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Medium-term Electricity Load Demand Forecasting using Holt-Winter Exponential Smoothing and SARIMA in University Campus

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Abstract — *This study was conducted to determine the best model in forecasting the electricity load demand for the next 1, 2, and 3 months in a university in Malaysia by comparing 4 error measures, such as Mean Squared Error, Root Mean Squared Error, Mean Absolute Percentage Error, and Geometric Root Mean Squared Error. Two forecasting methods were compared in this study to obtain the best forecasting results. The methods are Holt-Winter's Exponential Smoothing (HWES) method and Seasonal Autoregressive Integrated Moving Average (SARIMA). This study used 68 secondary data from January 2010 until August 2015. Microsoft Excel and JMP were used to determine the type of time series components, model estimation, and model evaluation. The results showed that seasonal and trend components exist in the dataset. The best model was SARIMA (0,0,1) (1,0,0)$_{12}$ models since it denoted the lowest error measurement compared to HWES. Then, this model is used for forecasting the next 1, 2, and 3 months in load demand of electricity.*

Keywords — *Electricity load demand, Holt-Winter exponential smoothing, Medium-term forecasting, Seasonal autoregressive integrated moving average*

I. INTRODUCTION

Electricity load demand (ELD) is the maximum amount of power demand registered to an electric utility company by a customer (https://www.tnb.com.my/about-tnb/corporate-profile/). ELD is an electric power generated from power plants, which is then called electricity energy once it is ready for use. The nature of electricity cannot be stored economically and cheaply in large volumes [1]. Since electricity cannot be stored, there must be sufficient available generation, transmission, and distribution capacity to meet the highest load demand. Therefore, the study on ELD forecasting is very important to assist utility companies in developing efficient operation of the power system to balance between generation and load demand [2]. Moreover, electricity is important to everyone in the world. Without electricity, all electronic components cannot perform their functions. It is thus important for us to estimate the electricity consumption to meet the growing demand of consumers with limited electricity supply to support this demand. It is hoped that electricity can be supplied at all times to avoid any disturbance in consumer's needs. Scheduling and planning are very important in this process to make sure that the electricity transmission systems work smoothly. Scheduling and planning enable us to coordinate the availability of electricity efficiency and how to distribute it according to the scheduling procedures [3]. They need to determine the places they are supplying more or less electricity due to the demand as scheduled and planned. Thus, scheduling and planning can ensure the efficient flow of electricity. For that reason, managing the optimal energy source becomes very important among energy planners and policymakers [4]. Therefore, it is essential to estimate optimum electricity demand so that no waste of excess electricity is supplied, which can also reduce the power system's operational cost [5]. This avoids wasting costs and financial resources, which results in higher operating costs for energy suppliers. Moreover, electricity surplus can also cause energy supply disruption. Hence, the modeling of ELD with the minimum forecast error is vital to obtain optimum cost and maximize profit.

ELD forecasting is not limited to large scale, but for small-scale, too. Large-scale ELD forecasting is normally conducted in big regions or a country. Meanwhile, small regions or buildings are considered small-scale ELD forecasting. University or campus ELD forecasting is categorized as an institution in small-scale ELD. The institution also consists of more than one building. Thus, institutional planning may differ for every institution. Some electricity load studies were conducted using electricity campus data and produced many forecasting models. For instance, some studies using campus ELD data were conducted in Universiti Teknologi Petronas [6], campus in Korea [7], and the University of California [8]. They applied the univariate time series models [6], Box-Jenkins models [7],[8], neural network model [7], and regression [8]. Meanwhile, forecasting electricity load consumption is also studied in Universiti Utara Malaysia (UUM) [9], Universiti Teknologi Tun Hussien Onn [10], and Afyon Kocatepe University, Turkey [11]. They modeled the campus electricity load consumption data into univariate time series models [9],[10], and Box-Jenkins models, such as the SARIMA model [9] and fuzzy inference model [11]. Generally, it is proven that a variety of forecasting models can be applied to campus electricity

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data and that the needs of forecasting electricity on campus are still relevant due to the nature of the campus, which normally consists of more than one building. The campus management also needs to identify the nature of the campus' electricity load demand as an assistant tool in decision-making and planning.

