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Solar Harvesting System for a Manufacturing Plant using Energy Forecasting ARIMA Model

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ABSTRACT

Load forecasting plays a substantial role in designing a power harvesting system. All manufacturing plants are highly dependent on the primary grid as their main power supply. Manufacturing plant consumes high electricity due to its nature that requires the plant to operate 24 hours a day. This study explores the potential of solar harvesting system for high grid consumer, and it is conducted to investigate the possibility for manufacturing plant X to rely on the renewable energy as an alternative power supply. Based on the demand of power that may vary during on-peak and off-peak in conjunction with business planning, a forecasting model has been developed to predict the plant's demand. Based on the model developed, an optimal design of the PV harvesting system for the manufacturing plant is proposed using Hybrid Optimization of Electrical Renewable (HOMER) software with respect to economic aspect. The designed system managed to supply 88.2% of the demand meanwhile 11.2% were supplied by the main grid. However, the cost is intolerable with calculated operating and maintaining the system is RM14.7M (USD 3.57M) per month as compared to current cost which is significantly less. Further research on hybrid renewable energy harvesting may be conducted that may improve the proposed system.

1. INTRODUCTION

The increasing price of conventional fossil fuel and depleting resources have led to climate change and global warming threats [1]. The United Nation has reported, globally, the usage percentage of renewable energy has reached up to 17.5% in the year 2016 rose from 16.6% in the year 2010, however, it is insufficient to battle global warming [2], [3]. Hence, development of smart cities with numerous green technology applications are profound with vast introduction of aiding schemes [4]-[7]. Small building businesses, domestic households and organizations are giving more attention to the use of renewable energies as the alternative power supplies such a solar energy. The performance of energy harnessing system has been immensely growing [5], [8], [9]. Similarly, new development on energy harvesting is widely researched.

Al-Saqlawi [10] had developed PV modules on a residential area with seasonal weather. Meanwhile, Wahid [11] had introduced the hybrid renewable energy consists of wind generation, photovoltaic, and biomass in villages and households in 3 different states in Malaysia. The output was highlighted to be able to provide approximately 600,000 kWh for various locations using different renewable energies. These researches had been done to expand green technology globally.

Huge capital for installation of solar harvesting system has been a challenge in technological world. Comparison has been done on two types of PV system, the on-grid PV system and the off-grid diesel generator (DG) system, in order to find the most economical PV system [12].

In developing an energy harvesting system, HOMER software is extensively used. HOMER software was used to simulate a hybrid PV system with other Renewable Energy (RE) namely micro-hydro, PV, biomass and biogas along with diesel and battery [13]. In another work [14], the researchers used different derating factor for the PV modules to obtain the optimum output. The research focuses on the economic design and compares two systems; the PV-Solar System connected to grid and the grid only system. These researches have taken the well-developed software to simulate harvesting system design in order to reach the purpose be it economical or maximum output.

Most of renewable energies are highly dependent on the nature [15]. Wind, tidal wave, and specifically solar are dependent on natural activity. In countries with seasonal weather, solar energy is not the best alternatives to the main grid as prevailing power supply. However, National Aeronautics and Space Administrations (NASA) had been able to provide the predictions of nature activity given by the precise site location. HOMER software can work with these data to predict the harvest [16], [17]. In countries with abundant

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sunlight, solar energy is considered influential due to its common locality. Buildings, households and properties with a wide area are considered suitable for solar panel installation [18]. Energy harvested may be consumed by the locals or sold to the authorities. Developing solar harvesting system on the roof of buildings has become a trend due to high power density from the solar irradiance specifically in countries with high population expansion rate [12], [19], [20]. A higher population will add to higher energy consumption. In countries with increasing population, accommodating electricity demand is a challenging task.

Various methods are used to predict the demand of electricity. Some of well used time series forecasting models are ARIMA modelling and exponential smoothing. The latter is more suitable for data with unclear trends, behaviour or seasonality. Meanwhile the former achieves stationarity time series by differencing. Kafazi *et al.* [21] had proposed the ARIMA model to forecast Morocco's energy demand by illustrating the difference and functionality of SARIMA forecasting and ARIMA forecasting. As aforementioned, [21] performed forecasting for Morocco whereby the novelty of this research will be focusing on manufacturing plant 'X' with an extremely high demand during on-peak and off-peak with the application of R, ARIMA and HOMER.

In [18], the application of the forecast package for R have been well demonstrated and it's auto.arima algorithm have been proven to be conclusive. Hyndman had also illustrated exponential smoothing and Seasonal Autoregressive Moving Average (SARIMA) modelling. The author discovered that ARIMA models is the best-suited forecasting model for non-seasonal time series forecasting.

The application of R in forecasting has been inevitable since its foundation. Many researchers benefited from the ARIMA modelling to predict and forecast the energy demand [22]-[24]. In this study, the researchers will use the model to predict the demand for plant 'X' by using R Language.

According to [25], [26], the industrial sector accounts for one third of total energy consumption in the United States. Zhong *et al* [27] developed time series models to describe and predict the variation of the energy load of manufacturing system and the irradiation of solar energy. The cost for building and running such an onsite generation system and its corresponding service level are examined and discussed.

HOMER Software was developed with ideas of improving renewable energy industry. Researchers have taken advantage of the software to develop renewable energy harvesting system in different locations which differs in demands, geographical landscapes and resources. This research aims to accommodate the electricity usage of a plant 'X' by developing a model of a solar farm by using HOMER software. In injecting reliability into the system, forecasting electricity demand using the ARIMA model will aide to supply sufficient amount of electricity to the plant hence ensuring the reliability of the solar farm. Finally, demand and supply analysis as well as cost analysis are done and discussed to provide economic assurance to the company.

The rest of the paper is organized as follows. Section 2 contains the methods and materials being applied by authors. Section 3 contains the result and discussion of the model output. Section 4 includes the forecasting demand for the following year. Section 5 consists of the cost analysis upon the system life cycle. Section 6 contains a conclusive summary of the findings.

2. MATERIALS AND METHODS

The steps of this research are illustrated in Figure 1.

2.1 Load Profile

A fully operational manufacturing plant undoubtedly consumes a large amount of electricity on a daily basis. Evidently proven by secondary data archived by the facility team in plant 'X', from the monthly report on the electricity consumption by the facility team in the plant, it consumes at least 25 MW of electricity consumed monthly. On average in the year 2018 the plant consumes 10 821 464.3 W during peak and 7 670 394.58 W during average off-peak. The tariff used on the plant (Tariff E3) was RM 0.337 (USD 0.083) per unit. As reported annually, the average monthly cost for the facility is RM6,231,756.45 (USD 1,534,930.59) [28]. Theoretically, current proposed solar harvesting system were able to harvest at most 2 MW. This harvesting amount may be able to support stable electricity to the manufacturing facility for 4 hours only. This is highly insufficient as it is crucial to have continuous electricity supplied to the plant.

