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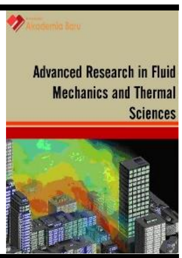

Output Power Forecasting for 6kW Thin-Film PV System using Response Surface Methodology

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ABSTRACT

Photovoltaic (PV) system is an attractive option for the energy sector nowadays due to its renewable nature. However, because of the unpredictable nature of weather, it is difficult to determine the generation of the PV system beforehand. Thus, forecasting is essential for the determination of Return of Investment (ROI) of a newly installed PV system. This paper proposes the application of Response Surface Methodology (RSM) to forecast the output power of the 6kW thin-film PV System. Three environmental elements are used; irradiance, module temperature, and ambient temperature. For that, MATLAB RStool which is consisting of four models; multiple linear regression (MLR), interactions, pure quadratic, and full quadratic was used. The 5 minutes sampling size data weather station from the year 2014 of the 3-phase three environmental elements and output power of 6kW thin-film was recorded and used. Whereas, yearly 2015 data of the aforementioned elements were used for validation. Forecasting performance measures such as the determination of coefficient (R^2) method and root mean square error (RMSE) approach are presented. The results indicated that a full quadratic model provides the best forecasting model with a resulting R^2 value of 0.9981 and gives the least amount of RMSE which is 18.74.

1. Introduction

Renewable energy technology for power generation has become worldwide used since it is an energy that can regularly be replenished as well as reducing the effect of greenhouse gas on the environment. Presently, solar photovoltaic (PV) has rapidly grown in this field as it is abundantly available everywhere in the global that comes with affordable price, smaller operating cost and

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proper size of the components to generate continuous supply without outages and to avoid contamination as well [1,2]. According to M. Almaktar *et al.,* [3], Malaysia is a country that received a high level of irradiance due to the geographic factor that allocated close to the equator line at between 1° and 7° north and between 100° and 120° east. The annual average per year of solar irradiance obtained is 1643 kWh/m^2 reported in Malaysia [4] with exposure to direct sunlight at a rate of 6 hours per day. Hence, it is an advantage for Malaysia to maximize solar power utilization through the development of solar technology systems.

In industrial sectors, solar PV has been widely implemented as it can generate millions of ringgit. By that, renewable government agencies have worked for many strategies as an initiative that supports the utilization of PV solar energy in Malaysia. Among them is the establishment of Sustainable Energy Development (SEDA) in the year 2011 [5]. This agency works as the administering of Feed-in tariff (FiT) program that allows the opportunity for people to get extra income by generating their own electric power as it is a concept that will enable renewable energy-based energy generated to be sold to the utility at a premium price for a certain period of time. Besides, the eligible consumer was also getting the opportunity to produce their own power supply by installing the solar PV system in their residence by joining the Net Energy Metering (NEM) program. Under this program, the consumer will export the excess energy to the grid and received credit by counterbalance part of the electricity bill from the Distribution license; Tenaga Nasional Berhad (TNB). Over time, these programs themselves have generated multi-millions worth of industries and also expedite the number of PV system installers in the market. In order to convince their customers to install PV system either by joining the FiT or the NEM, output power forecasting from the to be installed system is essential. By obtaining the forecasted output, the Return of Investment (ROI) for their customers can be expected.

Due to solar PV output system being periodic and fluctuating in nature, the system itself can be considered as a non-linear complex system, whereby it is problematic to determine the numeric or analytic forecasting model system. Since years ago, many researchers had studied forecasting of solar PV output system using various methods. Artificial Intelligence (AI) techniques such as Artificial Neural Network (ANN), fuzzy logic, genetic algorithm, etc. are some of the methods nowadays used by researchers to deal with the complex non-linear system through modelling, prediction and optimization of the system [6,7] with high accuracy algorithms. However, these AI methods will only produce the algorithms in terms of neuron models. These models are only usable with simulation software such as MatLab. Physically or on paper, these neuron models carry no meaning at all. Thus, an alternative to the AI methods is statistical techniques which produce the algorithms in terms of equation that are more meaningful and robust as it can be used in spreadsheet or even on papers.

