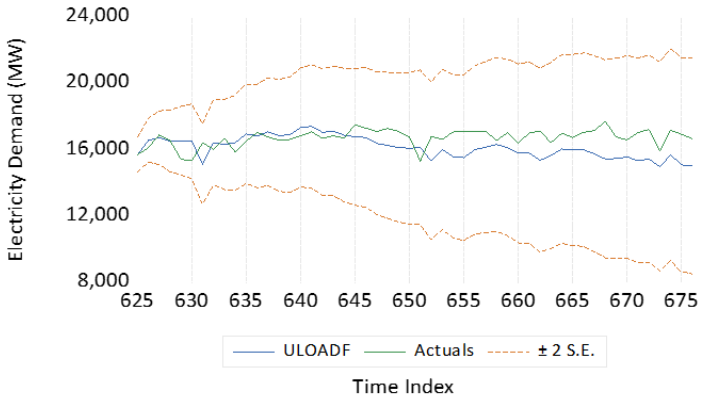


Figure 7. Weekly electricity demand forecast using $\mathrm{SARIMA}(1,1,0)(0,1,0)_{52} - \mathrm{EGARCH}(1,2)$.

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