The load profile of the user or customer provides the measurement or variation in demand or electrical load versus time and represents the electrical usage pattern of the user / customer. The load profiles are low for residential area and suburban area since the demand for residential area is significantly low compared to demand in a manufacturing plant [1], [11], [14], [28]-[30]. In this study, the load profile collected was fed to HOMER Software. Raw data collected is depicted in Figure 2 below.

An accurate load profile is vital in the design of a PV harvesting system for the manufacturing plant. Hence the selection of PV modules was done based on this profile. Electricity usage of the plant through the year 2018 is fed to the software as initial load profile.

Based on Figure 2, there is a significant demand drop at the end of the year. This is due to the plant annual shut down where the operation of the plant was stopped. During this period, all machines were to allow cleaning and maintenance to be done. In this study, the data for the shutdown is omitted. The shut-down activity is done annually, however, it is insufficient to provide a trend to the data. This new data is then used as a load profile for HOMER and for ARIMA forecasting and is shown in the following figure.

Using build in algorithm, HOMER has developed an hourly demand based on the load configuration set prior and is depicted in Figure 3.

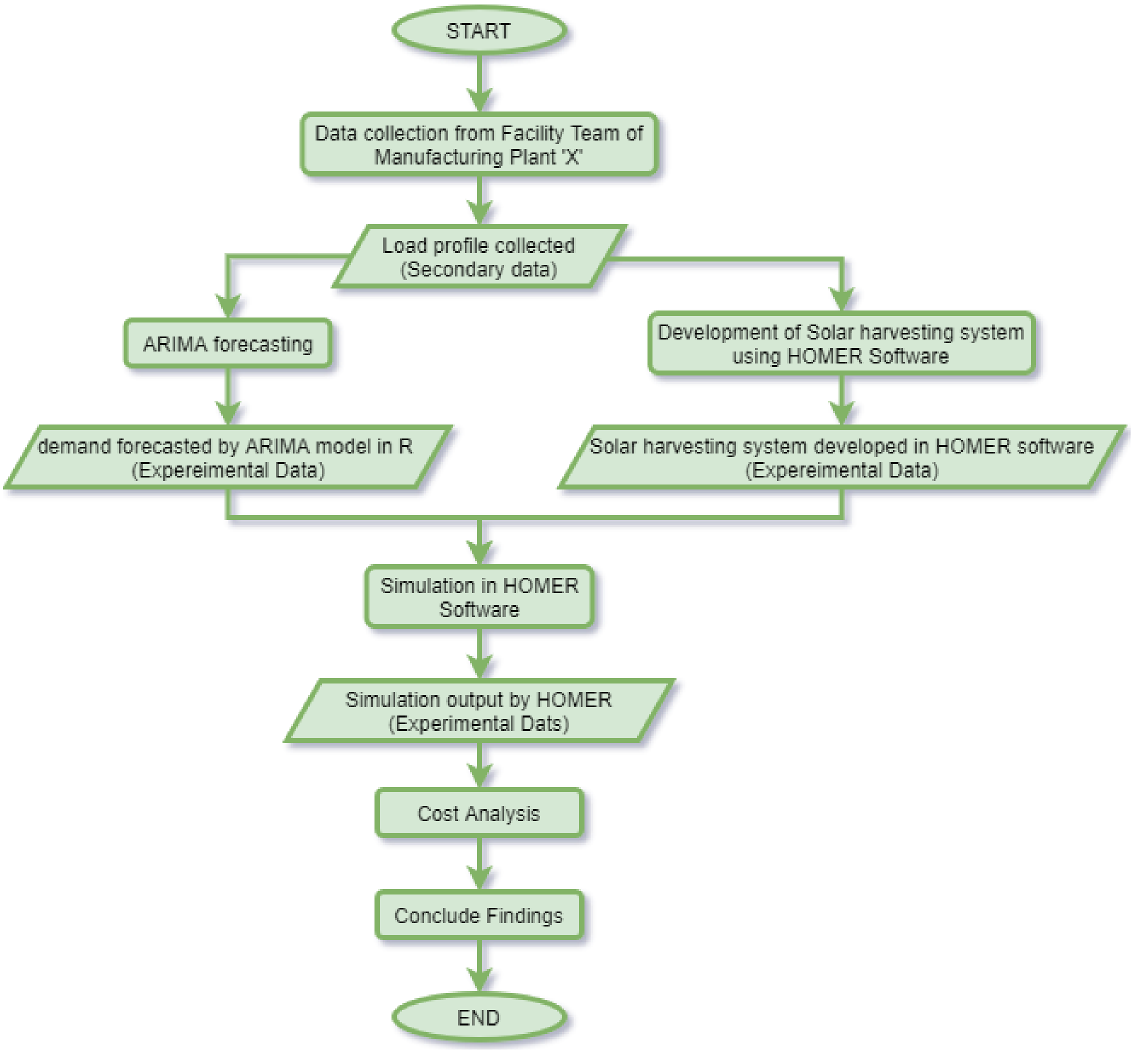

Fig. 1. Flow of this research.

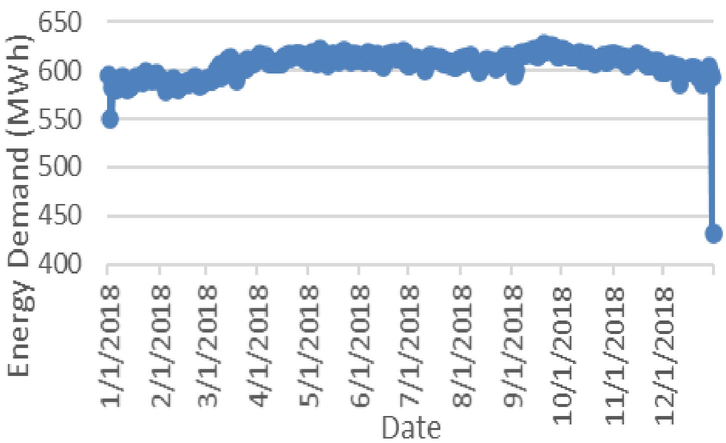

Fig. 2. Electricity demand for 2018.