One of the available statistical methods available is called Response Surface Methodology (RSM) which has prevalently been used in other field case studies. RSM is a model that can generate mathematical modelling that can describe the relationship between variables and then allow the prediction of output before any processing being finalized [8]. Apart from that, it is also able to produce optimum output results with efficiencies that are comparable with the AI methods. According to Gani [9], RSM method employed in the science field has succeeded in estimating the factor effects of extraction temperature, time processing and ethanol concentration input variables in order to optimize the extraction condition for antioxidant capacities of Curcuma zedoaria leaves. Besides, previous work of others, as shown in [10-13], the RSM method shows the capability to produce optimum prediction results with high efficiency even though it was applied to the dissimilar area.

Hence, this paper tries to implement RSM for three-phase output power (PV_{ac}) forecasting of 6kW of the thin-film solar PV system. Environmental elements such as irradiance, module temperature and ambient temperature are used against three-phase of thin-film PV solar system to produce the output power forecasting model. As there are several RSM models available, this study also tries to determine which of the RSM models of multiple linear regression (MLR), interaction, pure quadratic and full quadratic is the most accurate to forecast thin-film PV system output. Therefore, the input data (G, T_{mod}, T_{amb}) and PV_{ac} data of the year 2014 used to form the RSM model, as well as the input data (G, T_{mod}, T_{amb}) and PV_{ac} data from the 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 the resolution of coefficient (R^2) and root mean square error (RMSE) methods. From the previous work of others, it is expected that the full quadratic model will show the highest accuracy among other models by validation accuracy value of $R^2 > 0.75$.

2. Grid-Connected PV System Description and Weather Station Database

2.1 Grid-Connected PV System Description

PV solar system is the conversion of its energy into heat or electricity [14], which categorized into two; Stand-Alone PV System (Off-Grid System) and Grid-Connected PV System (On-Grid System). The Stand-Alone PV System (SAPV) is a system that does not associated to any electricity network and regularly used in rural areas. Whereas, Grid-connected PV system requires a set of components that includes PV modules, inverter, and other auxiliary components that are connected to the utility grid that suitable for high load power utilization [14,15]. With refer to Figure 1, the energy conversion process ensues when the number of PV modules is jointed inappropriate configuration; series, parallel or series-parallel that form of PV array that generates high of direct current (PV_{dc}) power, voltage, and current. The energy system is then converted to alternating current (PV_{ac}) for load power generation as well as interacting with the utility grid to deliver the exceeds power. This study developed of RSM model is makes use of 6kW inverters of Thin Film GCPV at the lab of PVSG Weather Station, Universiti Teknikal Malaysia Melaka (UTeM) that carry of a three-phase system with 2kW for each phase as shown in Figure 2 and comes with the specification as stated at Table 1. In PV solar technology, thin-film structured of the amorphous and micro-crystalline silicon cell; material made up of different fascination spectrum which is conveniently consolidated to attain a high quality of PV cells [15,16]. Indeed, thin-film indicates better performance at high temperatures due to the presence of amorphous material with low irradiation values when compared to the crystalline module [16,17].

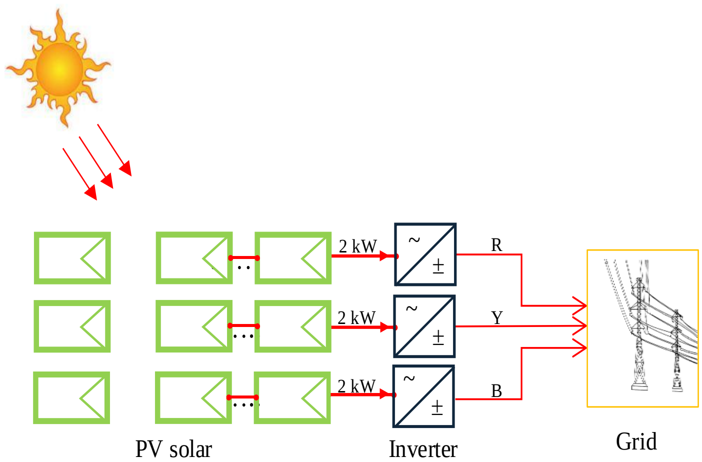


Fig. 1. Conversion process of Grid-Connected PV system

(a) (b)

