Output Power Forecasting for 2kW Monocrystalline PV System using Response Surface Methodology

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Abstract – *Photovoltaic (PV) system is a renewable energy source that not only able to reduce the effect of greenhouse gas towards the environment, but also a highly profitable industry nowadays. To determine the Return of Investment (ROI) of a newly installed system, forecasting is crucial. Thus, the purpose of this study is to produce a prediction model for the yearly output power of the PV system using three environmental elements; irradiance, back module temperature and ambient temperature by Response Surface Methodology (RSM). To do so, MATLAB RStool which is consisting of four models; multiple linear regression (MLR), interaction, pure quadratic, and full quadratic were used. The 5 minute sampling size of year 2014 weather station data of the three environmental elements and output power of a 2kW Monocrystalline real PV system were used for training. Whereas, year 2015 data of the aforementioned elements were used for validation. The coefficient of determination (R^2) method and root mean square error (RMSE) approach were used to determine the most accurate prediction model. Results shown that, full quadratic is the most accurate prediction model with R^2 value of 0.9995 and RMSE of 8%. It is hoped that the prediction model introduced can be a viable method to be used by the PV system installer.*

Keywords: *ambient temperature, back panel temperature, irradiance, Photovoltaic (PV), RSM*

Article History

Received 30 January 2019

Received 3 March 2019

Accepted 4 March 2019

I. Introduction

Fossil based fuel has become essential and widely used in many fields such as transportation, industrial, and commercial. However, the sharp increase of oil consumption has leads to the energy limitation in the world. Following this crisis, renewable energy sources were introduced and accepted throughout the world since they are energies that can regularly be replenished. The example of such energies are solar, wind, geothermal, biomass, and hydro. Among all of these renewable energies available, solar photovoltaic (PV) is the most interesting option especially for countries with equatorial climate. On July 1998, Universiti Tenaga Nasional had developed the first grid connected photovoltaic (GCPV) in Malaysia with a capacity of 3.15 kWp [1] and the development is rapidly growing by the installation of GCPV with full generation power capacity of 50 MW, which is a recent project of Large Scale Solar (LSS) by Tenaga Nasional Berhad in the year 2018 [2].

Additionally, PV has now became an industry that is able to generate millions of ringgit. Therefore, government related agencies; Ministry of Energy, Science, Technology, Environment & Climate Change (MESTECC), and Suruhanjaya Tenaga has taken several proactive steps to introduce many incentives and strategies to attain the growth of renewable energy in Malaysia. In 2011, Sustainable Energy Development Authority (SEDA) was established [3] to developed Tenaga Boleh Baharu (TBB) in industrial sector, as well as administering and implementing the Feed-in Tariff (FiT). This has allowed the opportunity for people to gain extra income by generating their own electricity as it is a concept that allows renewable energy-based electricity generation to be sold to the utility at a premium price for a certain period of time. In 2015, there was a total of 8,643 applications of FiT TBB and out of it, a total of 7,437 applications were approved with cumulative power generation of 1,154.26 MW [4], and the applicant increased to 13,830 with approved applications of 12,143 generating 1632.87 MW of electricity in 2017 [5]. In the meantime, Net Energy Metering (NET) programme was introduced with distinct concept, whereby for eligible consumer to installs PV solar system in their own residence to export exceeds energy to the grid, therefore received credit by offset part of the electricity bill from distribution licensee; Tenaga Nasional Berhad (TNB). Likewise, solar energy is the most efficient to drives constant and predictable power in renewable energy [6] as it enable the consumer to predict the Return of Investment (ROI). Nevertheless, PV solar output system is periodic and fluctuating in nature, as it highly depends on the solar irradiance and weather condition such as; temperature, wind speed and other environment conditions. Consequently, forecasting are proven models for alleviating the uncertain resource nature apart from reducing the schedule requirement of ancillary power generation [7].

An Artificial Intelligence (AI) approaches such as Neural Network (NN) is extensively applied in the forecasting studies of PV output system. Whereby according to M. Paras et.al [8], NN method has the ability to deal with complex problem, as well an efficient approach when deal with hybrid intelligent algorithm; Wavelet Transform technique. However, NN models is a complex algorithm employment that compromise with trial and error process, a part of the relation of input and output is intense in neuron form. Nowadays, there are numerous of researcher that employed time series statistical forecasting method; auto regressive moving average (ARMA) and auto-regressive integrated moving average (ARIMA) and auto-regressive moving average model with exogenous variables (ARMAX). These models were initially generalized from auto regressive (AR) models and moving average (MA) models, whereby the generalization was developed to improve related technique. For example, ARMAX technique was developed by adding compatible information of time series consideration for accuracy enhancement of univariate ARMA technique [9], and allow of exogenous input for power output forecasting instead of ARIMA models that has limited consideration of process behaviour [10].

