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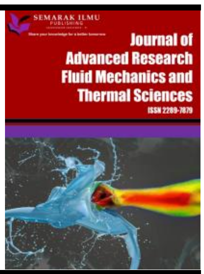

Load Profile Forecasting using a Time Series Model for Solar Rooftop and Integrated Carpark of a Public University in Malaysia

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ABSTRACT

A precise and accurate load prediction is critical in a developing country like Malaysia to save the energy consumption. Power producers use load profile data and statistics to analyze and forecast the quantity of electricity required to be available at a given time. Load forecasting is the process of predicting future load requirements and this research focuses on the short-term load forecasting (STLF) for solar rooftop and integrated car park built at one of the public universities in Malaysia. Power system planners and demand controllers must ensure that there is enough generation to meet the increased demand. Load forecasting models that are accurate can lead to better budgeting, maintenance scheduling, and fuel management. This project seeks to anticipate the highest demand of power utilized by the consumer based on prior load profiles using a Multiple Regression Time Series model developed using MATLAB software. It consists of the following steps: data collection, clustering, series transformation using differentiation transform to remove trend and seasonal structure from the dataset, model identification using autocorrelation function (ACF) and partial correlation function (PCF), model estimation using ARIMA time series errors and maximum likelihood probability, and finally model forecasting using Auto Regression (AR), Moving Average. In this case, the goal is to ensure the power production equals electricity demand, and achieving the target will assure energy security, dependability, and the capacity to maximize profits while minimizing losses.

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1. Introduction

The electrical component of a circuit that actively consumes electric power such as lighting and electrical appliances is referred to as the load. A load profile on the other hand, is a graph that depicts how the electrical load changes over time. Temperature, holiday seasons, and customer types such as commercial, industrial, and residential have a significant impact on load profiles. Power producers utilize this data and statistics to analyze and forecast the amount of electricity required to be available at a given time. A load profile also displays the average customer's pattern of electricity usage by day and year. There are also statistics that depict the average consumption pattern of a residential contestable customer over each half-hour interval, beginning at 0:00 hours as calculated and published by the authority depending on the forecasted horizon. Load forecasting on the other hand, is defined as the prediction of load profile trends. It reduces utility risk by forecasting future usage of goods transmitted or delivered by the utility. Load forecasting makes use of price elasticity, weather, demand response/load analysis, and renewable energy generation. Forecasts must be based on regional customer load data as well as changing customer load characteristics [1]. Distribution load projections must be matched with distribution network configuration as part of the distribution circuit load measurements. Forecasting the load profile is critical in making the best power production decision, therefore its accuracy will have a substantial impact on the power system, which is the primary goal of most energy management systems.

A precise and accurate load prediction is critical in a developing country like Malaysia to save energy and to ensure that no energy is wasted. Controlling the spot market price of energy is possible by forecasting a precise and accurate load profile. To maintain system stability, power distribution and generation must be exactly balanced [2]. Analytics that can anticipate energy security and dependability can improve energy security and dependability while also assisting in cost-cutting for the utility company and its users [3]. This indicates that load profile analysis and forecasting are critical, allowing the power provider to develop solid plans based on projected future load demand. Estimating future long-term load also assists the utility organization (Tenaga National Berhad) in developing economically viable strategies for future generation and transmission projects, allowing the utility company's risks being kept as low as possible because load forecasting can prevent under or over generation [4,5]. When there is good short-, medium-, and long-term planning, it will also aid in identifying the necessary resources, such as the number of solar panel installations required to ensure uninterrupted and cost-efficient power generation and delivery to consumer buildings. Furthermore, understanding the load demand is critical in formulating decisions and plans for power system maintenance, where the utility company may schedule repair and ensure that it has the least negative impact on customers.

2. Methodology

2.1 MATLAB Software

MATLAB software is a programming and numerical technology system used by engineers and scientists to analyze, to modify, and to create models. Matrix manipulation, data and function visualization, algorithm formulation, user interface design, and integration with other programming languages are all possible with MATLAB software. The MATLAB software application is based on the MATLAB programming language, which uses the "Command Window" as a mathematical interpreter to runs the MATLAB code. Machine learning is used in MATLAB software to train models, optimize parameters, and deploy models. Machine learning applications' regression learner trains regression models to forecast data [6]. This tool allows you to examine the data, pick features, select validation

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schemes, train models, and assess the results. It can also perform automatic training to determine the best regression model type, including linear regression models, regression trees, Gaussian process regression models, support vector machines, kernel approximation models, regression tree ensembles, and neural network regression models. A series of past samples of input data and recorded results can be used to do supervised machine learning. The results are used to train a model that predicts reactions to a future dataset.

2.2 Operation of the System

Figure 1 shows the full flowchart of this study, and the explanation of the flowchart is discussed in 5 (five) sections which are the Section 1: Data gathering and Clustering, Section 2: Series transformation, Section 3: Auto Correlation & Partial Correlation for Model Identification, Section 4: Model Estimation and Section 5: Model forecast.