Fig. 2. (a) 6kW inverters system and (b) Thin-film module of PV system installed at FKE rooftop, UTeM

Table 1
Specification 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
No. 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 %

The PV module data sheet provided by the manufacturer usually indicates the efficiency of PV module under Standard Test Condition (STC). The STC test is to estimate the amount of power reduction in PV solar system when the PV modules increases by every 1˚C above 25˚C (standard STC value for ambient temperature is 25˚C or 77˚F with solar irradiance at 1000 W/m^2 and air mass ratio AM=1.5. This value is usually based on the temperature coefficient (˚C), known as the different rate at which the PV modules underperform when increasing at each of degree Celsius (˚C) of temperature, where most panels have a temperature coefficient in between -0.4% /°C to -0.5%/°C [17,18]. All of these are the necessary criteria for PV module selection due to each of the semiconductor elements able to undermine voltage that causes by the temperature coefficient. This study using of NS-F130GF thin-film module as the datasheet description can be referred to in Table 2.

Table 2
NS-F130GF thin-film data sheet description

Part Name	Rating values
General	
Nominal output (W_p)	130
Module efficiency (%)	9.3
Electrical Characteristics	
Open circuit voltage, V_{oc} (V)	60.4
Short circuit current, I_{sc} (A)	3.41
Maximum power voltage, V_{pm} (V)	46.1
Maximum power current, I_{pm} (A)	2.88
System Voltage (V_{dc})	1000
αPm (%/°C)	-0.24
αIsc (%/°C)	0.07
αVoc (%/°C)	-0.30
Operating temperature (°C)	-40 to +90
Storage temperature (°C)	-40 to +90
Storage air humidity (%)	Up to 90
Physical Dimension	
Cell Type	Tandem structure of amorphous and micro-crystalline silicon cell
Dimension (L×H×W)(mm)	1402×1001×46

2.2 Weather Station Data Base

For better performance in PV solar system, the designation and its proper specification are essential to obtain optimum PV_{ac} generation. For that, IEC 61724 standard guideline requirement is used in this study. IEC 61724 is a common standard and procedures of general guidelines recommended for monitoring and performance analyzing in electrical PV systems, which focuses on evaluating the performance of PV system array [18,19]. It includes the system characteristics; in-plane irradiance, temperature and condition of input and output power for analyzing and exchanging of the monitored data. The standard peak sun for irradiance is 1000W/m^2, and this value is used to calculate the daily output. In-plane irradiance shall be measured as the same plane with PV array by using Pyranometer with the accuracy of irradiance sensors, including the signal conditioning that shall be better than 5 % of the reading. As refer to Figure 3, the type of Pyranometer used in the PVSG Lab Weather Station, UTeM is CMP11 Thermopile Pyranometers with ISO 9060 Secondary Standard and the specification stated in Table 3. Refer to [19,20], Standard Secondary Pyranometer is reliable for long-term stability with an expected low error at a maximum of 3 % in hourly radiation as well as for total daily error.

Fig. 3. CMP11 thermopile pyranometers using ISO 9060 Secondary Standard

Table 3
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 %

Besides, PV modules generate power when there are presents of voltage and current. The relation of these characteristics shall be derived as