In the same way, Response Surface Methodology (RSM) method has prevalent used in other field case study. RSM is a model that able to generate modelling of mathematical that can describe on the relation between variables and then allow the prediction of output before any processing being finalize [11], a part of capability to produce optimum output results with higher efficiency. For instance, A. Kasa et.al. [12] applied RSM method in Civil Engineering field and has succeed the study of prediction on geogrid reinforced segmental retaining wall in terms of FOS, surface and settlement and wall deflection. Moreover, based on previous work as in [13], [14], and [15], RSM method shows of capability to produce optimum prediction output results with higher efficiency despite comes from dissimilar area. Hence, this research is tries to use RSM method, whereby both input and output are connected with a certain equation which is more robust on paper interpretation.

Hence, this paper contributes to the implementation of response surface methodology (RSM) for output power (P_{AC}) forecasting of 2kW Monocrystalline PV system. The next aim was to study the effect of variable solar system input such as irradiance, module temperature and ambient temperature against PV_{AC} solar system. Finally, the purpose of this study is to determine which of the RSM models of multiple linear regression (MLR), interaction, pure quadratic and full quadratic is the most accurate to predict the solar PV system output. Therefore, the input data (G, T_{module}, $T_{ambient}$) and P_{AC} data of year 2014 used to form the RSM model, as well as the input data (G, T_{module}, $T_{ambient}$) and P_{AC} data from year 2015 which was used to validate the RSM model. Next, RStool function in MATLAB R2016b, 64-bit software is used to perform simulation of RSM model, whereas the determination of prediction model accuracy is achieved using coefficient of determination (R^2) method and root mean square error (RMSE) method as well. From previous work by others, this study is expected that full quadratic model will shows higher accuracy among others model by $R^2 > 0.75$.

II. Project Background

A. Grid Connected PV System

Photovoltaic (PV) systems is generally categorized into Stand-Alone PV System (Off-Grid System) and Grid-Connected PV System (On-Grid System) that converts sunlight irradiance directly into electricity. The Stand-Alone PV System (SAPV) is a system that does not connected to any electricity network and often used in rural areas. While, Grid-Connected PV System (GCPV) has widely used in infrastructure area that is connected directly to electricity network. Basically, GCPV comprises of 2 categories; Grid-tied system and Grid-tied system with battery storage. However, Grid-tied system has a simplicity circuit design with low cost compared to Grid-tied system with battery storage due to none storage battery requirement. This system requires few components that comprises of PV array, inverter, and grid utility as shown in Fig. 1. PV module is a source of power in PV system that generates direct current (P_{DC}) electricity supply in high voltage, current and power when a number of PV modules is wired in correct configuration such as series, parallel or series-parallel to form a PV array.

While inverters are required to convert DC to alternating current (P_{AC}) supply in the system, where the connection is interacting with the grid utility which it is not only capable for load power generation, yet it is able to send back exceeds PV power generation into the grid utility which is recorded by net meter. PV module comes in several types such as crystalline PV; Monocrystalline silicon and Multi-crystalline silicon module and Film modules (such as amorphous silicon and cadmium telluride). Recently, Monocrystalline PV module is often used by investors as it is more efficient because of the molecules structure of ingot is uniform from top to bottom which allows photon move large number of electron [10].

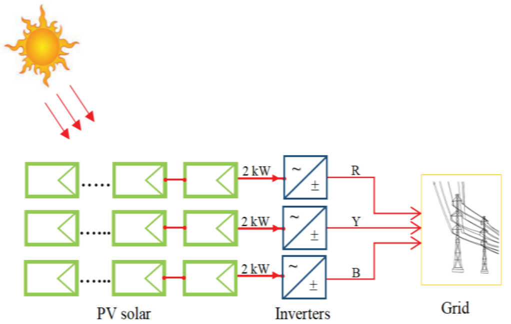

Fig. 1. Process of Grid-tied system

The 6kW inverters for Monocrystalline PV system at PVSG Lab Weather Station, Universiti Teknikal Malaysia Melaka (UTeM) were built for three phase system with of 2kW inverter at each phase, as seen in Fig. 2. However, this study is focusing on output power forecasting of single phase 2kW Monocrystalline PV system only, so that the accuracy of the generated forecasting model can be compared with the output of the other two phases later on. Fig. 3 displays the Monocrystalline of PV modules installed at the roof top of Electrical Engineering Faculty (FKE), UTeM with inverters data specification set in Table I, whereas it being monitored by PVSG Lab Weather Station, UTeM.