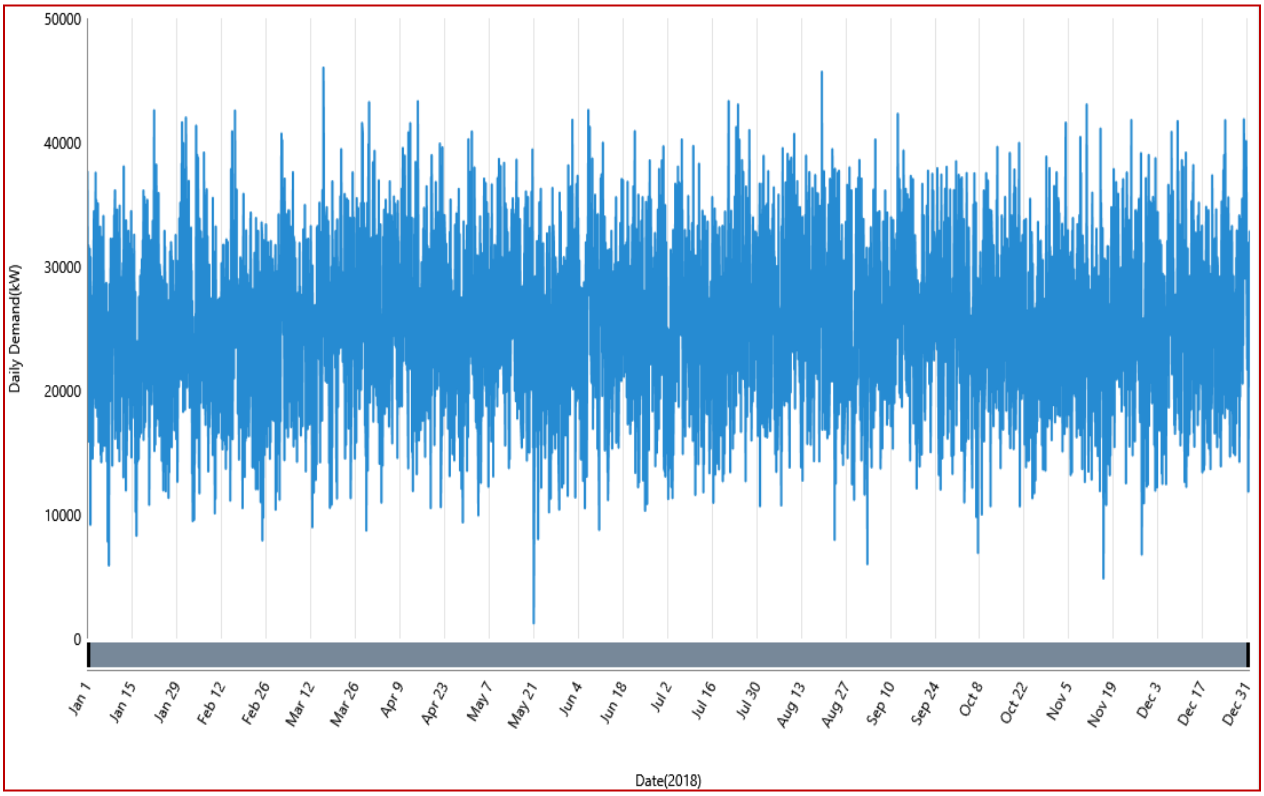

Fig. 3. Hourly load profile from HOMER.

Fig. 4. Site location was circled in red.

2.2 HOMER Software

2.2.1 Site Location

Plant 'X' is located in Klang Valley at the capital of Malaysia. Since Malaysia receives abundant sunlight throughout the year, the location is highly suitable for solar panel installation. Determining the exact location of the site location is crucial in order to obtain the data from NASA. By providing the accurate coordinates of the site, NASA can provide weather activity on the location. The precise site location is represented in the red circle in Figure 4.

2.2.2 Meteorological Data

NASA allows data extraction from their website which had fueled research on renewable energy. By configuring the accurate coordinates, HOMER extracted the irradiance data provided by NASA into the system

[30]. NASA developed these data by averaging the monthly values for 22 years from July 1983 to June 2005. Figure 5 shows the irradiance data that were collected from NASA Surface Meteorological and Solar Energy Database for the specific site location.

Based on the data collected from NASA, demand fed to HOMER, and the designed system, Homer would run continuous simulations for all hardware components considering the components input and output. The software then generates the expected outcome which would have feasible results. Users were then allowed to choose based on the cost, output and components listed by HOMER.

2.4 Forecasting Demand

In [15], the functionality of ARIMA model in forecasting Moroccan's electricity demand was successfully done and illustrated. The dependent variable is the electricity demand meanwhile the independent variable is time. This time series and the non-seasonal character of the data set and implied the importance of ARIMA as the forecasting method used. ARIMA model forecasting techniques are used to forecast the electricity demand through the year 2020.

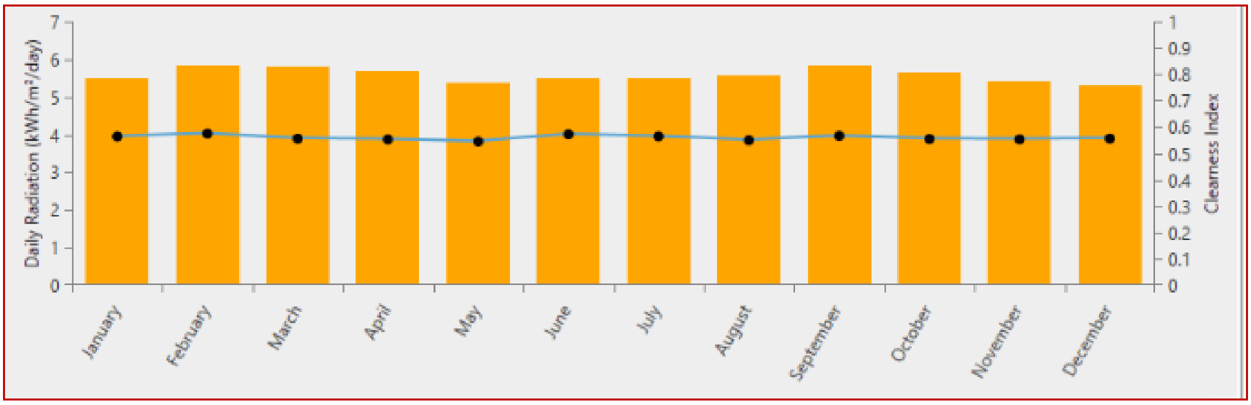

Fig. 5. Daily sun irradiation.

ARIMA model or Auto-Regressive Integrated Moving Average model, uses previous data to predict the future. Therefore, the higher number of periods the higher the accuracy of the prediction. In this research the data structure is as below:

$$\begin{gathered} period = 2\ years(year\ 2018\ and\ 2019) \\ frequency = 365(days) \end{gathered} \tag{1}$$

ARIMA model is the integration of two other time-series modelling; Auto-Regressive (AR) and Moving Average (MA). ARIMA composed of *p*, *d*, and *q*. In time-series forecasting, it is most important to have the series to be stationary. In order to ensure the data are stationary, differencing is done upon the data hence providing the component *d* to the model.

AR model gives the *p* component in ARIMA and is represented in the following mathematical equation.

AR Model:

$$Y_t = \alpha + \sum_{i=1}^{p} \beta_i Y_{t-i} + \varepsilon_1 \tag{2}$$

where;
Y_t = dependent variable measured at time t
α = model coefficient
β_i = constant at Y_{t-i}
ε_t = error term

Equation 2 can be further broken down to the following shown in Equation 3.

$$Y_t = \alpha + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + .. + \beta_p Y_{t-p} + \varepsilon_1 \tag{3}$$

Meanwhile, the MA model gives the component *q* in ARIMA and is represented in the following mathematical equation.