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

The production of current PV modules is directly proportional to the amount of irradiance, yet contrariwise to voltage. During a sunny day, the PV modules received abundantly of irradiance, which has led to the increment of PV modules temperature due to the hot weather condition that also affects the PV_{ac} solar system performance. This is because, the elevated module temperature will change the current flow amount and voltage value, thus affected to the PV_{ac} output performance [20,21]. Hence, thermocouple sensor is an essential equipment installed at the back of thin-film PV module FKE, UTeM as display in Figure 4 to measure and monitor the temperature by following IEC 61724 guideline criteria [18,19], 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. In addition, the designation criteria of ambient temperature measurement should be taking into account as output power in the PV system is significantly affected when excessive to heat. According to IEC 61724 standard guideline [18,19], the device is installed in a radiation shield with accuracy shall be better than 1K for the sensor prevention from exposure to direct sunlight that can cause of imprecise output. Figure 5 is a Vaisala HUMICAP HMP155 temperature and humidity sensor that used to measure ambient temperature in this study with the criteria described as shown in Table 4. Another guideline referred to in this study is an Australian Technical Guideline for Monitoring and Analysing PV System. The guideline emphasizes the criteria of data collection for PV performance forecasting. The criteria include the sampling time data; 5 minutes, 30 minutes or hourly, and the period of monitoring for PV performance forecasting shall not less than one year [21,22].

Fig. 4. Thermocouple sensor installed at the thin-film PV solar modules FKE, UTeM

Fig. 5. HMP155 of temperature and humidity sensor used for ambient temperature measurement

Table 4
Relative humidity and temperature specification of HMP155 sensor

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

2.3 Response Surface Methodology Model (RSM)

For the forecasting model, a statistical technique known as RSM is used. This model is often used for modelling and analyzing the problem that determinant by several variable factors that will affect the yield. Instances, the generation of PV_{ac} (y) power in PV solar system is usually affected by certain of independent natural elements such as irradiance (x_1), module temperature (x_2) and ambient temperature (x_3). Whereby, the PV_{ac} power is represented as

$$y = f(x_1, x_2, x_3) + \varepsilon \tag{2}$$

whereas, ε is defined as the error and f is the response that mostly undefined in analyzing of problem. For that, RSM is useful to find the functional relationship between the response of interest and design variables using a mathematical term. There are two types of model in RSM, which is known as 1st order model and 2nd order model. The 1st order model is generally called as multiple linear regression (MLR) by respect to 3 variables that can be expressed as

$$y = b_0 + b_1 x_1 + b_2 x_2 + b_3 x_3 + \varepsilon \tag{3}$$

Then, the 2nd order comprises of several function that known as interactions, pure quadratic and full quadratic. These functions are used to estimate P_{ac} (y) power in PV solar system by that can be derived as below

Interactions

$$y = b_0 + b_1 x_1 + b_2 x_2 + b_3 x_3 + b_4 x_1 x_2 + b_5 x_1 x_3 + b_3 x_3 + b_6 x_2 x_3 + \varepsilon \tag{4}$$

Pure quadratic

$$y = b_0 + b_1 x_1 + b_2 x_2 + b_3 x_3 + b_4 x_1^2 + b_5 x_2^2 + + b_6 x_3^2 + \varepsilon \quad (5)$$

Full quadratic

$$y = b_0 + b_1 x_1 + b_2 x_2 + b_3 x_3 + b_4 x_1 x_2 + b_5 x_1 x_3 + b_6 x_2 x_3 + b_7 x_1^2 + b_8 x_2^2 + b_9 x_3^2 + \varepsilon \quad (6)$$

whereby, the values of b_0 until b_9 are unknowns and to be determined using the least-squares method in the MATLAB RStool- Interactive response surface modelling.

3. Methodology

This section will explain the methodology of this study. Figure 6 tells the flowchart of how the procedure and process that include being done to forecast the three phases output of 6kW thin Film GCPV System using RSM simulation. The initial step is performing the literature review of PV solar system background as well as the RSM model to be used as a prediction method via books, journals and internet surfing.