Fig. 2. Installation of 6kW Inverters for monocrystalline PV system at PVSG Lab Weather Station, UTeM


Fig. 3. Monocrystalline PV module at roof top of FKE, UTeM

TABLE I
SPECIFICATIONS ADOPTED FOR THE SIMULATED INVERTER

Technical Data	Specification
Input (DC)	
Max. DC power	2100 W
Max. DC voltage	700 V
MPP voltage range	175 V – 560 V
DC nominal voltage	530 V
Min. DC voltage	175 V / 220 V
Max. input current / per string	12 A / 12 A
Number of MPP trackers / strings per MPP tracker	1 / 2
Output (AC)	
AC nominal power	2000 W
Max. AC apparent power	2000 VA
Max. output current	11. 4 A
Max. efficiency	96.3 % / 95.0 %

B. Weather Station for GCPV System

In a PV system, the performance has to be considered in terms of the energy efficiency as well as to generate optimum P_{AC}. Therefore, it is important to design a PV system with proper specification and guidelines. In this study, the designation of PV system is based on IEC 61724 standard guideline requirement [16], whereby IEC 61724 is a recommend standards and procedures of general guidelines to monitor and performance analysing of electrical for PV systems, which focuses on evaluate the performance of PV system array. It includes the characteristics of the system such as in-plane irradiance, temperature and condition of input and output power for analyzing and exchanging of the monitored data. PV modules is typically produce current and voltage when exposed to the sun, thus generate power which can be defined as;

$$Power\ (P) = Current\ (I) \times Voltage\ (V) \quad (1)$$

Whereas, the production of current is directly proportional to irradiance and inversely proportional to voltage. Meanwhile, the standard peak sun for irradiance is 1000W/m^2 and this value is used to calculate daily output. For standard IEC 61724 guideline [16], in-plane irradiance shall be measured as the same plane with PV array by using Pyranometer with accuracy of irradiance sensors, including the signal conditioning that shall be better than 5 % of the reading. The type of Pyranometer used in the PVSG Lab Weather Station, UTeM is CMP11 Thermopile Pyranometers with ISO 9060 Secondary Standard as shown in Fig. 4. Standard Secondary Pyranometer is reliable for long-term stability with expected low error by World Meteorological Organization at a maximum of 3% in hourly radiation as well as for daily total error [17].

TABLE II
SUNMODULE PLUS SW 255 MONOCRYSTALLINE DATA SHEET

Part name	Rating values
Performance Under STC	
Max. power, P_{max}	255 Wp
Open circuit voltage, V_{oc}	37.8 V
Max. power point voltage, V_{mpp}	31.4 V
Short circuit current, I_{sc}	8.66 A
Max. power point circuit	8.5 A
*STC : 1000 W/m², 25 °C, AM 1.5	
Thermal characteristics	
NOCT	46 ℃
TC I_{sc}	0.04 %/ ℃
TC_{voc}	-0.3 %/℃
TC P_{mpp}	-0.45 %/℃
Operating temperature	-40 ℃to 85 ℃

Fig. 4. CMP11 thermopile pyranometers witth ISO 9060 Secondary Standard

TABLE III
CM11 THERMOPILE PYRANOMETER SPECIFICATION

Specifications	Rating values
Classification to ISO 9060:1990	Secondary Standard
Spectral range	285 to 2800 nm
Sensitivity	7 to 14 µV/W/m²
Impedance	10 to 100Ω
Detector type	Thermopile
Operational temperature range	-40°C to +80°C
Storage temperature range	-40°C to +80°C
Non-stability	< 0.5 %
Non- linearity	< 0.2 %
Spectral selectivity	3 %
Temperature response	< 1 % (-20 °C - 50 °C)
Tilt response	< 0.2 %

Moreover, monitoring of module temperature is an essential role as the changes of temperature will influence the performance of PV system. This is because, the increment or reduction of module temperature will change the amount of current flows and voltage value, thus affected the production of P_{AC} as well. Fig. 5 displays the thermocouple sensor which was installed at the back of Monocrystalline PV module FKE, UTeM, whereby it is used to measure the temperature of PV module by following IEC 61724 guideline criteria [16], that the installation of temperature sensor shall be located on the back panel surface of one or more modules with accuracy shall be better than 1K.

Fig. 5. Thermocouple Sensor connected to monocrystalline PV module at FKE, UTeM

Besides, the design criteria of ambient temperature measurement should be taken into account as output power in PV system is significantly affected when excessive to heat. Fig. 6 shows a temperature and humidity sensor, called as Vaisala HUMICAP HMP155 probe which is used to measure ambient temperature. As stated in IEC 61724 standard guideline [16], the device was installed in radiation shield with accuracy better than 1K. The radiation shield is important as it able to prevent the sensor exposed to direct sunlight, which can cause for inaccurate output. Moreover, the device is built up with relative humidity specification at measurement range from 0 - 100 % RH, temperature from -80 to +6- ℃ as written in Table IV.