UUM is one of the leading public universities in Malaysia. The university campus has a comprehensive range of facilities, including administration buildings, colleges, libraries, multipurpose halls, school halls, hostels, clinics, sports centers, and more. Therefore, the usage of electricity in UUM is extremely large. Thus, scheduling and planning can assure the efficient flow of electricity. Therefore, the university management should provide a sufficient amount of load electricity to its users. They also need to control electricity during the semester on and a semester off because semester on will require more electricity compared to a semester off. Hence, there is a need to forecast UUM ELD for future decisions, especially on electricity generation. This study focused on evaluating the performance of several forecasting models by using different types of error measurement. Then, based on that, the best model is identified to forecast the ELD in UUM. Therefore, this study aims to model the UUM campus ELD using the univariate time series model and Box-Jenkins models and then forecast the medium-term forecasting; 1, 2, and 3 months ahead.

This paper is structured as follows. Section II presents some related works on ELD forecasting, starting with the forecast of time horizons. Section III presents the application of the methodology. The results are presented in Section IV. Finally, some discussions and conclusions are highlighted in Section V

II. RELATED WORKS

There are many studies done on ELD either inside or outside Malaysia. Various methods have been used and proposed based on the type of data used. Researchers used different forecasting methods in their study according to the data type and regional factors. The ELD forecasting techniques can be categorized into 3 groups; statistical-based modeling, artificial intelligence-based modeling, and hybrid methods [3]–[5]. In statistical-based modeling, the models are in the form of a mathematical equation. It consists of multiple regression [12]–[14], exponential smoothing [15], decomposition method [16],[17], naïve model [18], and ARIMA [6],[19]. In artificial intelligence-based modeling, it involved the models, which represent human intelligence or knowledge. It consists of the neural network [20]–[22], fuzzy time series [3],[23]–[25], fuzzy rule-based system [26]–[28] support vector machine [29], and deep learning [30]. Meanwhile, combining forecasting methods to form a single forecasting method is known as the hybrid method. The aim of this combined approach is to improve the accuracy of the forecast values. A few applications of hybrid models in the area of ELD can be found in [31]–[33].

Recently, researchers in Malaysia implemented some forecasting methods for the Malaysian ELD demand series. For example, [34] conducted moving holiday ELD forecasting in Malaysia using multiple regression, [35] compared the performance of the autoregressive model with ARIMA in forecasting ELD in Malaysia. Another paper by [19] compared the performance of combined ARIMA with regression model in forecasting ELD in Johor Bahru with ARIMA and regression models. [32] proposed to combine methods using empirical mode decomposition and dynamic regression, namely the EMD-DR method to forecast TNB ELD. They used half-hourly load demand from January 1, 2013, to May 31, 2013. Meanwhile, [14] focused on macroeconomic factors affecting the ELD in Johor Bahru for the 2005 to 2011 dataset. In 2013, [15] studied about a half-hourly ELD by using 5 exponential smoothing methods to forecast ELD.

ELD forecasting models are typically divided into three-time frame terms, depending on the period of study, such as short-term forecasting (STF), medium-term forecasting (MTF), and long-term forecasting (LTF) [4],[36],[37]. The STF is carried out for an interval ranging valid for a few hours or half an hour ahead to a few weeks. It plays a crucial role in the daily operations of a utility, such as unit commitment, economic dispatch, hydrothermal coordination, load management, and so on. There are many researchers who worked on STF in ELD, including [5][29][30][38]. Next, the MTF is carried out for an interval ranging from a few weeks to a few months and even up to a few years. It helps in fuel procurement of planning, scheduling unit maintenance, and energy trading, as well as revenue assessment. The MTF needs more attention because of its important role, especially in planning maintenance schedules. Researchers, such as [36] [13][39], have also worked on medium-term forecasting. However, the LTF is carried out in an interval ranging from 5 to 25 years. It is vital in decision-making on the system generation and transmission expansion. However, a limited number of researchers, including [40]–[42], were involved in this long-term ELD forecasting.