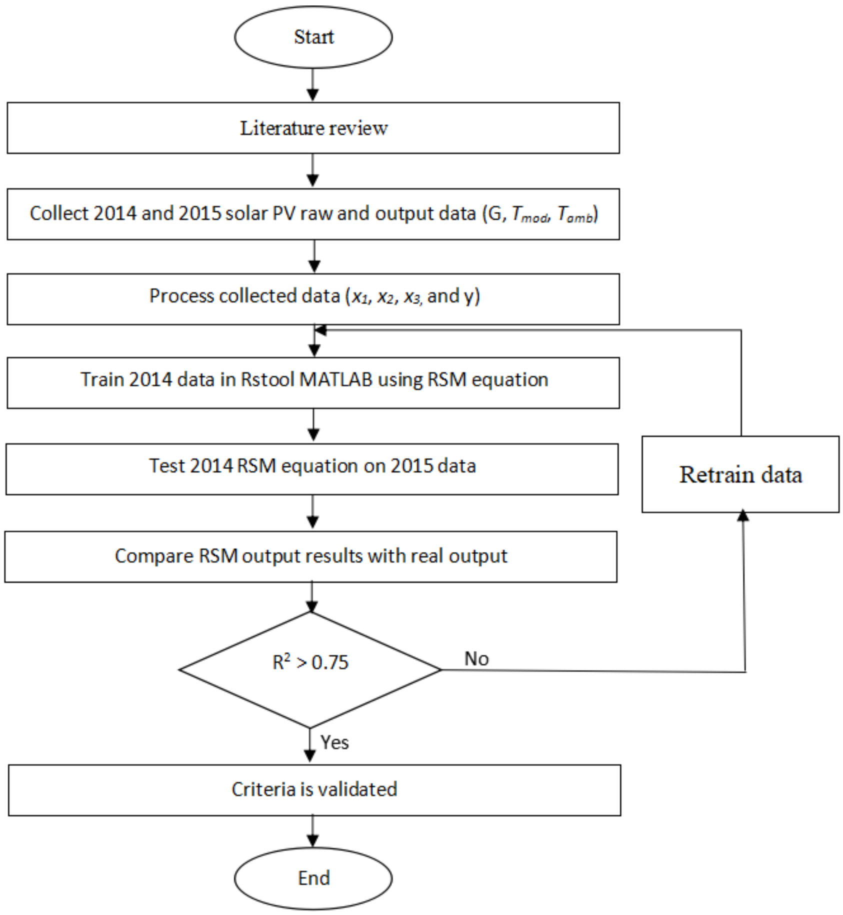
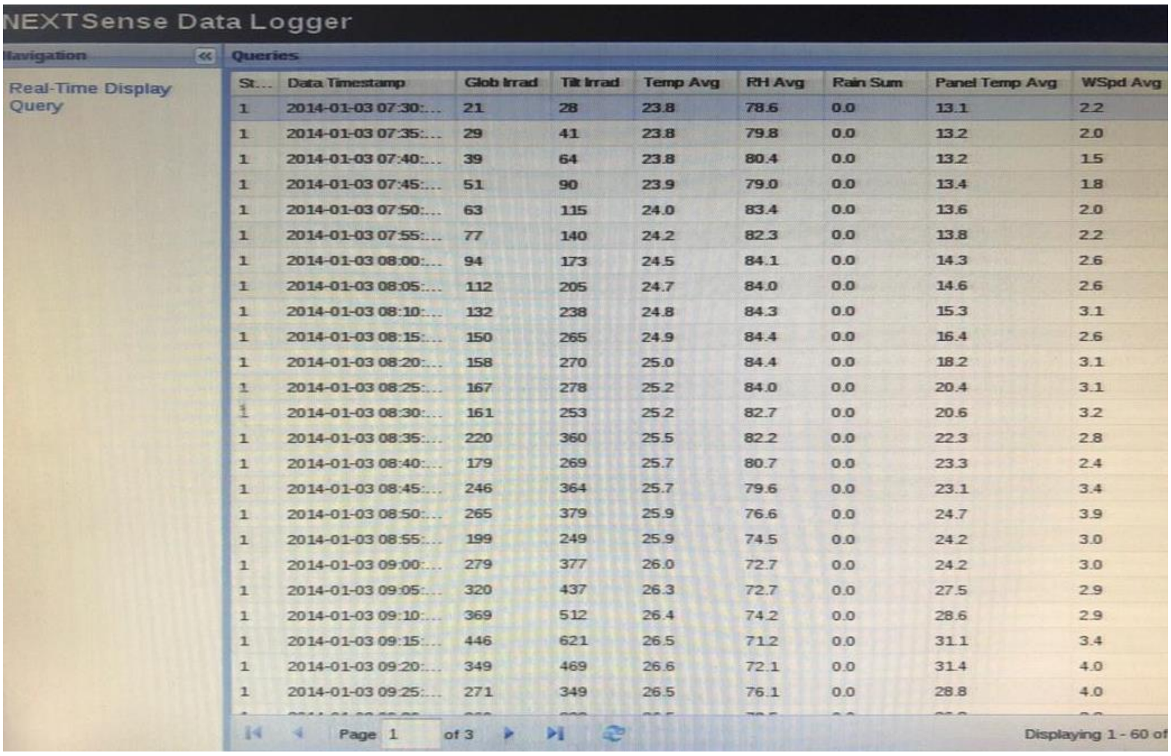