Fig. 6. Temperature & humidity sensor used to measure ambient temperature

TABLE IV
RELATIVE HUMIDITY AND TEMPERATURE SPECIFICATION OF HMP155 SENSOR

Description	Value
Relative Humidity	
Measurement range	0...100 % RH
Accuracy (include non-linearity, hysteresisand repeatability) :	
at +15… 25 °C	± 1 % (0 - 90 % RH) ± 1.7 % (90 - 100 % RH)
at -15… +40 °C	± (1.0+0.008 ×reading) %RH
at -40… -20 °C	± (1.2+0.012 ×reading) %RH
at +40… +60 °C	± (1.2+0.012 ×reading) %RH
at -60… -40 °C	± (1.4+0.032×reading) %RH
Temperature	
Measurement range	-80… +60 °C
Accuracy with voltage output :	
at -80… +20 °C	± (0.226+0.0028× temperature) °C
at +20… +60 °C	± (0.055+0.0057× temperature) °C

The PV module data sheet provided by manufacturer is usually indicates the efficiency of PV module under Standard Test Condition (STC), whereby 25˚C or 77˚F for ambient temperature with solar irradiance at 1000 W/m^2 and air mass ratio AM=1.5. This STC test indicates that the reduction of output power occurs when the temperature of PV module increases by +1˚C above 25˚C, whereas the value reduces based on the temperature coefficient (in degree). Temperature coefficient is the different rate at which the PV modules underperform when increase at each of degree Celsius (˚C) of temperature, where most panels have a temperature coefficient in between -0.2% /°C to -0.5%/°C. Therefore, the selection type of PV module need to take into account as each of its semiconductor component may leads to undermine voltage due to the temperature coefficient.

Another guideline referred is Australian Technical Guideline for Monitoring and Analyzing PV System [18]. The guideline emphasizes on the criteria of data collection for PV performance forecasting. The criteria includes the the sampling time data; 5 minutes, 30 minutes or hourly and the period of monitoring for PV performance forecasting shall not less than 1 year. Therefore, this study was conducted by collecting 5 minutes of sampling PV input and output data from year 2014 and 2015 to forecast one year of PV output performance.

C. Response Surface Methodology

Response Surface Methodology (RSM) is a collection of mathematical and statistical technique that is used to optimize response by modelling and analyzing the problem which is influenced by several variables, thus make changes to the output. By constructing a mathematical model of RSM, the independent variable that cause the response variable value to be optimal is known. In this study, application of RSM is to analysis and optimize the power output PV solar as the response variable that are affected by several variable inputs which is irradiance, temperature and ambient that are set as the independent variable. In mathematical term, it is useful to find the functional relationship between response of interest and design variable.

There are 2 types of model in RSM which is known as 1st order model and 2nd order model. In 1st order model, the model is called as step ascent or multiple linear regression by respect to 3 variables that can be expressed as:

$$Y_0 = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \varepsilon \qquad (2)$$

Whereas, this model method can determine the existence of curvature on response surface. For case of unknown variables, the screening method is used before proceed to the 1st order model which can be determined as:

$$Y_0 = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_1 X_2 + \beta_5 X_1 X_3 + \beta_3 X_3 + \beta_6 X_2 X_3 + \varepsilon \qquad (3)$$

For case curvature found on the response surface, then 2nd order model will be used to approximate the response variable to obtain optimum point. Basically, 2nd order model of RSM is a combination of 1st order model method, screening method and pure quadratic method. Meanwhile, Pure Quadratic method is expressed as:

$$Y_0 = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_1^2 + \beta_5 X_2^2 + + \beta_6 X_3^2 + \varepsilon \qquad (4)$$

Therefore, the 2nd order model of RSM can be written as:

$$Y_0 = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_1 X_2 + \beta_5 X_1 X_3 + \beta_6 X_2 X_3 + \beta_7 X_1^2 + \beta_8 X_2^2 + + \beta_9 X_3^2 + \varepsilon \qquad (5)$$

The parameter Y_0 is referred as predicted PV output value, X_1- irradiance, X_2- panel temperature, X_3- ambient temperature and ε is to be defined as error. While, β_0 until β_9 are unknowns and to be determined using least squares method in the MATLAB RStool, an interactive response surface modelling.

III. Methodology

Fig. 7 indicates the project flow chart on how the process of RSM simulation. Briefly, the raw data of 2014 was firstly collected. The data then were processed and trained by using MATLAB R2016b, 64-bit software. The data then was tested and compared with the 2015 data. RSM model will only valid when the coefficient of determination, R^2 > 0.75 and afterwards the simulation process ends.