III. METHODOLOGY

This section describes the five main steps of research methodology. The steps are presented as follows:

Step 1: Collecting and dividing the time series data.
Step 2: Identification of time series components.
Step 3: Constructing ELD estimation model.
  Step 3.1: Modeling of HWES.
  Step 3.2: Modeling of SARIMA.
Step 4: Evaluating model performance.
Step 5: Forecasting ELD.

A. Step1: Collecting and Dividing the Time Series Data.

Data that had been used is in medium-term time horizon, which is known as monthly data. The data are collected from Unit Electrical Engineering, and it is secondary data because some methods require previous data to compare with the forecast data to obtain an accurate estimation of the project. The time-series data collected are for 68 months, which is approximately five years. This study uses monthly data because the University management needs good planning and scheduling in electricity to prevent blackout and wastage. The time-series data were divided into two parts of analysis, which are the estimation and evaluation parts. These two different parts will perform different purposes in analysis and interpret the data. In the estimation part, there are 63 months used to carry out its process. The process involves time-series component identification and constructing the forecasting model. Meanwhile, five months of data are used as evaluation data to identify which model is the most appropriate method for forecasting electricity load demand. This study also uses the kilowatt (kW) scale in calculating electricity load demand.

B. Step2: Identification of Time Series Components

There are four types of time series components, which are a trend, seasonal, cyclical, and irregular components. The trend is a long-term movement and rate of change in time-series data. It shows the upward or downward line and represents the long-run growth or decline over time. The seasonal component is a regular fluctuation or known as periodic patterns that complete themselves within a calendar year and then repeated on a yearly basis. The methods used in this study to assist us in indicating the seasonal components are by calculating the seasonal indices, using the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF); and roughly from the data time series plot. The cyclical component in time series data refers to the rises and falls of the series over an unspecified period of time. The irregular component is the erratic movements in a time series that have no set or definable pattern. It is the variability remaining in the data when the effects of the other components are removed from the time series data. This component is also known as residuals or errors.

C. Step3: Constructing ELD Estimation Model.

There are a variety of methods to be used in constructing the estimation model of ELD. The models that can be applied depending on the situation, such as the type of time horizon used, which will affect the models that we choose, and the type of time series components. Due to the time series components in Step 2 results, in this study, two methods will be applied to forecast the ELD, which is the Holt-Winter's exponential smoothing (HWES) method and Seasonal Autoregressive Integrated Moving Average (SARIMA) Box-Jenkins Methodology.

a) Holt-Winter's Exponential Smoothing Method (HWES). The HWES method was selected among other exponential smoothing methods because it takes into account the trend and seasonality components. This method can handle data that has a linear trend as it can easily smooth the trend and slope directly by using different smoothing constants. Addictive effect assumption had also been used in this study because there are no multiple effects or double changes in the data. The model is then replaced with the number of t respectively for estimating 1, 2, and 3 steps ahead by using JMP software. The forecast value is calculated as [43]:

$$F_{t+m} = (L_t + b_t \times m)S_{t-s+m}$$

Where F_{t+m} is the forecast value for different number of a step ahead, L_t is the level component of the series, comprising of the smoothed values, but does not include the seasonality component, b_t is the estimate of the trend component, m is the number of step-ahead to be forecast, and S_tIs the estimate of the seasonality component.

b) Seasonal Autoregressive Integrated Moving Average (SARIMA). The first step to develop the SARIMA method is to indicate whether the seasonal component is present or not and check the stationarity of time series data.

There are five steps in the SARIMA modeling procedure:

Step 1: Check the data series for stationarity. If the data series is stationary, develop the ARMA (*p*,*q*) model.

Step 2: Check for the presence of the seasonality effect. If seasonality effect is not present, then perform the non-seasonal difference, $\Delta y_t = y_t - y_{t-1}$ Hence develop ARIMA (*p*,*d*,*q*). If the seasonality effect is present, proceed to Step 3.

Step 3: Perform seasonal differencing, $z_t = y_t - y_{t-12}$ for monthly data or $z_t = y_t - y_{t-4}$ for quarterly data.

Step 4: If the series, z_t is still non-stationary, then perform the non-seasonal difference on z_t series, $w_t = z_t - z_{t-1}$.