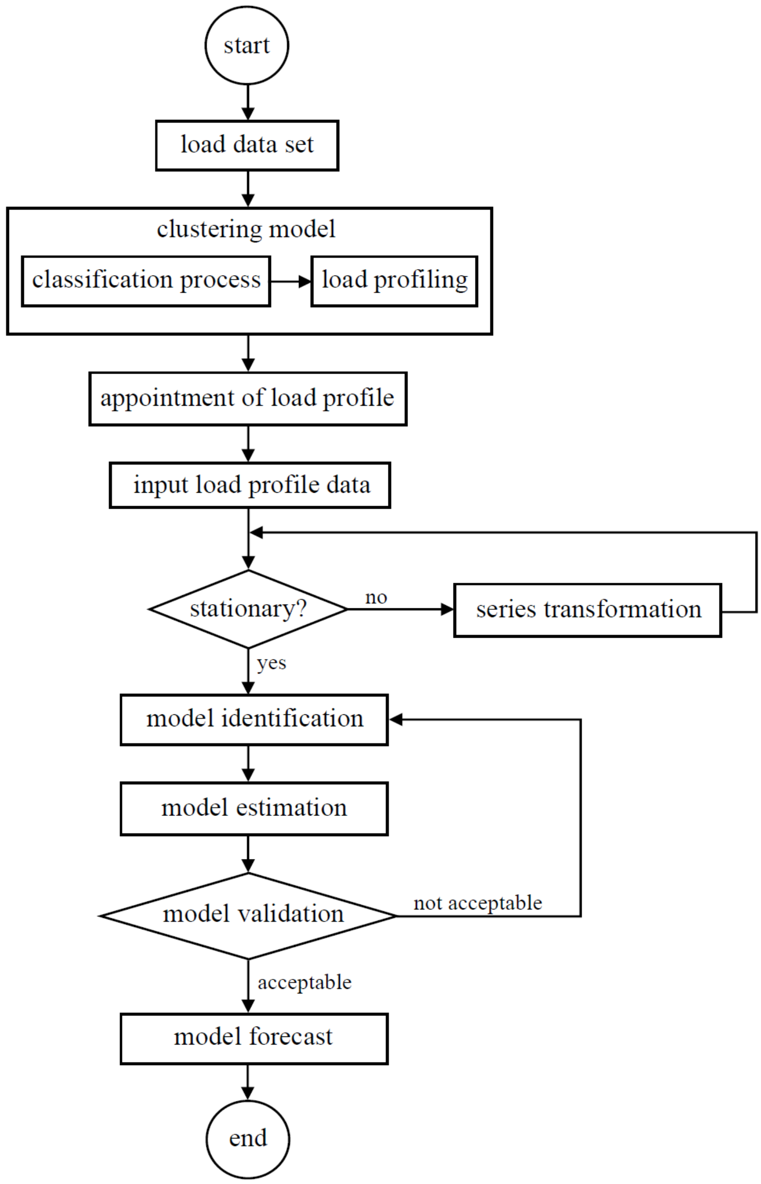


Fig. 1. Flowchart of overall system load profiles using a Multiple Regression Time Series model developed using MATLAB software

2.2.1 Section 1: Data gathering and clustering

The main utilities firm in Malaysia, Tenaga Nasional Berhad (TNB) has provided the time series load data for the solar rooftop and integrated carpark in one of the public universities in Malaysia, which illustrates the average consumption pattern throughout each half-hour period beginning at 0:00 hours. The information obtained pertains to the electrical load utilization in April, October, and November of 2019. The load data set has been supplied as an input into the MATLAB software to go through the clustering procedure, which involves data classification and load profiling. Clustering is a machine learning-based data mining technique that classifies groupings of abstract items into classes of similar things. It is beneficial to divide data into subgroups. Each of these clusters is made up of data that has a high inter-similarity but a low intra-similarity. There are several types of clustering approaches, including partitioning methods, hierarchical methods, density-based methods, grid-based methods, model-based methods, and constraint-based methods [7]. Clustering is used to categorize electricity usage into three groups: highest, medium, and lowest. It will display the pattern and difference in electricity usage over the time.

2.2.2 Section 2: Series transformation

The data is then displayed as time domain and frequency domain signals. The load profile data is assigned to the stationary verification procedure, which allows the series transformation to take place. In machine learning, four transformations are commonly used: difference transform, power transform, standardization, and normalization. To make forecasting easier, the differencing transform operation is used to remove both trend and seasonal structure from the dataset [8]. A difference transform is a simple approach for removing the systematic structure of a time series. To erase the trend, first order differencing is performed by subtracting the previous value from each value in the series. A single differenced value in a series is computed using the custom function difference (data, interval). To calculate the difference, the function requires the time series and the interval. To eliminate second-order trends, the method can be repeated to differentiate the differentiated series [9,10]. Similarly, by subtracting data from the preceding season, a seasonal structure can be extracted. The data is filtered based on the seasonality found based on the harmonics in the frequency domain signal. The signal is then deseasoned to eliminate the seasonal signal from the daily time series data [11,12].