MA Model:

$$Y_t = \mu + \epsilon_t + \sum_{i=1}^{q} \varphi_i \epsilon_{t-i} \tag{4}$$

Y_t = dependent variable measured at time t
μ = model coefficient
φ_i = coefficient at Y_{t-i}
ε_{t-1} = error term from previous period

Equation 4 can be broken down further into Equation 5 shown below.

$$Y_t = \mu + \epsilon_t + \varphi_1 \epsilon_{t-1} + \varphi_2 \epsilon_{t-2} + .. + \varphi_q \epsilon_{t-q} \tag{5}$$

The integration of these two models produces and ARIMA model and is represented by the mathematical equation as shown in Equation 6.

ARIMA Model:

$$Y_t = \mu + \sum_{i=1}^{p} \gamma_i Y_{t-i} + \epsilon_t + \sum_{i=1}^{q} \varphi_i \epsilon_{t-i} \tag{6}$$

2.4.1 Input of ARIMA

The same data obtained from the facility team is used for the forecasting phase. The drop in the demand for the years 2018 and 2019 is omitted because the shutdown is not considered seasonal. It is one–day event and cannot produce a definite trend to the load and is due to the non-seasonal feature of the drop. The data was then fed as the input of the model. Figure 6 represents raw data obtained from the plant.

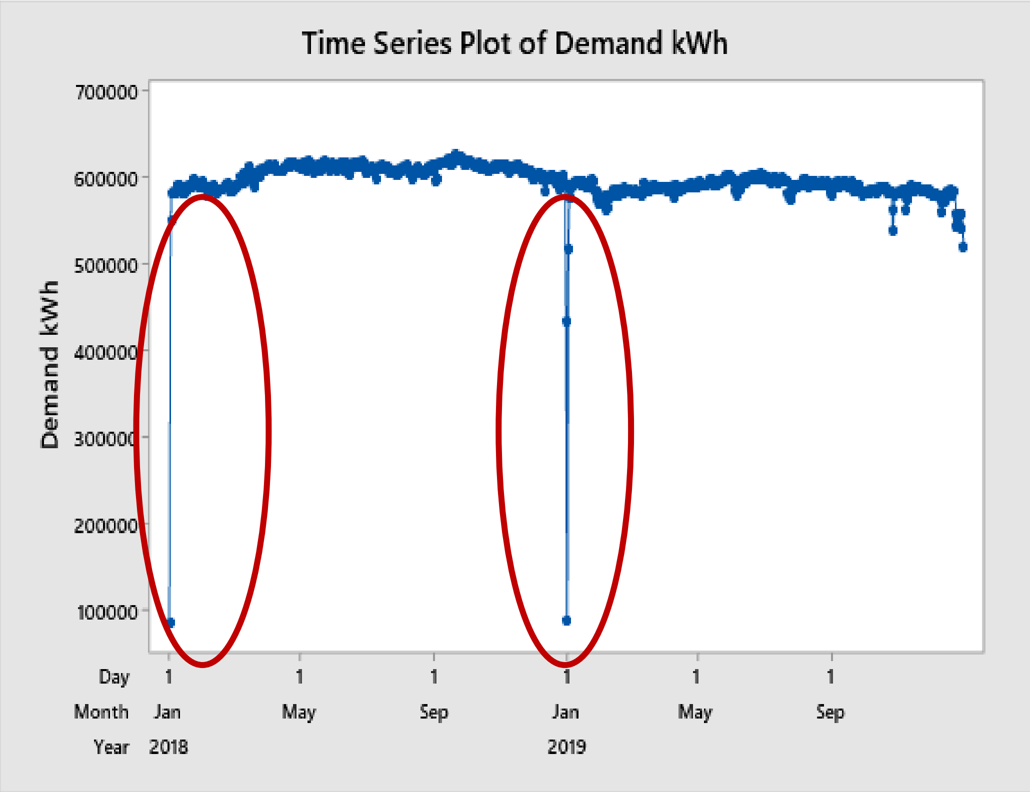

Fig. 6. Raw data from plant 'X".

2.4.2 R-Software

Forecasting using ARIMA model will benefit from the R Software which was equipped with auto.arima algorithm. Dhamo Gjika and Puka, [31] used the algorithm and managed to extract the best model by the algorithm. The algorithm runs through all possible ARIMA models to determine the best ARIMA model to be used. The chosen model was then going through the validation process.

2.4.3 ARIMA Validation

The validation process is done to ensure that the chosen ARIMA model is suitable for forecasting. As mentioned, prior, the input data is required to be stationary. The data went through stationarity test to ensure stationarity. Stationary refers to the condition where mean, variance and autocorrelation are constant over time. Augmented Dickey Fuller (ADF) Test was done upon the data. Figure 7 shows the dataset before differencing at d=1 and Figure 8 shows the data set after differencing at d=1. After the dataset went through differencing, the data is then go through stationarity test to ensure stationarity before proceeding with ARIMA forecasting.

Prior to testing, the data is differenced once hence providing the *d* component of the model. Data when d = 1 is used for ADF test. The model was then further validated by performing Box-Pierce Test. Box-Pierce Test is a statistic test and is done upon the dataset to test for white noise. Meanwhile the Box-Jenkins Methodology is used to examine Autocorrelation function (ACF) and partial correlation (PACF). This test was executed to test on lack of fit. All these validation processes were done using R Software.

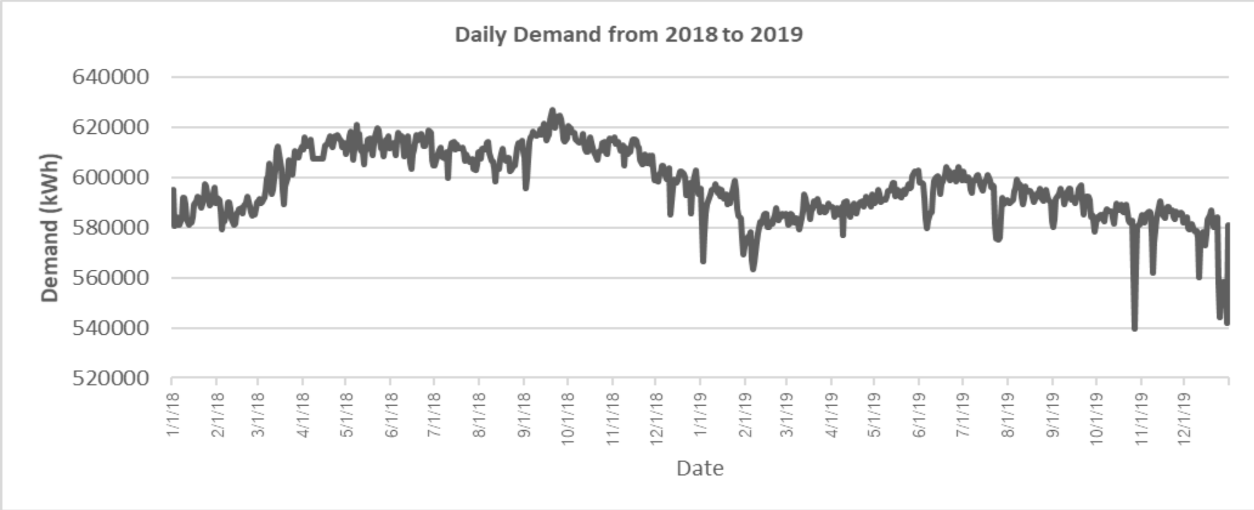

Fig. 7. Initial data before d = 1.