Fig. 6. Flowchart of the research process

From the literature review, independent variables; irradiance, module temperature, and ambient temperature is used as the input variables and PV_{ac} as the yield data, that are available at PVSG Weather station lab, UTeM. This study is conducted using data from the years 2014 and 2015, whereby all the data is first collected. For example, Figure 7 showed the raw data recorded and collected on 3/1/2014 at 9.00 am is 377 W/m2 for tilted irradiance, 26 °C for ambient temperature and 24.2 °C for module temperature. The data then being processed by rearranging the 411 of raw data (from 7.30 am to 6.50 pm) for every five minutes sampling of independent variables input data and PV_{ac} solar in a day, month and year. All steps were done to all raw input data of G, T_{mod} and T_{amb} that labelled as the variable of irradiance (x_1), module temperature (x_2), and ambient temperature (x_3).



St...	Data Timestamp	Glob Irrad	Tilt Irrad	Temp Avg	RH Avg	Rain Sum	Panel Temp Avg	WSpd Avg
1	2014-01-03 07:30:...	21	28	23.8	78.6	0.0	13.1	2.2
1	2014-01-03 07:35:...	29	41	23.8	79.8	0.0	13.2	2.0
1	2014-01-03 07:40:...	39	64	23.8	80.4	0.0	13.2	1.5
1	2014-01-03 07:45:...	51	90	23.9	79.0	0.0	13.4	1.8
1	2014-01-03 07:50:...	63	115	24.0	83.4	0.0	13.6	2.0
1	2014-01-03 07:55:...	77	140	24.2	82.3	0.0	13.8	2.2
1	2014-01-03 08:00:...	94	173	24.5	84.1	0.0	14.3	2.6
1	2014-01-03 08:05:...	112	205	24.7	84.0	0.0	14.6	2.6
1	2014-01-03 08:10:...	132	238	24.8	84.3	0.0	15.3	3.1
1	2014-01-03 08:15:...	150	265	24.9	84.4	0.0	16.4	2.6
1	2014-01-03 08:20:...	158	270	25.0	84.4	0.0	18.2	3.1
1	2014-01-03 08:25:...	167	278	25.2	84.0	0.0	20.4	3.1
1	2014-01-03 08:30:...	161	253	25.2	82.7	0.0	20.6	3.2
1	2014-01-03 08:35:...	220	360	25.5	82.2	0.0	22.3	2.8
1	2014-01-03 08:40:...	179	269	25.7	80.7	0.0	23.3	2.4
1	2014-01-03 08:45:...	246	364	25.7	79.6	0.0	23.1	3.4
1	2014-01-03 08:50:...	265	379	25.9	76.6	0.0	24.7	3.9
1	2014-01-03 08:55:...	199	249	25.9	74.5	0.0	24.2	3.0
1	2014-01-03 09:00:...	279	377	26.0	72.7	0.0	24.2	3.0
1	2014-01-03 09:05:...	320	437	26.3	72.7	0.0	27.5	2.9
1	2014-01-03 09:10:...	369	512	26.4	74.2	0.0	28.6	2.9
1	2014-01-03 09:15:...	446	621	26.5	71.2	0.0	31.1	3.4
1	2014-01-03 09:20:...	349	469	26.6	72.1	0.0	31.4	4.0
1	2014-01-03 09:25:...	271	349	26.5	76.1	0.0	28.8	4.0

Fig. 7. Query raw data recorded in NEXTSense Data Logger at PVSG Weather station lab, UTeM

After processing, the independent variables input data for the year 2014 is being trained using the RSM equation model in RStool MATLAB R2016b, 64-bit software where the data is set as x_1, x_2, and x_3 as shown in Table 5. After the simulation, the acquired equation of beta, b from each RSM model will appear and give the RMSE value as well in the workspace section as presented in Figure 8.