2.2.3 Section 3: Auto correlation and partial correlation for model identification

ARIMA models are used to describe the autocorrelations in data. The signal's auto correlation and partial auto correlation are then evaluated to determine whether the model is AR (Auto Regressive), MA (Moving Average), or ARMA (Auto Regressive Moving Average). To analyze the properties of time series data, match the appropriate models, and produce forecasts, autocorrelation and partial autocorrelation functions are used. A time series data autocorrelation is the correlation of two values at distinct time points. The lag is the length of time between two data points [13]. Values separated by intervals can have a highly positive or negative correlation. When these relationships exist, it indicates that former values influence the present value. The autocorrelation function (ACF) assesses the relationship between data points in a time series given a set of lags. The ACF formula for the time series y is as in Eq. (1):

$$\mathrm{Corr}\ (yt,\ yt\text{-}k),\ k=1,2,... \tag{1}$$

In mathematical terms, k time units represent the lags where the data is split at yt and yt-k to determine whether the lags have significant correlations to analyse the patterns and attributes of the time series and then to model the time series data using this insight [14,15]. ACF can be used to examine time series data variation and stationarity, as well as current that surpasses the red parallel line shown in Figure 2, Figure 3, and Figure 4. The partial autocorrelation function (PACF), on the other hand, is comparable to the ACF in that it only indicates the link between two observations that cannot be explained by the shorter delays between them. For example, the auto correlation function (ACF) can be used to evaluate the properties of a time series, whereas the partial auto correlation function (PACF) is more useful when creating an autoregressive model. Partial autocorrelation graphs are commonly used to specify regression models with time series data and Auto Regressive Integrated Moving Average (ARIMA) models [16].

2.2.4 Section 4: Model estimation

The model is then estimated based on seasonality before proceeding to the validation process. The estimator function in MATLAB uses maximum likelihood probability to estimate the parameters of the regression model using ARIMA time series errors [9]. The autoregressive integrated moving average (ARIMA) model is used to fit the data [17]. These time series models are examined and validated to ensure that they work properly and produce accurate forecasts.

2.2.5 Section 5: Model forecast

Load projections are classified into three types: short-term (STLF), medium-term (MTLF), and long-term (LTLF) [18]. This project focuses on STLF, which can span from one hour to one week and is concerned with hourly and daily peak system load forecasts as well as daily or weekly system energy projections. STLF approaches include multiple linear regression, stochastic time series, and an artificial intelligence-based solution. The main method in this project is the multiple linear regression method. Forecasting models are based on available resources and data, the dependability of competing models, and the intended application of the forecasting model [19]. The primary goal is to foresee future events rather than to analyze their causes. A time series model forecasts more precisely than an explanatory or mixed model. Time series forecasting methods include decomposition models, exponential smoothing techniques, and ARIMA models. The most common technique to time series forecasting is ARIMA models, which provide a variety of solutions to the problem [20]. Following that, the load profile data is used for forecasting with the predetermined amount of samples, 400 samples, and 10 iterations. In the autoregression model, the electrical load is projected using a linear combination of the previous values of the electricity load. The term autoregression refers to the process of regressing a variable against itself. An autoregressive model of order p is written as in Eq. (2):

$$y_t = c + \emptyset_1 y_{t-1} + \emptyset_1 y_{t-2} + \cdots + \emptyset_p y_{t-p} + \varepsilon_t \tag{2}$$

where ε_t is the white noise. This is similar to a multiple regression, except the variables are lagged by y_t values. It is known as an AR(p) model, which is an autoregressive model of order p. Autoregressive models are exceptionally pliable in their ability to accommodate a broad variety of time series patterns.Meanwhile, the moving average model (MA) leverages previous forecast errors in a regression-like model and the equation of the moving average of order q, MA(q) model is expressed as in Eq. (3).

$$y_t = c + \varepsilon_t + \theta_1\varepsilon_{t-1} + \theta_1\varepsilon_{t-2} + \cdots + \theta_q\varepsilon_{t-q} \tag{3}$$

Combining differentiation with autoregression and a moving average model produces a non-seasonal ARIMA model. The abbreviation of ARIMA stands for Auto Regressive Integrated Moving Average. The full model of ARIMA (p,d,q) can be written as in Eq. (4).

$$y'_t = c + \emptyset_1 y'_{t-1} + \ldots + \emptyset_p y'_{t-p} + \theta_1\varepsilon_{t-1} + \theta_q\varepsilon_{t-q} + \varepsilon_t \tag{4}$$

where y't is the differenced series, p is the order of the autoregressive component, d is the degree of first differencing included, and q is the order of the moving average section. The "predictors" comprise both lagged values of yt and lagged errors. ARIMA models are subject to the same stationarity and invertibility criteria as autoregressive and moving average models [20]. Finally, the result of the forecasted result is exported and sorted in Microsoft Excel to be presented as a load profile for future usage.