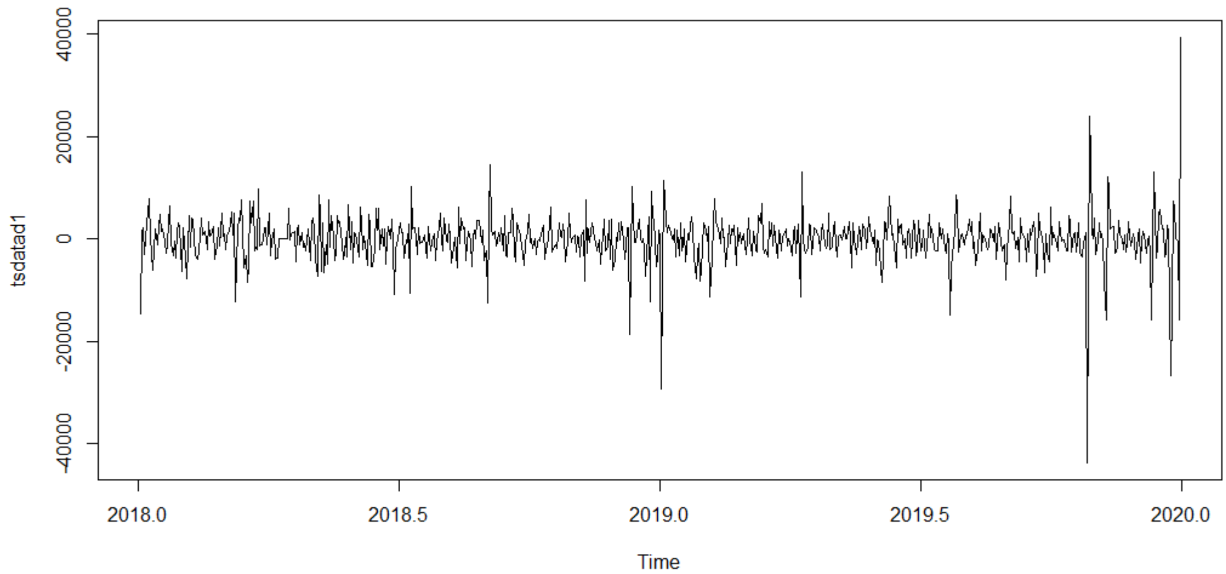

Fig. 8. The data after d = 1.

3. RESULTS AND DISCUSSION

3.1 Solar Harvesting System

In designing the system, previous research had provided significant input towards developing the system. Shilpa and Sridevi [12] had emphasized the use of suitable battery as backup power supply to the system. In this design however, the battery is not used as backup power system but for storing the harvest in the event of supply is greater than demand [30]. In another research [14], it has proven that it was more reliable to have a system connected more than one supply. Connecting the system to the main grid ensures reliability of the system in an event of supply shortages. These precautions were taken into considerations due to the plant's operating feature which requires stable and continuous power supply.

Redesigning the system is needed due to low harvesting for a system with a low initial cost. Upon redesigning, the system was improved by adding main-grid, and battery and is shown in Figure 9. This will increase system reliability [28]. As mentioned prior, the plant 'X' has scheduled shutdown where all the machines were turned off for cleaning, and scheduled service and maintenance. These will lead to the event that supply is greater than demand. Adding the battery will help to store the energy collected and will be used at a later point. The main grid is added in redesigning phase as well. The initial design fails to accommodate the demand and the gap between the system supplies and the demand is significantly high.

The designed system manages to supply 88.2% of the demand meanwhile 11.2% were supplied by the main grid as illustrated in Table 1 and Figure 10. This design is considered to be the best design since 88.2% is the highest harvest simulated using various component configurations. To obtain the production of electricity to accommodate maximum of 88.2 % of the demand, the cost for installation of the PV modules is RM 1.19 B which is equivalent to USD 288.94 M. The main grid is added where the price is set according to Tariff E3. The sell back price is added according to the authorities as shown in Figure 11.

According to Sustainable Energy Development Authority (SEDA) Malaysia, government initiatives had proposed a higher sellback price in order to induce the use of renewable energy [32].

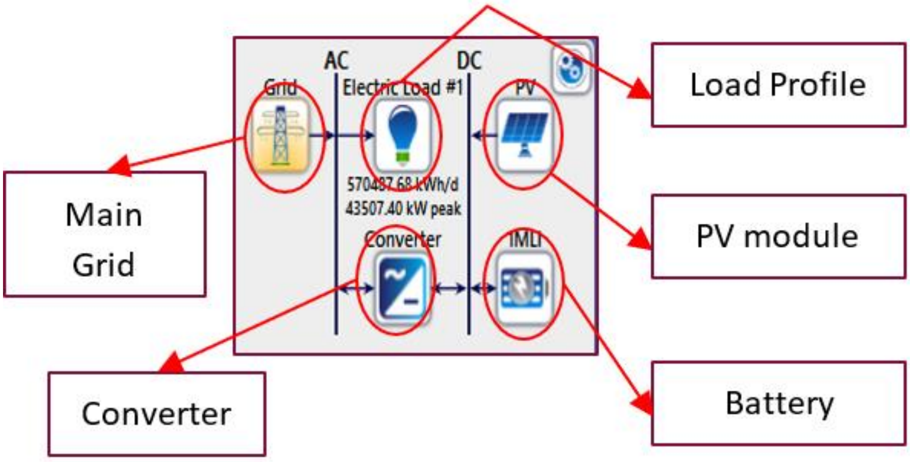

Fig. 9. Architecture design of the system.

Table 1. Electricity production of PV-grid system.

Production	kWh/yr	%
Generic Flat PV System	808, 579, 507	88.2
Grid Purchases	108, 240, 557	11.8
Total	916, 820, 064	100

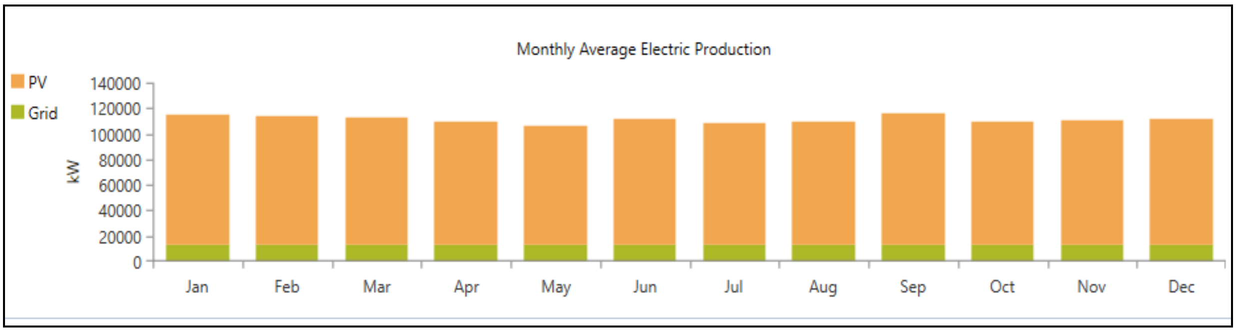

Fig. 10. Electricity production for the design.