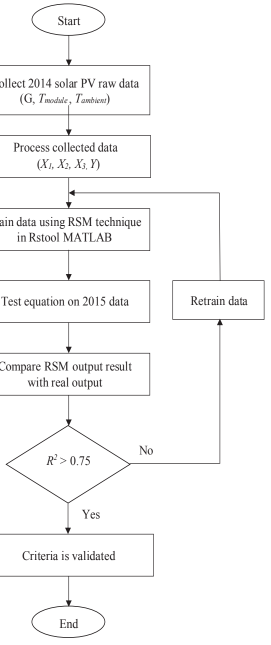

Fig. 7. Flowchart of RSM simulation process

The raw data is referred as an independent variables input of PV solar; irradiance (G), module temperature (T_{module}) and ambient temperature ($T_{ambient}$). There are 411 of raw data (from 7.30am to 6.50pm) for every 5 minutes sampling data of independent input variables and PV_{AC} solar output (year 2014 and 2015) that were collected from the FKE Weather Station Monitoring System, displayed in Fig. 8. It shows that on 1/1/2014 at 7.35 am, the value recorded for tilted irradiance is 39 W/m^2, ambient temperature at 23.9℃ and module temperature with low reading which is 13.4℃.

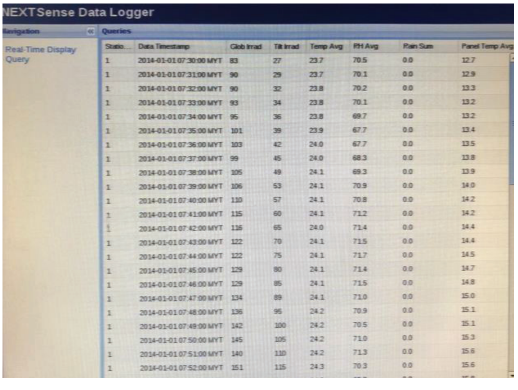

Fig. 8. Display of Query raw data

Next, the selected processed raw data was rearranged separately by G, T_{module} and $T_{ambient}$. All the processed data was compiled at average of 5 minutes data for day, month and year. All steps were done to all raw input data of G, T_{module} and $T_{ambient}$ that labelled as variable of irradiance (X_1), module temperature (X_2), and ambient temperature (X_3). Table 5 exhibits the independent variables input data for 2014 to be trained in RStool MATLAB, whereby, the processed independent variables input data of X_1, X_2 and X_3 as set in Table V was then been trained in MATLAB R2016b, 64-bit software to generate the unknown equation of β by using RSM model; MLR, interaction, pure quadratic and full quadratic to obtain predicted P_{AC} results.

TABLE V
2014 INPUT DATA TO BE TRAINED IN RSM USING MATLAB SOFTWARE

INPUT				OUTPUT
Time	Irradiance X_1	Panel temperature X_2	Ambient temperature X_3	Target Y_0
7 : 30	39.61	21.63	24.23	25.84
7 : 35	50.40	21.80	24.27	39.28
7 : 40	62.20	22.01	24.32	55.41
7 : 45	76.16	22.22	24.37	76.85
7 : 50	89.75	22.49	24.44	97.55
7 : 55	103.97	22.81	24.52	120.50
:	:	:	:	:
:	:	:	:	:
:	:	:	:	:
18 :35	54.45	28.13	29.10	59.95
18 :40	47.06	27.82	29.02	47.64
18 : 45	40.43	27.53	28.92	36.60
18 : 50	34.01	27.22	28.84	26.95

After simulation, the acquired equation of β from each RSM model will appears and give the rmse value as well in workspace section as shown in Fig. 9. Then, the equation from each of RSM model was used to generate predicted P_{AC} result and to be compared with the P_{AC} data of 2014 which was used as target data.

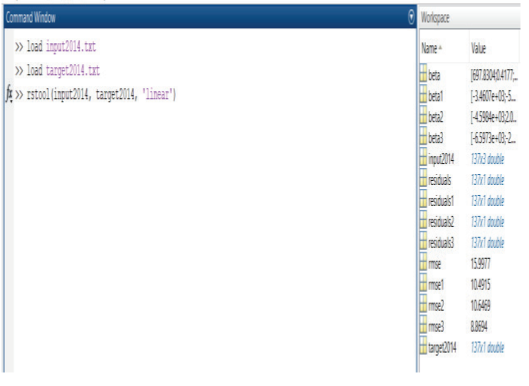

Fig. 9. Simulation using RSM technique in RStool Matlab

This comparison was done to observe the relationship between predicted P_{AC} generate by RSM models with target P_{AC} data for 2014. Thus, it will determine the most accurate RSM models to be used to compare with the real

P_{AC} data on 2015 by choose the highest of $R^2 > 0.75$.