3. Results and Discussion

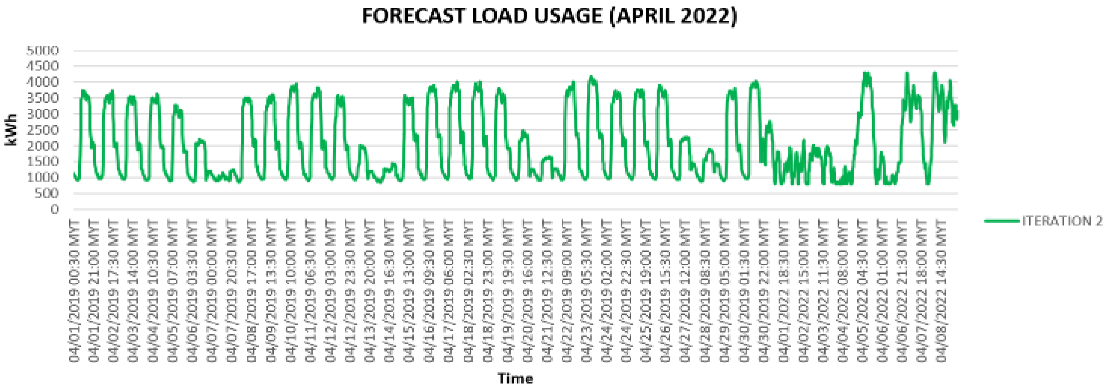
3.1 Load Forecasting of April 2019 Data

Table 1 summarizes the anticipated load data in the month of April, where it is expected that the student capacity for the upcoming year is 100%. It consists of the load profile's minimum load demand of 800 kWh as the base load and Figure 2 expresses the forecasted simulation of April 2019 electricity load usage from the Multiple Regression Time Series model developed using MATLAB software for iteration 2, 3, 6 and 7 that shows significant impact to the value of load forecasted in kWh. From the graph, it is shown that the maximum and minimum load were 4300kWh and 800kWh for all iterations, as tabulated in Table 1.

Table 1
Summary of The Forecasted Load In Data April

Number of Iteration	Minimum Load (kWh)	Maximum Load (kWh)	Average Load (kWh)
Iteration 1	800	4300	2625.079110
Iteration 2	800	4300	1856.745172
Iteration 3	800	4300	2605.953211
Iteration 4	800	4300	2461.925949
Iteration 5	800	4300	2301.070631
Iteration 6	800	4300	2366.587601
Iteration 7	800	4300	2627.724528
Iteration 8	800	4300	2665.769778
Iteration 9	800	4300	2853.834919
Iteration 10	800	4300	2645.972618

The lowest average value was 1856.745172 kWh at iteration two, and the rest of the value was similar for iteration 1 and iteration 3-10. Based on this value it is concluded the Multiple Regression Time Series up until 10^{th} iteration is needed to determine the exact average value for the load in kWh to prevent the disorientation of the calculated value the maximum load demand of 4300 kWh as the peak load. From iteration 1 through iteration 10, the average load demand per hour is 2625 kWh, 1857 kWh, 2606 kWh, 2462 kWh, 2301 kWh, 2367 kWh, 2628 kWh, 2666 kWh, 2854 kWh, and 2646 kWh, respectively. As a result, the lowest average load demand is 1857 kWh, and the maximum is 2854 kWh. Meanwhile, for iteration 1 through 10, the total anticipated load demand was 877999 kWh, 622975 kWh, 871300 kWh, 824006 kWh, 771009 kWh, 794008 kWh, 878656 kWh, 891492 kWh, 957429 kWh, and 884766 kWh. As a result, the lowest weekly total load demand is 622975 kWh, and the maximum weekly average load demand is 957429 kWh.



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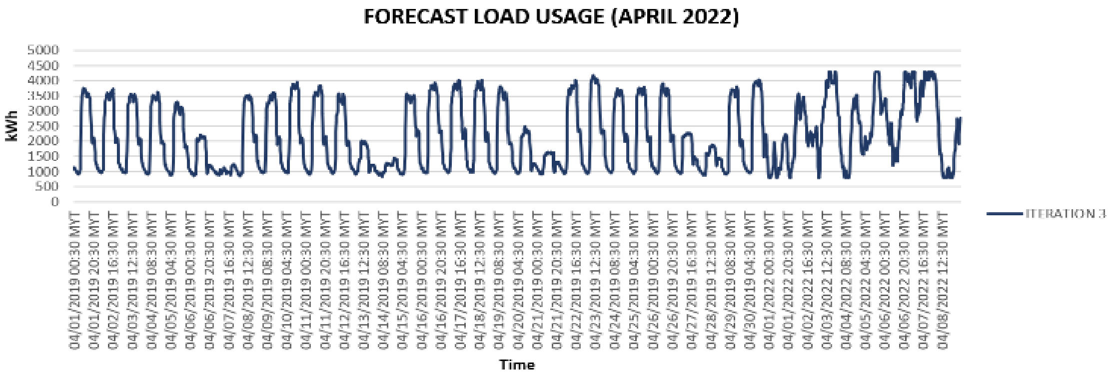

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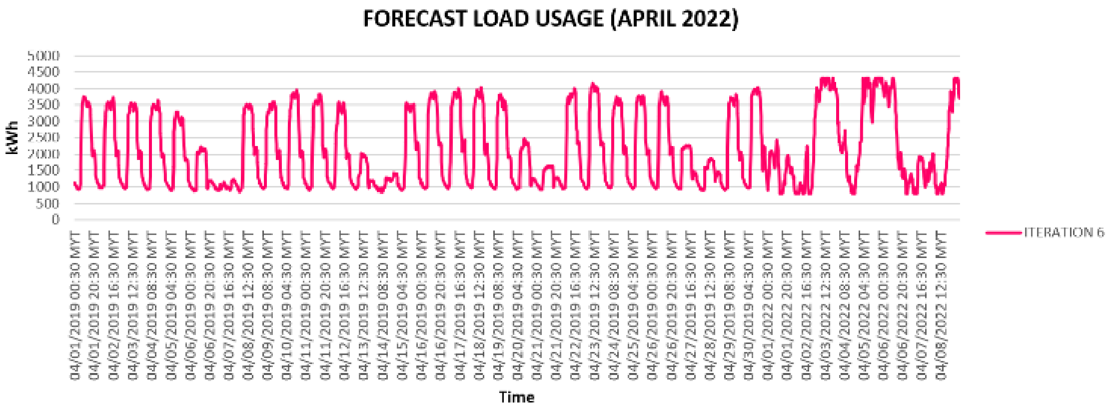