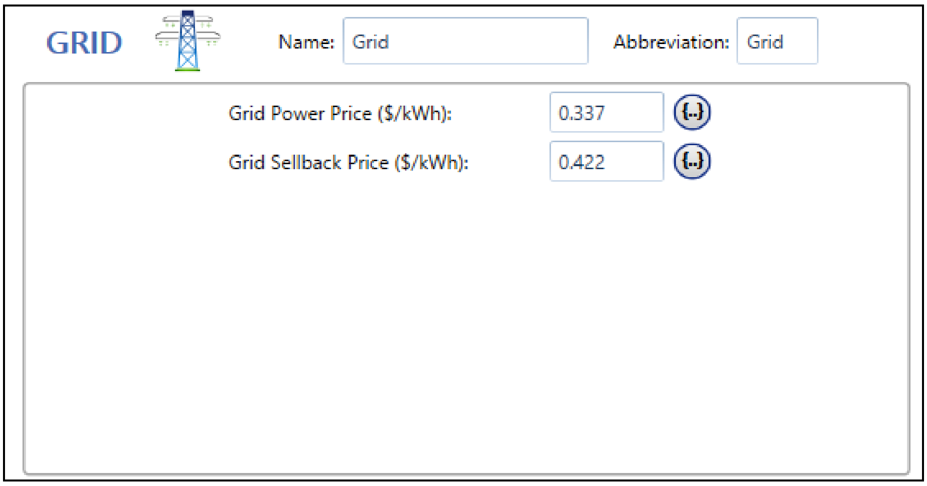

Fig. 11. Sellback price with Tariff E3 cost.

The battery is added for excess generation of electricity. In any situation where the supply is greater than the demand, the generated electricity will be stored in a battery for the use of the plant at any later time. The battery used is a lithium-ion battery with a lifetime of 15 years.

A flat panel PV plate is chosen as the renewable resource collection point. According to a study [33], the performance of dual axis PV system allows the panel to follow the location of the sun in achieving maximum sun radiation absorption compared to single axis PV system. The PV system was design to collect sun radiation only. Temperature harvesting is not included because the electricity generation from temperature will require a higher cost on the capital of the system with lower production rate as shown in Table 2 below.

In Table 2, another PV System is simulated by adding temperature harvesting into the system resulting in higher cost and lower production by the system. Hence, temperature harvesting is removed from the design. As a result, with initial cost of RM 1.19B (USD 288.94M), the system will be able to accommodate 88.2% of monthly demand of the plant.

Table 2. Electricity production of PV-Grid System with adding temperature as one of the harvest variables.

Production	kWh/yr	%
Generic Flat PV System	763, 976, 463	87.6
Grid Purchases	107, 999, 782	12.4
Total	871, 976, 244	100

```
> ARIMAfit = auto.arima(tsdata, approximation=FALSE,trace=TRUE)

 ARIMA(2,1,2)           with drift         : 14339.59
 ARIMA(0,1,0)           with drift         : 14411.58
 ARIMA(1,1,0)           with drift         : 14406.3
 ARIMA(0,1,1)           with drift         : 14401.04
 ARIMA(0,1,0)                              : 14409.58
 ARIMA(1,1,2)           with drift         : 14337.64
 ARIMA(0,1,2)           with drift         : 14360.05
 ARIMA(1,1,1)           with drift         : 14341.35
 ARIMA(1,1,3)           with drift         : 14339.56
 ARIMA(0,1,3)           with drift         : 14344.19
 ARIMA(2,1,1)           with drift         : 14338.1
 ARIMA(2,1,3)           with drift         : 14341.62
 ARIMA(1,1,2)                              : 14335.88
 ARIMA(0,1,2)                              : 14358.16
 ARIMA(1,1,1)                              : 14339.6
 ARIMA(2,1,2)                              : 14337.83
 ARIMA(1,1,3)                              : 14337.8
 ARIMA(0,1,1)                              : 14399.05
 ARIMA(0,1,3)                              : 14342.39
 ARIMA(2,1,1)                              : 14336.34
 ARIMA(2,1,3)                              : 14339.85

 Best model: ARIMA(1,1,2)
```

Fig. 12. ARIMA(1,1,2) from auto.arima is the best model simulated by R Software.

```
Series: tsdata
ARIMA(1,1,2)

Coefficients:
         ar1      ma1      ma2
      0.5186  -0.7120  -0.1449
s.e.  0.0771   0.0833   0.0584

sigma^2 estimated as 20169610:  log likelihood=-7163.91
AIC=14335.83   AICc=14335.88   BIC=14354.2

Training set error measures:
                   ME     RMSE      MAE         MPE      MAPE      MASE
Training set -98.09472 4478.738 2830.083 -0.02192933 0.4782227 0.1495817
                     ACF1
Training set -0.001221054
```

Fig. 13. Summary if ARIMA (1,1,2).

4. FORECASTING

Forecasting the demand in the year 2020 was done using ARIMA forecasting model and the auto.arima algorithm in R Software. The model uses input from the demand of the year 2018 through 2019 as shown in Figure 8. After going through auto.arima algorithm, the best ARIMA model output is ARIMA (1, 1, 2) where $p = 1$, $d = 1$ and $q = 2$ and is depicted in Figure 12.

Figure 13 shows the detailed ARIMA model from R Software after the best model were obtained from auto.arima algorithm.

4.1 ARIMA (1,1,2)

Normally, validating ARIMA forecasting is easily done by comparing the forecasted data with original data. In most cases, before forecasting, the data is divided into 2; training set and test set. In this study however, the data collected is limited to 2 periods with frequency of 365, ARIMA models requires at least a period of 2 for lag calculation. Due to this, the dataset was not divided. Other methods which are Augmented Dickey-Fuller (ADF) Test and Box-Pierce Test and Box-Jenkins Test were done for model validation.

Upon obtaining the model, validation process started by validating the stationarity of the data when d = 1. As mentioned before ADF Test was done in order to ensure stationarity and is depicted in Figure 14 below. The differenced data is denoted as tsdatad1.

In validating the values of p and q, autocorrelation function (ACF) and partial autocorrelation function (PACF) are applied to tsdatad1. Figures 15 and 16 below show the ACF and PACF for tsdatad1.

In determining the value of p and q, ACF is analysed. If ACF indicates sinusoidal decay and PACF converges zero after lag p, it is a pure AR model of order p or ARIMA (p, d, 0). If ACF converges zero after a lag q, and PACF has sinusoidal decay, then it becomes an MA model of order q or ARIMA (0, d, q). If both ACF and PACF have sinusoidal decay, and become zero after lags q and p respectively, then it becomes an ARMA process of order (p, q) and correspondingly ARIMA process of order (p, d, q).

Validating using Box-Pierce Test is shown below in Figure 17.