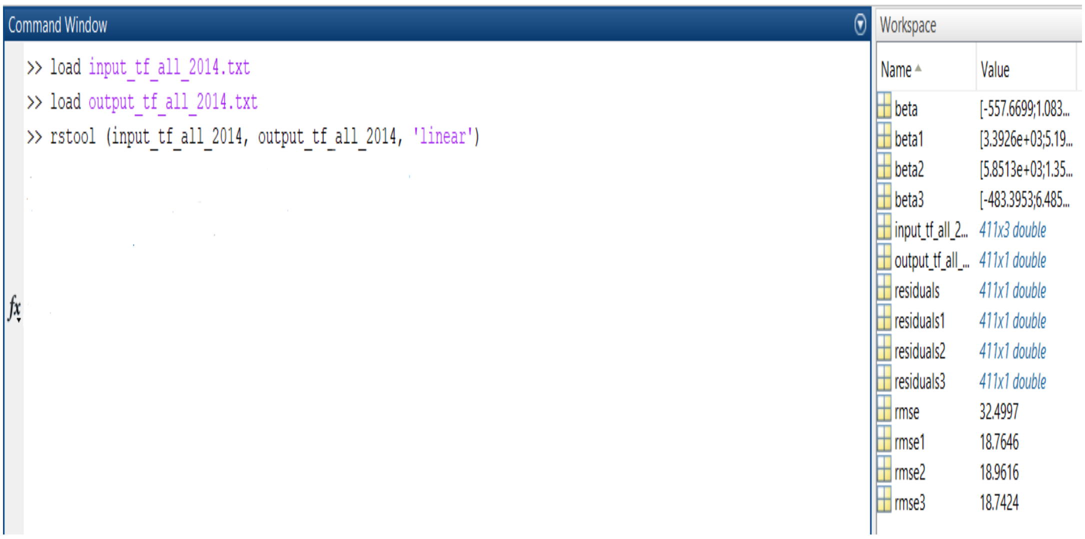


Fig. 8. Simulation using RSM model in Rstool MATLAB

Then, the equation from each of the RSM models was used to generate predicted PV_{ac} results and to be compared with the PV_{ac} data of 2014, which was used as target data. This comparison is to observe the relation of predicted PV_{ac} produce using RSM models with target PV_{ac} data for the year 2014. The results will determine the most accurate RSM models to be used to compare with the real PV_{ac} data in 2015 by choosing the validated model with criteria of $R^2 > 0.75$.

Table 5
2014 trained input data using RSM model in MATLAB software

	Input			Output
	Irradiance, x_1	Module temperature, x_2	Ambient temperature, x_3	Target, y
7:30	41.33	21.63	24.21	18.63
7:35	52.37	21.82	24.26	31.24
7:40	64.75	22.04	24.32	46.69
7:45	77.57	22.27	24.37	65.94
:	:	:	:	:
:	:	:	:	:
18:35	51.01	27.93	29.02	59.00
18:40	44.00	27.62	28.93	44.16
18:45	37.56	27.34	28.84	30.79
18:50	31.27	27.04	28.77	20.41

4. Results

In order to understand the pattern of independent variables input of irradiance, module temperature, and ambient temperature, the raw data collected was averaged to yearly data for both years in 2014 and 2015 and plotted. Figure 9 displays averaged of annual solar irradiance vs time for the daily pattern for the three-phase system (L1, L2, and L3) of thin-film in the year 2014. It can say that Melaka, Malaysia is experiencing Peak Sun Hour (PSH) from time 11.30 am to 2.30 pm every day, which PSH is referred to when the solar power intensity is 1000 Wm^{-2} that equal to the number of hours in a day. The production of higher irradiance shows the presence of high-temperature levels as well.