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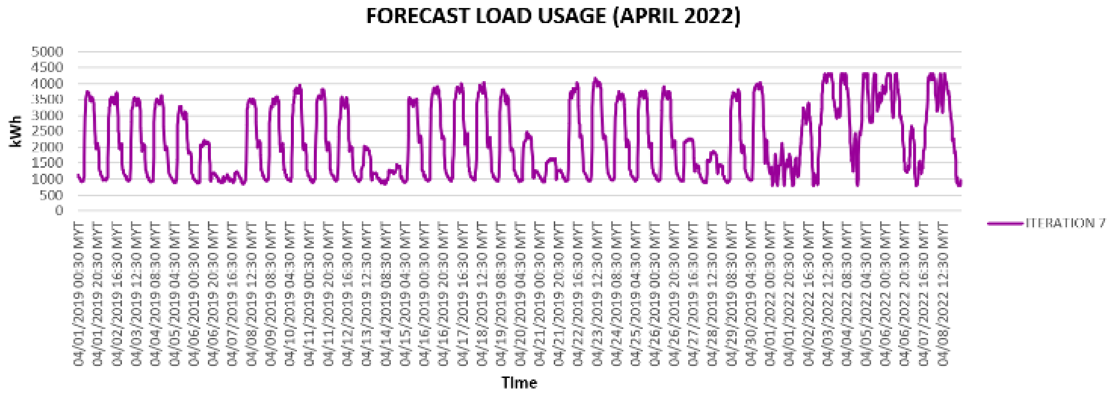

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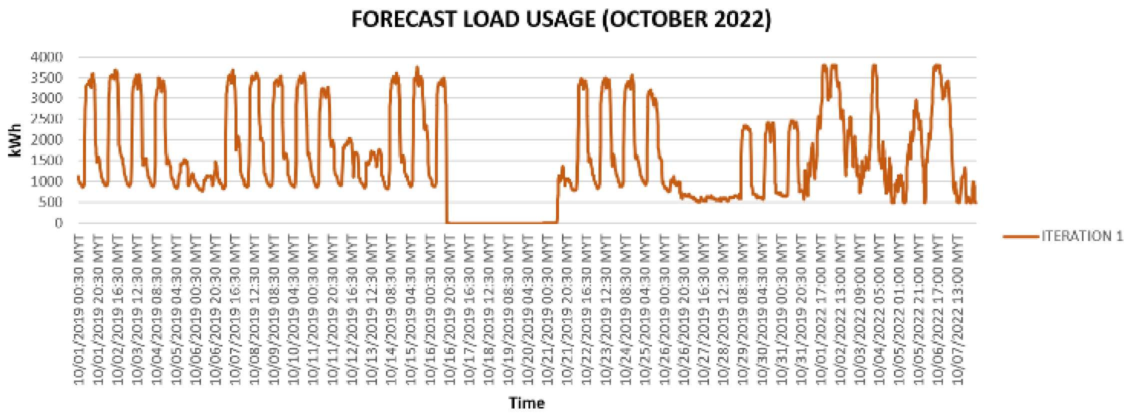
Fig. 2. Forecasted simulation of April 2019 electricity load usage at different iterations (a) Iteration 2 (b) Iteration 3 (c) Iteration 6 (d) Iteration 7

3.2 Load Forecasting of October 2019 Data

Figure 3 expresses the forecasted simulation of October 2019 electricity load usage from the Multiple Regression Time Series model developed using MATLAB software for iteration 1, 4, 6 and 10 that shows significant impact to the value of load forecasted in kWh. From the graph, it is shown that the maximum and minimum load were 3800kWh and 500kWh for all iterations, as tabulated in Table 2. The lowest average value was 1507.625562 kWh at iteration 4, and the second lowest is 1549.423105kWh at iteration 3. As shown in the table, the rest of the value was similar for iteration 1 and iteration 7-10. Based on this value it is concluded that the average value for October 2023 is not as high as April 2019 and the reason is because students were on their semester break on October each year. The outline of the predicted load data for the month of October 2019 is shown in Table 2. It consists of the minimum load demand of 500 kWh as the base load and the highest load demand of 3800 kWh as the load profile's peak load. From iteration 1 through iteration 10, the average load demand per hour is 1984 kWh, 2948 kWh, 1549 kWh, 1508 kWh, 2171 kWh, 1929 kWh, 2004 kWh, 2026 kWh, 2815 kWh, and 2006 kWh. Thus, the lowest average load demand is 1507 kWh, while the highest is 2947 kWh. Meanwhile, for iteration 1 through 10, the total anticipated load demand was 672057 kWh, 995699 kWh, 524364 kWh, 510585 kWh, 734576 kWh, 651217 kWh, 675451 kWh, 684481 kWh, 951876 kWh, and 677015 kWh. As a result, the lowest weekly total load demand is 510585 kWh and the highest weekly average load demand is 951876 kWh.