IV. Results and Discussion

One year of 5 minutes PV solar sampling data from year 2014 was collected and averaged to one year data, which includes of independent variable input; irradiance (G), panel temperature (T_{module}) and ambient temperature ($T_{ambient}$). From the collected data, Fig. 10 shows that Malaysia has greatly received solar irradiance throughout year, as Malaysia has constantly experienced the same weather at most time due to its location near the equator.

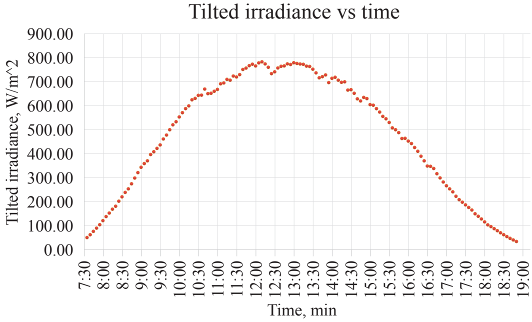

Fig. 10. 2014 tilted irradiance pattern

Moreover, the amount of irradiance absorbed by PV solar module can be influenced by the panel temperature. This is because the output power in the PV system requires high production of current, in order to obtain optimum power output. When panel temperature increases, the current produce will increases as well, and therefore, it has the potential of producing higher P_{ac}. The pattern of PV module temperature used in this study is shown in Fig. 11.

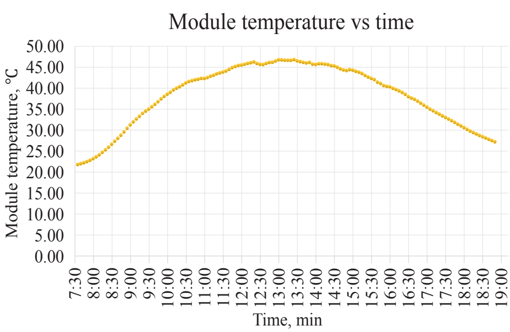

Fig. 11. 2014 module temperature pattern

At the same time, Fig. 12 indicates that Malaysia has uniform average of ambient temperature every year, which is between 21℃ to 32 ℃. This temperature increased during 12 pm to 2 pm due to the weather condition is hot with high humidity, yet under normal temperature level. Thus, the slightly increment of ambient temperature does not give huge impact to the output power in PV solar system. Whereas, graph in Fig. 13 present that average output power of PV solar system is highly produced, with highest value of 1171 Watt. In addition, the similarities pattern of irradiance graph determine that the output power is strongly dependent on the irradiance produced by PV solar module, apart from being influenced by the module temperature and ambient temperature.

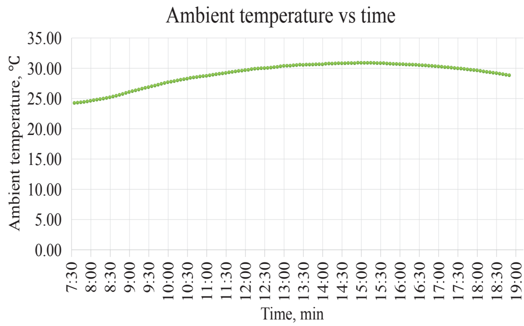

Fig. 12. 2014 ambient temperature pattern

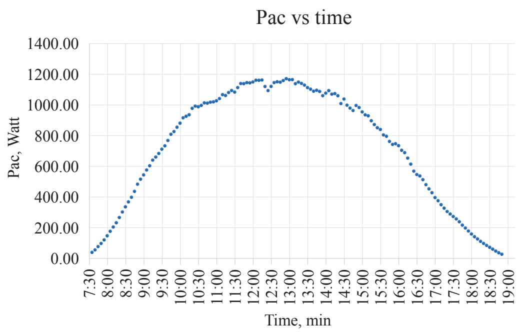

Fig. 13. Average output power at FKE, UTeM on year 2014

To be compared with the trained data on 2015 indicates by Fig. 14, it is relatively identical of irradiance pattern raw data on year 2014. Further, hot climates is constantly experienced in Malaysia on year 2015 as the module resulting of very much alike value temperature level with year 2014 that can be seen in Fig. 15, as well as similarly happens to ambient temperature that shown in Fig. 16.