In this test, the null hypothesis is set that the model fails to show lack of fit. Meanwhile alternative hypothesis is that the model does show lack of fit. All this validation processes were done using R Software. It is shown that the $\chi^2 > p - value$. Therefore, it is failed to reject null hypothesis. It can also be concluded that the test fails to show that the model is lack of fit.

4.2 Forecasting

Once the model is validated, the forecasting was done using the best model which is ARIMA (1,1,2). Figure 18 is the result of the algorithm and the forecasted demand. Meanwhile Figure 18 is the output plotted into the timeline of the original demand.

The forecasted data was then represented in the time series below in Figure 19.

Blue shadings represent the higher limits and the lower limits of the forecasted value. In laymen terms, they represent the allowable deviation from the forecasted values obtained from Figure 18. ARIMA modelling works better with a bigger number of periods used. The idea of forecasting using ARIMA is that the models are highly dependent on previous data fed. Future data is forecasted from previous data. In this research, the model managed to provide variation of prediction in the frequency of 1 to 21 before converges to constant after frequency 21 (Figure 18).

These forecasted data were then fed to HOMER as new load profile. Homer Software analyses the load profile and the cost for the system is analysed.

```
        Augmented Dickey-Fuller Test

data:  tsdatad1
Dickey-Fuller = -28.629, Lag order = 0, p-value = 0.01
alternative hypothesis: stationary

Warning message:
In adf.test(tsdatad1, alternative = c("stationary", "explosive"),  :
  p-value smaller than printed p-value
>
```

Fig. 14. ADF Test when d=1.

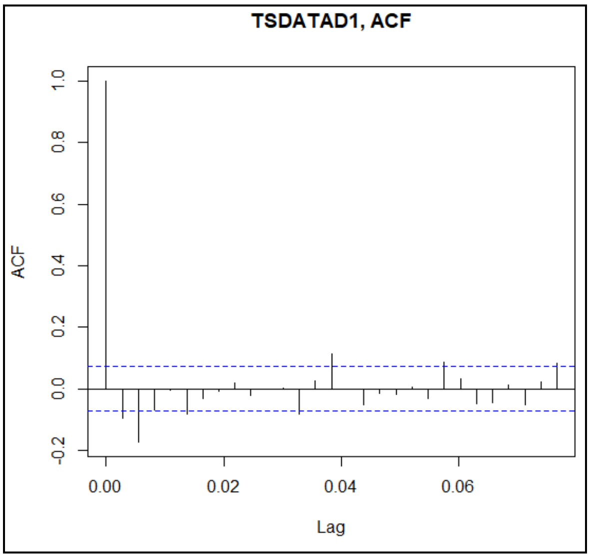

Fig. 15. ACF for tsdatad1.

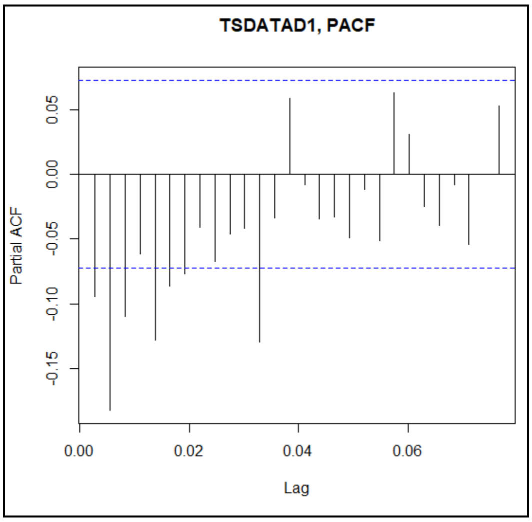

Fig. 16. PACF for tsdatad1.

```
        Box-Pierce test

data:  tsdatad1
X-squared = 6.4908, df = 1, p-value = 0.01084
```