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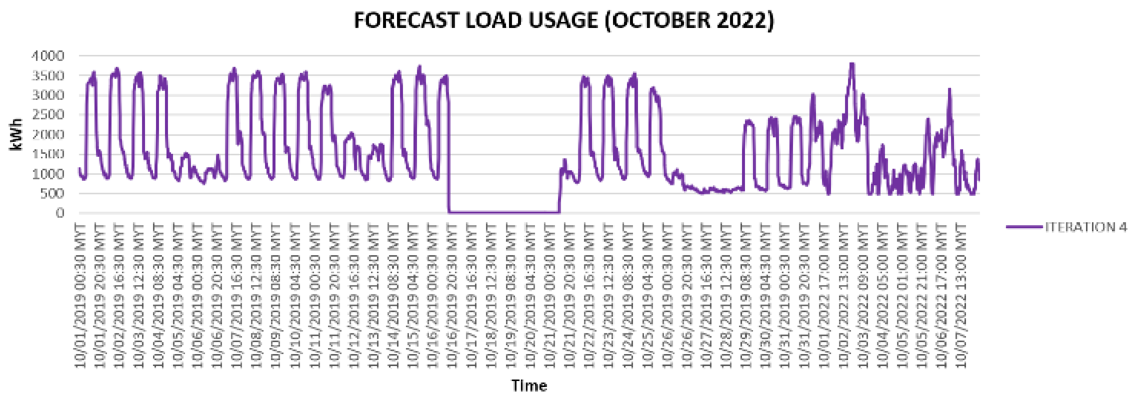

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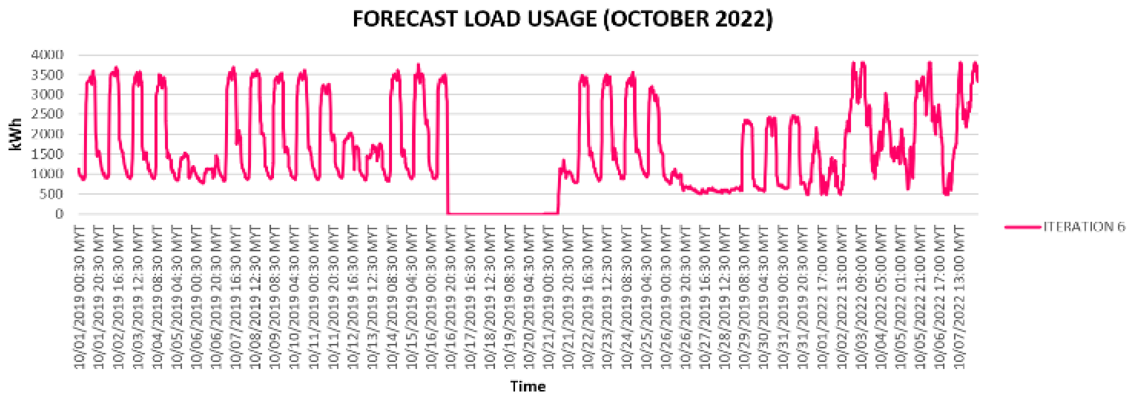

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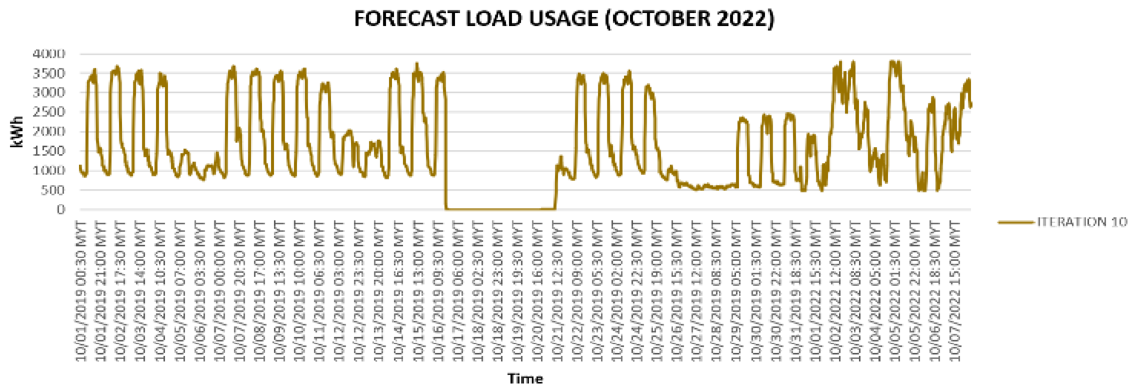


(d)

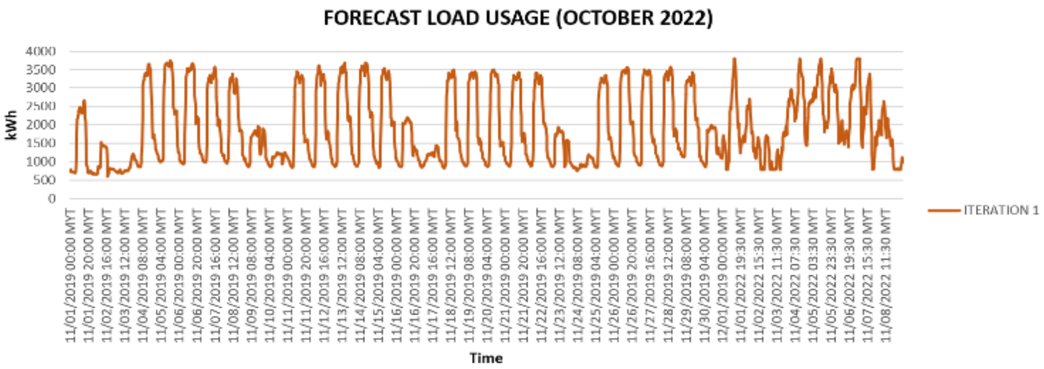
Fig. 3. Forecasted simulation of October 2019 electricity load usage at different iterations (a) Iteration 1 (b) Iteration 4 (c) Iteration 6 (d) Iteration 10