Step 5: Check stationarity. If the data series is now stationarity, develop SARIMA $(p,d,q)(P, D, Q)_{12}$ for monthly data or SARIMA $(p,d,q)(P, D, Q)_4$ for quarterly data.

After stationary is achieved and seasonal is identified, JMP will be used to find the best model of SARIMA through ARIMA model group based on some criteria of selection model, such as Akaike information criterion (AIC), Schwarz criterion (SBC), Ljung-box test, and significant parameter test [43],[44]. The formula is expressed as follows:

$$z_t = y_t - y_{t-12}$$

This formula is applied to monthly data series only.

D. Step4: Evaluating Models Performance.

In this process, the best model in forecasting the ELD had been chosen to predict the *m* step ahead of ELD. In the evaluation part of the data, we used MSE, RMSE, MAPE, and GRMSE as forecasting error measures. These four forecasting error measures were chosen to calculate the error because these error measures are the most popular used in forecasting. Error measures are used to determine the models that have the lowest error of measure in order to determine the best model in forecasting ELD.

E. Step 5: Forecasting ELD.

Finally, 1-month, 2-month, and 3-month ahead of ELD forecast values will be obtained based on the best forecasting model identified from Step 4.

IV. DATA ANALYSIS AND RESULTS

A. Pattern of Data

To illustrate the data, Microsoft Excel was used to plot all the data points, which represent the data collected by using a line plot. The time-series data are displayed inline graph, where the *Y*-axis represents the maximum ELD while the *X*-axis represents the month.

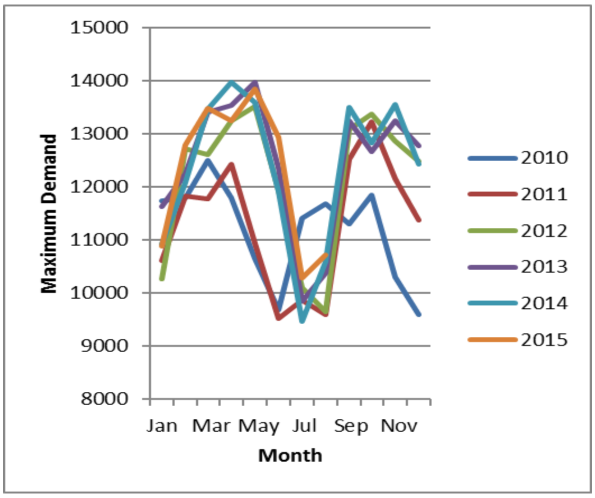
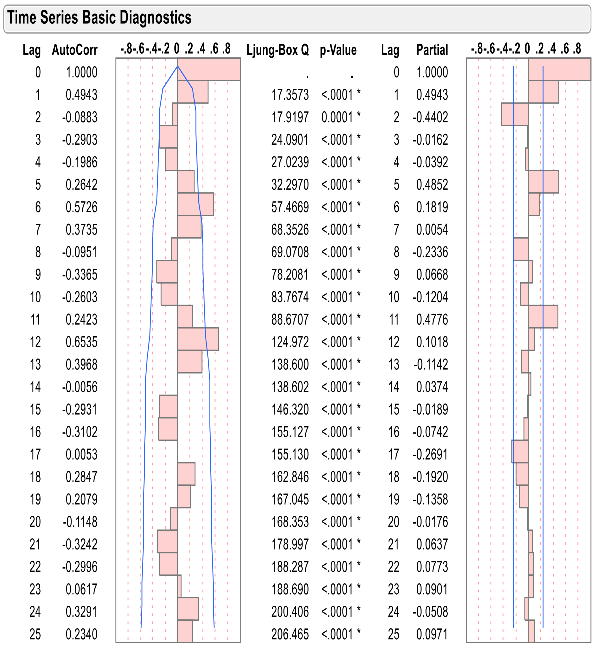


Fig 1: Overall time series data for maximum ELD

According to Fig. 1, based on the overall data collected, the highest maximum demand is in April 2014, which is 13976 kilowatt (kW), and the lowest maximum demand was also located in the same year, which is 9466 kW in July. The highest maximum demand may be due to the requirement of the lecture hall and student activities, whereas the lowest maximum demand is caused by the starting of a long semester break (two months).