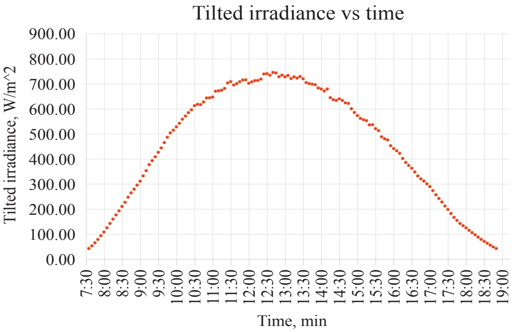

Fig 14. 2015 tilted irradiance pattern

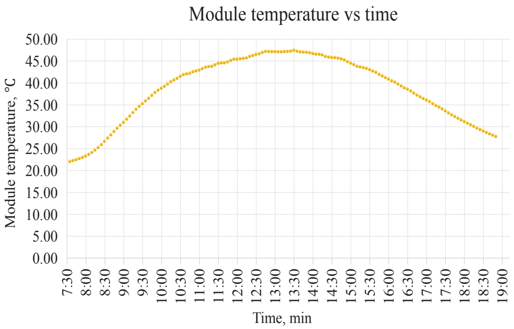

Fig. 15. 2015 module temperature pattern

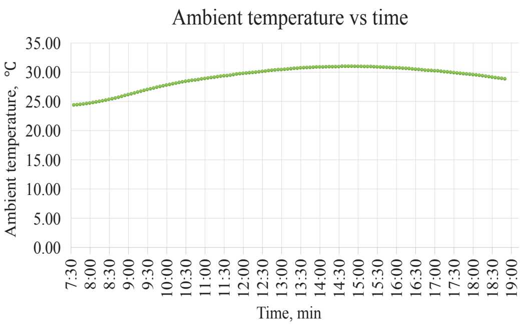

Fig. 16. 2015 ambient temperature pattern

From raw data of output power that has been collected in year 2014 and 2015, Fig. 17 apparently shows independent variables in PV system in overall have constant irradiance, module temperature and ambient temperature characteristics throughout the year in Malaysia, as well as it has strong relationship on PV output solar due to PV modules typically produce current and voltage when directly exposed to sunlight that carry irradiance, thus generate power output. When module temperature high, the current will increases as well generates of huge P_{AC}, yet decreases when ambient temperature is high.

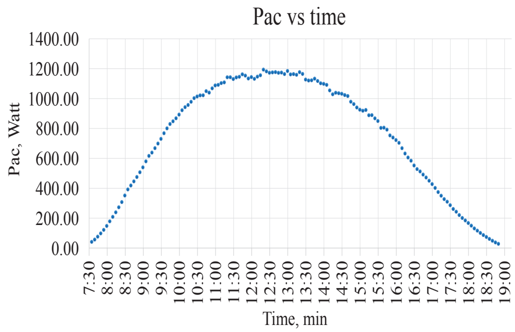

Fig. 17. Average output power at FKE, UTeM on year 2015

The value of R^2 was used to explain the variation of model in which it shows how accurate is the model predict the response in order to predict yearly solar PV output system. In this study, any value of $R^2 > 0.75$, the RSM model is acceptable and valid. For MLR, the equation of Beta is expressed in Table VI. The result is 0.9983 which almost approaching to the exact output response. It demonstrates that MLR model of RSM is valid to obtain optimized predicted response value as it shows slightly error to the target response.

TABLE VI
BETA EQUATION OF MLR

Beta, β	Equation
β_0	6.98×10^2
β_1	4.18×10^{-1}
β_2	4.90×10^1
β_3	-7.04×10^1

Meanwhile, the results of beta equation for Interaction model is stated in Table VII. It shew that R^2 of interaction model was greater than MLR model by value of 0.9993 which varies by 0.0001. Adding an interaction model can cause changes to the interpretation for all of the coefficients. Without interaction model, β_1 would be interpreted as the unique effect of the irradiance on the output power response (Y). Yet, the interaction means that the effect of irradiance on Y is different for different values of module temperature and ambient temperature. Therefore, the effect of irradiance on Y is not only limited to β_1, but also depends on the values of β_4, β_5, module temperature and ambient temperature. This situation will also occurs to β_2 and β_3 of module temperature and ambient temperature

TABLE VII
BETA EQUATION OF INTERACTION

Beta, β	Equation
β_0	-3.46×10^3
β_1	-5.20×10^0
β_2	1.94×10^2
β_3	1.03×10^2
β_4	-3.16×10^{-2}
β_5	2.69×10^{-1}
β_6	-6.15×10^0

Next, pure quadratic model contraindicate results in Table VIII. The R^2 of pure quadratic model shows no difference at all when compared to interaction model as both of these model contribute same R^2 value of 0.9993. This results tell that there are no curvature found on the surface of the model.

TABLE VIII
BETA EQUATION OF PURE QUADRATIC

Beta, β	Equation
β_0	-4.60×10^3
β_1	2.05×10^0
β_2	-3.82×10^1
β_3	3.72×10^2
β_4	-8.75×10^{-4}
β_5	6.47×10^{-1}
β_6	-6.76×10^0

In contrast, full quadratic bring forth highest R^2 with value of 0.9995, shown in Table IX. As this model is the full sets model of MLR, interaction and pure quadratic, thus it results of better approximation. Full quadratic is the best model to be used to test the input data from year 2015, whereas to validate the predicted PV_{AC} output RSM results with the real PV_{AC} output data on year 2015.