Table 2
Summary of the Forecasted Load Data in October

Number Of Iteration	Minimum Load (kWh)	Maximum Load (kWh)	Average Load (kWh)
Iteration 1	500	3800	1984.033931
Iteration 2	500	3800	2947.695180
Iteration 3	500	3800	1549.423105
Iteration 4	500	3800	1507.625562
Iteration 5	500	3800	2170.585038
Iteration 6	500	3800	1929.493357
Iteration 7	500	3800	2003.519876
Iteration 8	500	3800	2026.265289
Iteration 9	500	3800	2815.398880
Iteration 10	500	3800	2006.248225

3.3 Load Forecasting of November 2019 Data

From the graph shown in Figure 4, the minimum load demand is 800 kWh as the base load, and the highest load demand is 3800 kWh as the peak load of the load profile, according to Table 3 of anticipated load demand from November 2019 data. From iteration 1 through iteration 10, the average load demand per hour is 2162 kWh, 2206 kWh, 2013 kWh, 2445 kWh, 2543 kWh, 2230 kWh, 2377 kWh, 2414 kWh, 1616 kWh, and 2253 kWh, respectively. As a result, the minimum average load demand is 1616 kWh, and the maximum average load demand is 2543 kWh. Meanwhile, for iteration 1 through 10, the total anticipated load demand was 730254 kWh, 746753 kWh, 679464 kWh, 826675 kWh, 860026 kWh, 752885 kWh, 802003 kWh, 814759 kWh, 545302 kWh, and 762937 kWh. Thus, the lowest weekly total load demand is 545302 kWh, and the greatest weekly average load demand is 860026 kWh.



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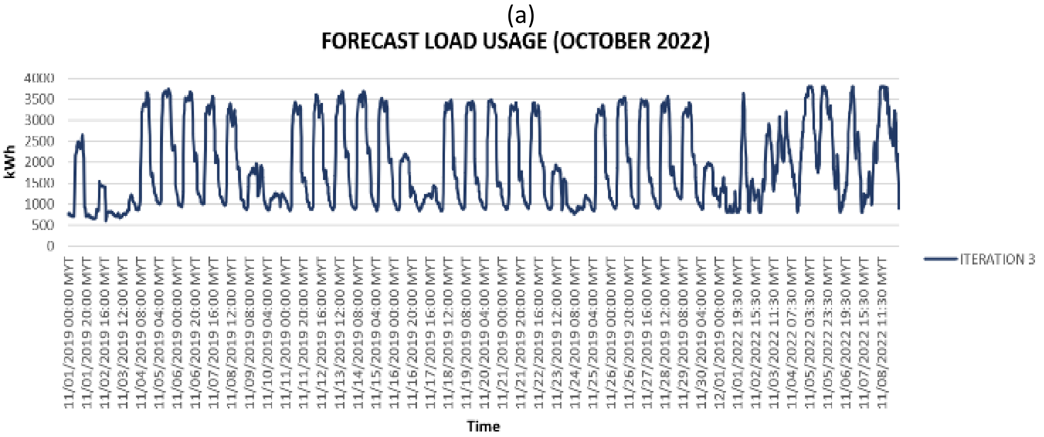

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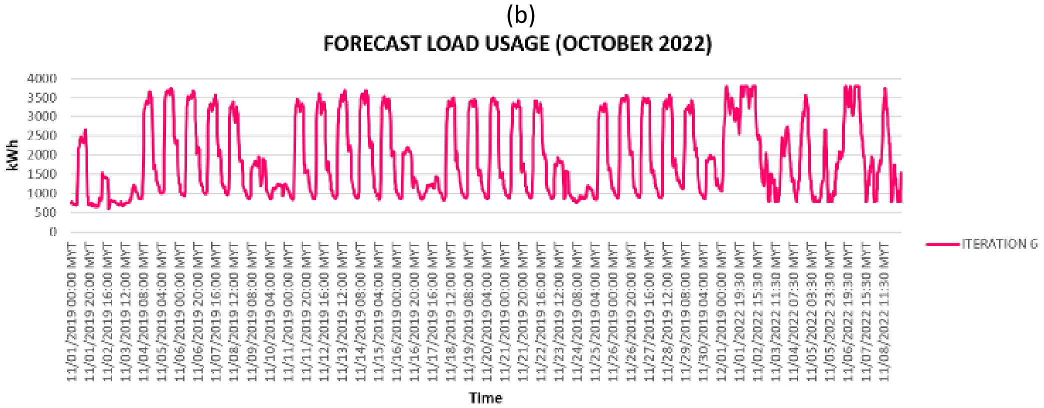