B. Verification of Time Series Components

There are four types of components, which are seasonal, trend, irregular fluctuation, and cyclical. The time-series data need to be identified whether the components exist in the graph or not. There are different methods that can be used to identify the existence of different components. Fig. 2-4 are used to identify time series components. Fig. 2 shows the diagram of ACF and PACF, and by referring to the diagram, this study can conclude that seasonal components exist in the data because there are up and down and high and low changes that indicate that there is a seasonal component. Based on Fig. 3, there is an upward line showing that the data has an upward tendency from January 2010 until August 2015. Therefore, the trend component exists. Fig. 4 shows that there is no irregular or sudden pop-out point. Therefore, the irregular component does not exist in the time series data. Meanwhile, for checking the cyclical component, the relative cyclical residual values were calculated and based on those values, there are no sudden large differences of increase or decrease in value. Therefore, there is no cyclical component in the data. In conclusion, only seasonal and trend patterns exist in the data.



Time Series Basic Diagnostics

Lag	AutoCorr	Ljung-Box Q	p-Value	Lag	Partial
0	1.0000	.	.	0	1.0000
1	0.4943	17.3573	<.0001 *	1	0.4943
2	-0.0883	17.9197	0.0001 *	2	-0.4402
3	-0.2903	24.0901	<.0001 *	3	-0.0162
4	-0.1986	27.0239	<.0001 *	4	-0.0392
5	0.2642	32.2970	<.0001 *	5	0.4852
6	0.5726	57.4669	<.0001 *	6	0.1819
7	0.3735	68.3526	<.0001 *	7	0.0054
8	-0.0951	69.0708	<.0001 *	8	-0.2336
9	-0.3365	78.2081	<.0001 *	9	0.0668
10	-0.2603	83.7674	<.0001 *	10	-0.1204
11	0.2423	88.6707	<.0001 *	11	0.4776
12	0.6535	124.972	<.0001 *	12	0.1018
13	0.3968	138.600	<.0001 *	13	-0.1142
14	-0.0056	138.602	<.0001 *	14	0.0374
15	-0.2931	146.320	<.0001 *	15	-0.0189
16	-0.3102	155.127	<.0001 *	16	-0.0742
17	0.0053	155.130	<.0001 *	17	-0.2691
18	0.2847	162.846	<.0001 *	18	-0.1920
19	0.2079	167.045	<.0001 *	19	-0.1358
20	-0.1148	168.353	<.0001 *	20	-0.0176
21	-0.3242	178.997	<.0001 *	21	0.0637
22	-0.2996	188.287	<.0001 *	22	0.0773
23	0.0617	188.690	<.0001 *	23	0.0901
24	0.3291	200.406	<.0001 *	24	-0.0508
25	0.2340	206.465	<.0001 *	25	0.0971