TABLE IX
BETA EQUATION OF PURE QUADRATIC

Beta, β	Equation
β_0	-6.60×10^3
β_1	-2.21×10^0
β_2	7.06×10^1
β_3	4.33×10^2
β_4	1.93×10^{-1}
β_5	-1.33×10^{-2}
β_6	3.41×10^0
β_7	-3.47×10^{-3}
β_8	-3.46×10^0
β_9	-9.60×10^0

After validation, Fig. 18 exhibits overall view of predicted P_{AC} in 2015 generated by RSM model; MLR, interaction, pure quadratic and full quadratic. From the graph, found that full quadratic is clearly produced the best prediction of output power in this study, as this model resulting highest R^2 value of 0.9984 as displayed in Fig. 19. Yet, Figure 20 tells that all RSM models have a huge of RMSE value rather than a proper value which is closest to zero. This is due to the fact, that, the data processed for irradiance (X_1), module temperature (X_2) and ambient temperature (X_3) of year 2014 is averaged for every 5 minutes data according to the output target which causes a change in the accuracy of the value. However, it still shows that full quadratic is the most accurate prediction model as the value of RMSE for the model has the most inferior value compared with the other model with value of 8.87.

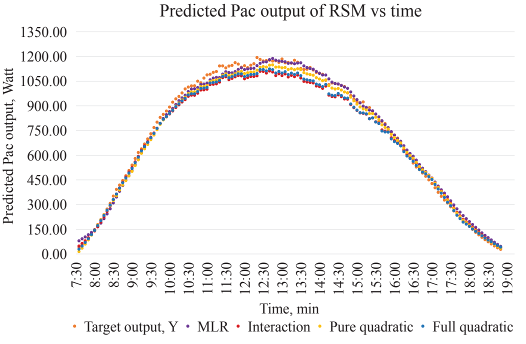

Fig. 18. Predicted P_{AC} generate by RSM module

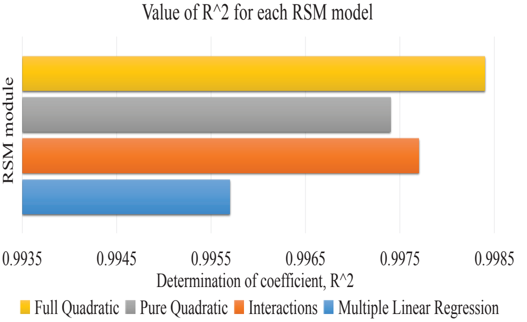

Fig. 19. determination of coefficient (R^2) of RSM model

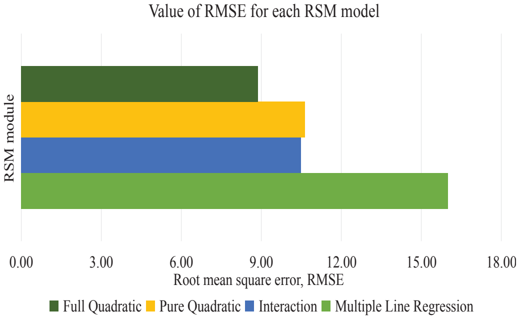

Fig. 20. Root mean square error (RMSE) of RSM model

V. Conclusion

This research explores the possibility of RSM to be used as prediction model for the yearly output power of PV system. To do so, MATLAB RStool which is consisting of four models; multiple linear regression (MLR), interaction, pure quadratic, and full quadratic was used. The 5 minute sampling size of yearly 2014 weather station data of three environmental elements and output power of a 2kW Monocrystalline real PV system are used for training. Whereas, 2015 data of the aforementioned elements were used for validation. The coefficient of determination (R^2) method and root mean square error (RMSE) approach were used to determine the most accurate prediction model. Results show that, full quadratic is the most accurate prediction model with the highest value of R^2 and the lowest value of RMSE.

This experiment is an initial study on power output forecasting for 2 kW Monocrystalline PV system using RSM method. Moreover, the model produce is true for this particular system only and for any particular year as suggested by the results and validation produced. For further study, output power forecasting for larger PV solar system will be conducted using the generated model in order to determine its viability, as well as at different areas in equatorial climate and to be compared with some other approach such as artificial intelligent. It is hoped that the prediction model introduced can be a feasible method to be used by the PV system installer.

Acknowledgements

This research was financially and logistically supported by the Ministry of Education, Malaysia and Universiti Teknikal Malaysia Melaka (UTeM), under the FRGS/1/2017/TK04/FKE-CERIA/F00331 grant.

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