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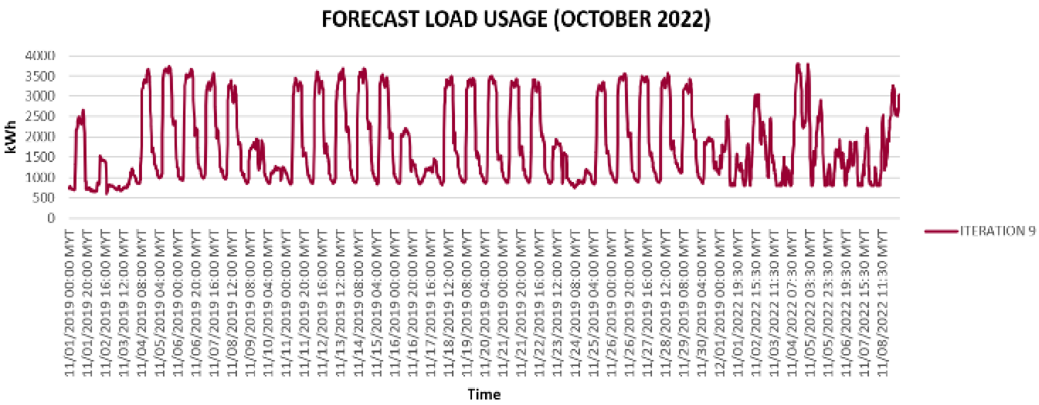

(d)

Fig. 4. Forecast simulation of November 2019 electricity load usage at different iterations (a) Iteration 1 (b) Iteration 3 (c) Iteration 6 (d) Iteration 9

Table 3
Summary of The Forecasted Load Data in November.

Number Of Iteration	Minimum Load (kWh)	Maximum Load (kWh)	Average Load (kWh)	Total Load For 1 Week (kWh)
Iteration 1	800	3800	2162.211676	730253.9373
Iteration 2	800	3800	2205.559346	746752.9855
Iteration 3	800	3800	2013.302390	679464.0066
Iteration 4	800	3800	2444.947603	826674.8429
Iteration 5	800	3800	2543.226672	860026.4519
Iteration 6	800	3800	2229.612244	752884.5029
Iteration 7	800	3800	2376.861085	802003.3842
Iteration 8	800	3800	2413.93898	814759.2649
Iteration 9	800	3800	1615.732558	545301.8721
Iteration 10	800	3800	2252.906436	762937.1446

In this study, the load profile from Solar Rooftop and Integrated Carpark for a few months in 2019 is used to anticipate the load demand in 2022. Because Malaysia has been plagued by a Covid-19 epidemic, the load profile for 2020 and 2021 has been removed due to data ambiguity. As a result, this project is focused on future load demand after the pandemic has finished and students have begun to enroll the university at full capacity. Table 4 displays the minimum and highest load demand for the months of April, October, and November 2019, which are 847 kWh to 4173 kWh, 0 kWh to 3754 kWh, and 603 kWh to 3744 kWh, respectively. For that year, the average electrical load is 2081 kWh, 1469 kWh, and 1867 kWh for each of the specified months. Furthermore, for one week, the total load is 659869 kWh, 619461 kWh, and 595091 kWh. When comparing raw load data to anticipated load data, the minimum, maximum, and average load are nearly identical across each month. The total load utilization for 1 week in the future, on the other hand, is predicted to increase because the discrepancy between the historical data and the forecasted result is roughly 5% to 10%. This could be related to the growing popularity of UiTM students. In 2019, the popularity of students at the university is around 181501, while in 2021, the popularity is 185303. This indicates that the number of students at UiTM has risen by 1%. Furthermore, as many modern technologies are designed to be rechargeable, this increase in load demand could be driven by an increase in electrical appliance consumption. As a result, more electricity will be used in the future. Through this project, the utilities firm (Tenaga National Berhad-TNB) can create power near to the load by detecting sites or regions with high or rising demand [21].

Table 4
Summary of Raw Data In 2019

Year 2019 Load Data	April	October	November
Minimum Load (kWh)	847	0	603
Maximum Load (kWh)	4173	3754	3744
Average Load (kWh)	2080.758306	1469.060352	1867.239095
Total Load For 1 Week (kWh)	659869	619461	595091

4. Conclusion and Recommendation

In conclusion, a precise and accurate load prediction is crucial to save the energy. Load profile data and statistic are used by power producers to analyze and forecast the amount of electricity that is needed to be accessible at a particular time. Load forecasting is the technique of anticipating future load requirements. The type of load forecasting that is focusses on this research is short term load forecasting (STLF). It is important for power system planners and demand controllers to ensure that there is sufficient generation to meet the rising demand. Accurate load forecasting models can result in improved budgeting, maintenance scheduling, and fuel management. Using multiple regression time series model with MATLAB, this research attempts to predict the highest demand of power used by the consumer based on the past load profiles. It includes the steps of data gathering, clustering, series transformation using differentiation transform to eliminate trend and seasonal structure from the dataset, model identification using autocorrelation function (ACF) and partial correlation function (PCF), model estimation that estimates the parameters of the regression model with ARIMA time series errors using maximum likelihood probability and lastly model forecasting using Auto Regression (AR), Moving Average (MA) and Auto Regression Integrated Moving Average (ARIMA) model.

In contrast, the recommendation that can be done to this project is gathering more load profile dataset from different years to compare and analyze in detail about the load demand in the campus. The unavailability of the 2022 load profile data from TNB has affected the analyzation of the future load demand where the comparison cannot be done. Further analyzation with more data will result in more accurate forecasted load demand that will be beneficial to the university and authority. In instant, the goal that supposed to be achieved is when the comparison of power production and the power demand is equal. Achieving the goal will ensure great energy security, reliability, and the ability to maximize profit and minimize losses.

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