Fig 2: Diagram of ACF and PACF for seasonal component

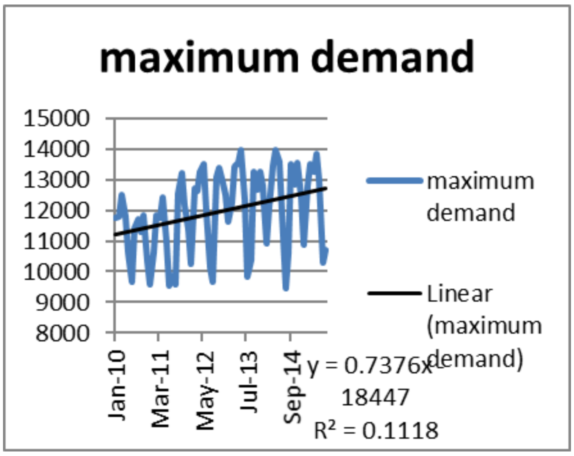


Fig 3: Trend component obtained in the graph

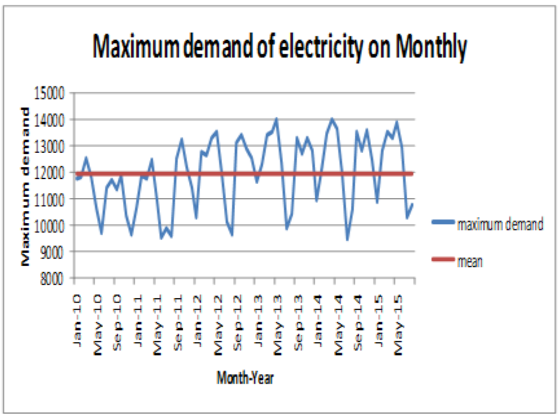


Fig 4: Maximum demands and mean for overall time-series data

C. Model Estimation

After defining the type of time series components, this study continued to identify which model is the best to forecast ELD. Two forecasting methods were constructed to forecast ELD using the HWES method and SARIMA Box-Jenkins Methodology.

After determining the types of time series components, this study continued to identify the best model in predicting maximum ELD. In the model estimation part, we used 63 data to model ELD using the HWES method and SARIMA Box-Jenkins Methodology.

a) Holt-Winter's Exponential Smoothing Method (HWES)

Table 1 shows the fitted values of the HWES method for 1, 2, and 3 steps ahead. The fitted values are obtained from JMP software by using confidence intervals of 0.95, and the constraint is between 0 and 1.

Table 1: Fitted values for HWES method

Month -Year	Actual	Fitted		
		One step	Two step	Three step
April -15 (t=64)	13248	13974.04		
May -15 (t=65)	133856	13529.48	13602.38	
Jun -15 (t=66)	12943	11884.47	11853.72	11950.18
July -15 (t=67)	10291	9547.57	9453.99	9412.29
August -15 (t=68)	10725	10821.31	10737.50	10606.3

b) Seasonal Autoregressive Integrated Moving Average (SARIMA)

Fig. 5 shows the ACF (left-side diagram) and PACF (right-side diagram) of the time series data calculated using JMP software. Both results can be considered stationary because the patterns do not indicate a significant change.

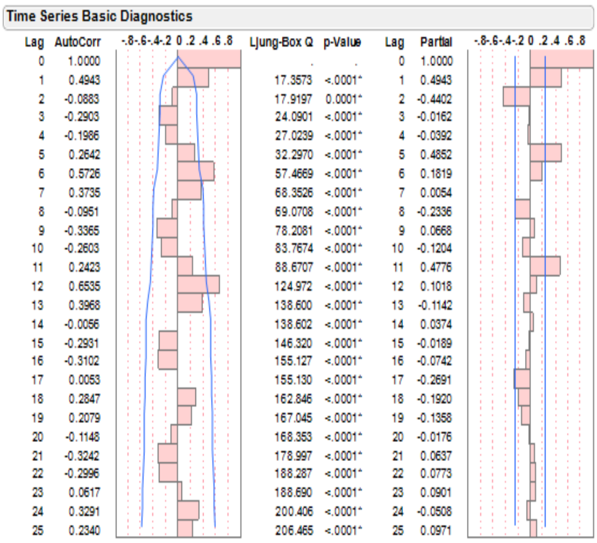


Fig. 5: The ACF and PACF of maximum ELD

For ACF, there are 6 spikes that can be found at lag 0, lag 1, lag 3, lag 6, lag 7, and lag 12. At lag 3 and lag 7, they are barely touching the standard error line. On the other hand, the PACF shows 7 spikes, where the most significant values are at lag 0, lag 1, lag 2, lag 5, and lag 11 because they exceeded the standard error line. Meanwhile, at lag 8 and lag 11, both barely touch the standard error line. After that, the best SARIMA model is selected. The value of *p* (autoregressive model, PACF) and *q* (moving average model, ACF) can be determined by looking at the number of spikes in PACF and ACF, respectively. The value of *d* is representing the order of differencing, and the assumed *p*-value is 0.05. By using the ARIMA group data in JMP software, the best model for SARIMA is SARIMA (0,0,1) $(1,0,0)_{12}$ because it has the lowest AIC and SBC, which are 1104.24881 and 1110.90733 respectively, and all the models that are significant can found in Table 2. The model is then used to calculate the 1, 2, and 3 steps ahead. Table 3 shows the fitted values of SARIMA for 1, 2, and 3 steps ahead.