Fig. 17. Box-pierce test or box-pierce test.

```
$pred
Time Series:
Start = c(2020, 1)
End = c(2020, 365)
Frequency = 365
  [1] 580308.2 575142.1 572462.8 571073.3 570352.6 569978.9 569785.1 569684.5 569632.4 569605.4
 [11] 569591.3 569584.1 569580.3 569578.3 569577.3 569576.8 569576.5 569576.4 569576.3 569576.3
 [21] 569576.3 569576.2 569576.2 569576.2 569576.2 569576.2 569576.2 569576.2 569576.2 569576.2
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 [41] 569576.2 569576.2 569576.2 569576.2 569576.2 569576.2 569576.2 569576.2 569576.2 569576.2
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Fig. 18. Output of forecasting from ARIMA (1,1,2).

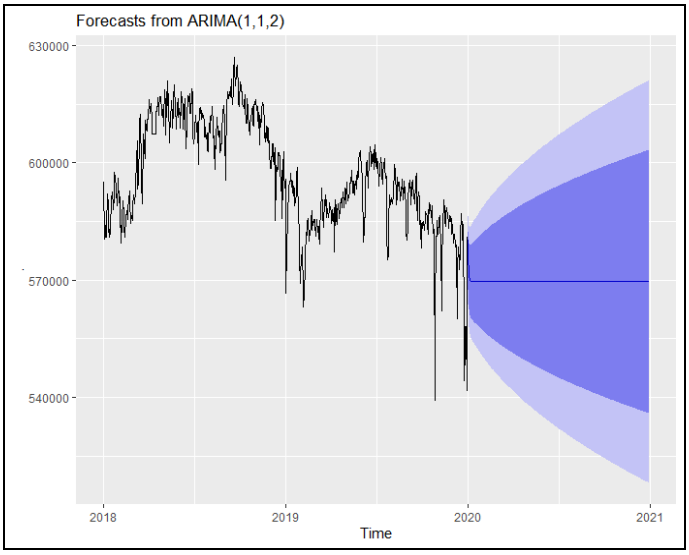

Fig. 19. Forecasted data.

5. COST ANALYSIS

Plant 'X' had total dependency on the main grid which was charged based on Tariff E3. As a high-grid consumer, the company endured the electricity cost of approximately RM 6,231,756.45 equivalent to USD 1,513,113.47 per month. Main purpose in designing the system is to attempt to accommodate the demand of Plant 'X'. Based on the load profile, Homer output the cost analysis comparing current system where the plant is connected to the main grid only and the system designed based on the forecasted data for the year 2020. The following Figure 20 shows the summary of the system's cost throughout the lifetime of the system.

The capital cost to install the system on the plant's roof is RM 1.19B (USD 288.94M) with an annual operating cost of RM 175M (USD 42.49M) throughout the system lifetime. Meanwhile the total of Operating and Maintenance cost of the system annually is RM 177M (USD 42.98M). This value will remain constant given that the scheduled maintenance for each component is obeyed. After 15 years, the system is expected to have parts replacements as compulsory service maintenance scheduling.

Figure 21 shows the system's simple payback which refers to a situation where the system will be able to provide cumulative cashflow equivalent to the capital cost, in which is RM 1.19B and is equivalent to USD 288.94M. Simple payback does not include the O&M cost. The analysis showed that after 4.84 years of the installation, the system will be able to provide simple payback. This tells that the cumulative amount of the 5th year of installation will be able to generate positive cashflow. However, the company is still responsible for the O&M of the system.

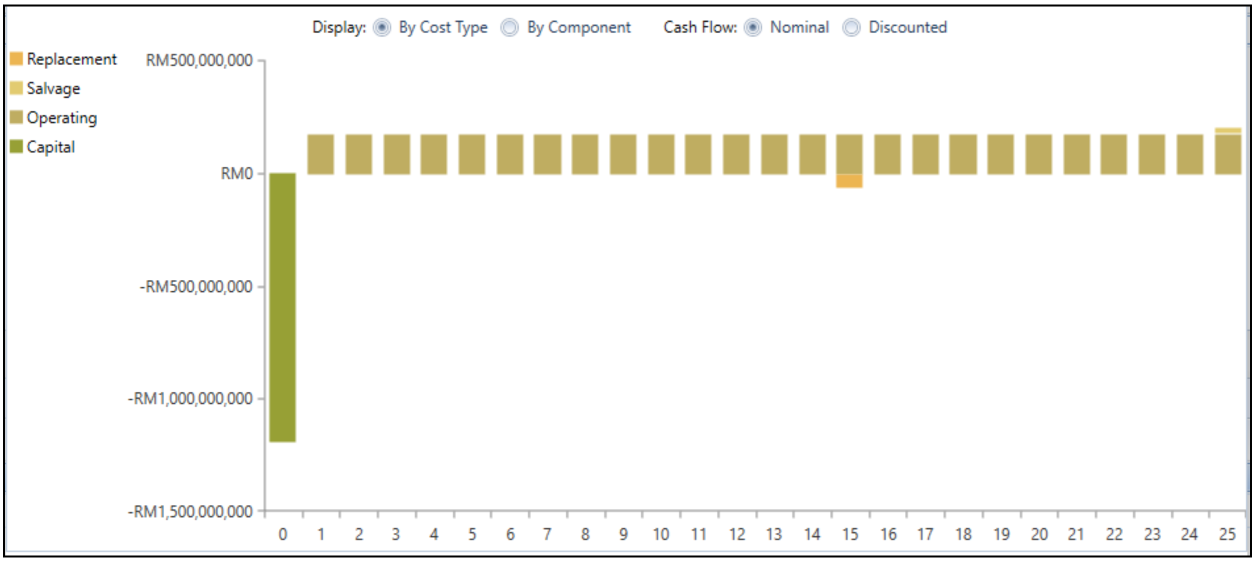

Fig. 20. Cost for solar harvesting system.

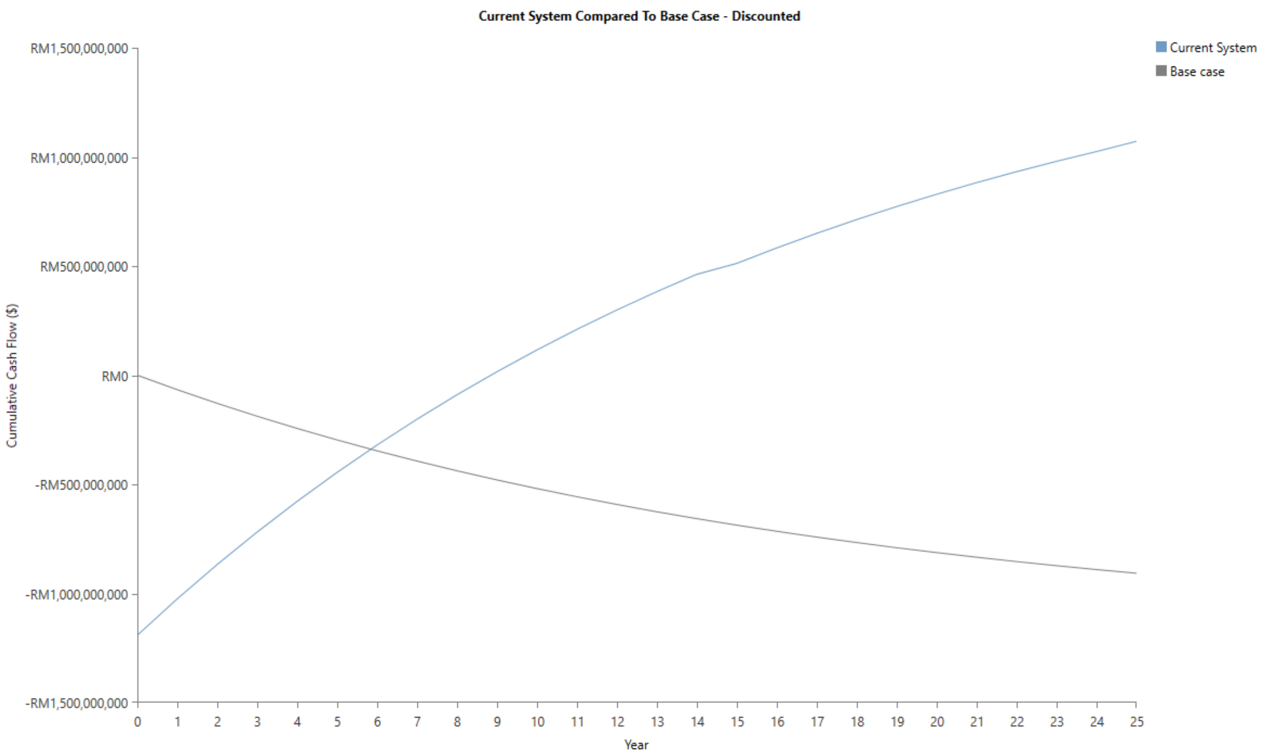

Fig. 21. System's simple payback.

It is also possible to design a low capital cost PV system at the same location. However, the electricity production is unable to accommodate the daily demand. Electricity production from low capital cost model is sufficient for electricity supply in locations with low daily demand, mostly are residential area with mid-dense populations.

Although it is possible to generate electricity enough to accommodate 88.2% of the plant's demand, the cost is not tolerable for implementation of the system. Operating and maintaining the solar harvesting system cost RM14.7M (USD 3.57M) per month. Current on-grid costed RM 6,231,756.45 (USD 1,513,113.47) which is significantly less than the solar harvesting system. The capital cost and O&M cost are not acceptable by the company to bear the extremely high cost as compared to the current main-grid system.

6. CONCLUSION

A manufacturing plant is categorized as high voltage peak/off peak consumers. The model designed were able to produce energy harvested from the sun irradiation. It is said to be able to accommodate the energy demand by the plant however, a huge capital is required. ARIMA model is a very sophisticated forecasting techniques in forecasting energy demand. The forecasting highly dependent on previous period. In this research, period of 2 and frequency of 365 is used to forecast the next period of energy demand. In order to achieve a higher accuracy of forecasting, higher number of periods is suggested in which will allow more possible ARIMA model.

This has proven that current PV system were unsuitable for high demand consumption. Manufacturing industry requires generous amount of electricity. Installation of PV system to accommodate the demand is significantly costly. However further research on hybrid renewable energy harvesting system may improve the energy harvested from the roof of the manufacturing plant in Malaysia.

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