Table 2: Parts of output from SARIMA

SARIMA Model	AIC	SBC	Significant	Comment
(0,0,1) (1,0,0)12	1104.2488	1110.9073	All significant.	Yes
(0,0,1) (2,0,0)12	1104.0053	1112.8834	AR2,24 not significant.	No
(0,1,1) (0,0,2)12	1104.3797	1113.1985	All significant.	No
(0,2,2) (0,2,1)12	712.6560	719.6067	MA2,12 not significant.	No
(0,2,2) (1,2,1)12	713.3501	722.0384	AR2,12 and MA2,12 not significant.	No
(0,2,2) (2,2,0)12	713.6221	722.3104	AR2,24 not significant.	No
(1,2,2) (0,2,1)12	711.1422	719.8305	AR1,1 and MA2,12 not significant.	No
(1,2,2) (0,2,2)12	711.9432	722.3692	AR1,1,MA2,12 and MA2,24 not significant.	No
(1,2,2) (2,2,0)12	713.5767	725.7404	AR1,1, AR2,12, AR2,24 and MA2,12 not significant.	No
(2,0,1) (2,0,2)12	1104.0559	1121.8119	AR2,12, AR2,24 and MA2,24 not significant.	No

Table 3: Fitted values for SARIMA

Month -Year	Actual	Fitted		
		1 step	2 step	3 step
April -15 (t=64)	13248	13756.01		
May -15 (t=65)	13856	12985.05	13225.37	
Jun -15 (t=66)	12943	12302.39	11883.57	11993.02
July -15 (t=67)	10291	10759.59	10422.46	10213.62
August -15 (t=68)	10725	11093.2	11314.16	11146.5

D. Model Evaluation

In the model evaluation part, we used 5 data to calculate 4 error measures in order to identify the best model for forecasting ELD. Tables 4-6 indicate the overall evaluation of error for 1 month ahead, 2 months ahead, and 3 months ahead of forecast, respectively, between HWES and SARIMA model. Based on Tables 4-6, the results demonstrate that SARIMA is the best model to be used in forecasting ELD because it has the lowest error measurements for all situations.

Table 4: Overall evaluations for 1 month ahead

Model	MSE	RMSE	MAPE	GRMSE
HWES Method	463240.7	680.6179	4.827479	447.6079
SARIMA	210146.1	458.417	2.845644	259.9292

Table 5: Overall evaluations for 2 months ahead

Model	MSE	RMSE	MAPE	GRMSE
HWES Method	487900	698.4984	4.624098	231.8862
SARIMA	443678.8	666.0922	4.275507	367.7974

Table 6: Overall evaluations for 3 months ahead

Model	MSE	RMSE	MAPE	GRMSE
HWES Method	590634.7	768.5276	5.772014	469.5898
SARIMA	379398.2	615.9531	3.723301	269.0252

E. Forecast Electricity Load Demand for Next Month by Using Best Model

From the model evaluation part, SARIMA (0,0,1) $(1,0,0)_{12}$ is the best model to forecast ELD for this study. Therefore, this SARIMA model will be used to predict the future values for the next 1, 2, and 3 months. By using JMP, the forecast values for next month, next 2 months, and next 3 months are 12956.27 kW, 12556.88kW, and 13063.16 kW, respectively.

V. CONCLUSIONS

This study demonstrates the successful application of exponential smoothing and the Box-Jenkin method in medium-term ELD forecasting. In conclusion, after testing all the methods chosen, this study found that SARIMA is the best model to forecast ELD in UUM. In this study, ELD in UUM has both trend and seasonal components. SARIMA (0,0,1) (1,0,0)12 model is the best model to be used for forecasting the next 1, 2, and 3 months ahead. It is shown that the SARIMA model from Box-Jenkins methodology is adequate in medium-term ELD forecasting due to MAPE values in m-step ahead, which are below 5%. This study also discovered that ELD is low during a long semester break, and the load demand is high when the semester begins. This study will assist university management in predicting the ELD of the campus for the next month. It can also help in planning future ELD to avoid wastage. This study uses only monthly data, otherwise known as medium-term data, to predict ELD. If there are different types of data, especially in daily or weekly data, they can help the university management to plan load requirements more efficiently.

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