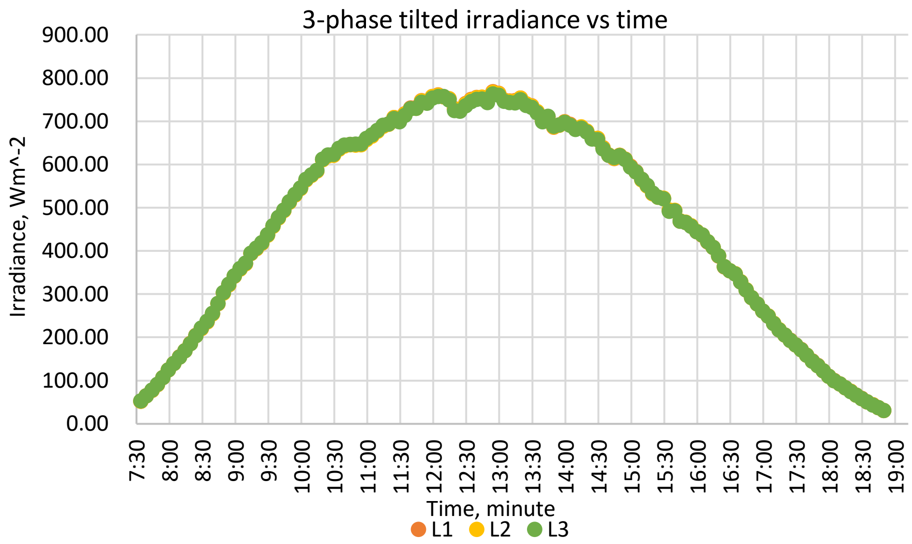


Fig. 9. Daily average of 3-phase tilted irradiance vs time on year 2014

As can be seen in Figure 10, the graph plotted display that the average of ambient temperature on the year 2014 for all phases in thin-film PV system seems to be alike with lower value at 24 °C in the morning and started to increase its temperature up to the highest level which is 32 °C. It shows that Malaysia typically has a uniform average of ambient temperature throughout the year with hot weather conditions as, yet with high humidity, whereby the increment of ambient temperature tends to increase the temperature module.

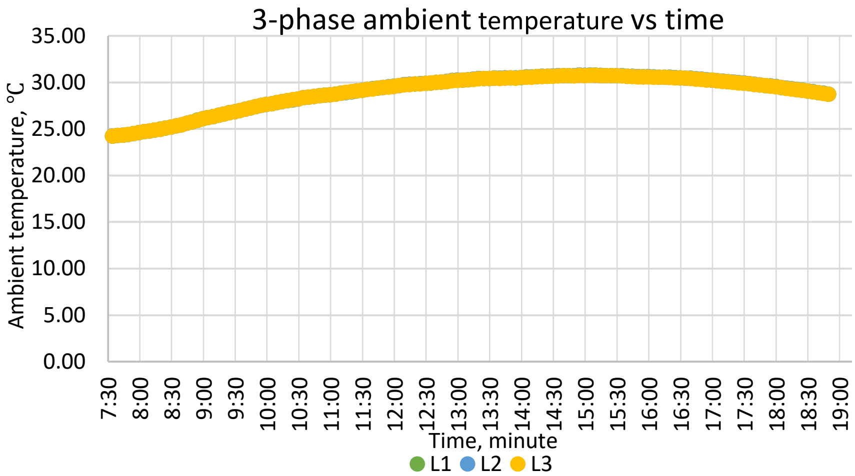


Fig. 10. Daily average of 3-phase ambient temperature vs time on year 2014

In the PV solar system, when the PV modules increase by every 1˚C above 25˚C, it will reduce the PV_{ac}. In other words, module temperature affects the production of solar irradiance that leads to the changes in power generation, whereby to observe the module temperature in this study is significant. The study data shows that the graph in Figure 11 has a consistent PV module temperature pattern for all phases, which is between 23 °C to 47 °C.

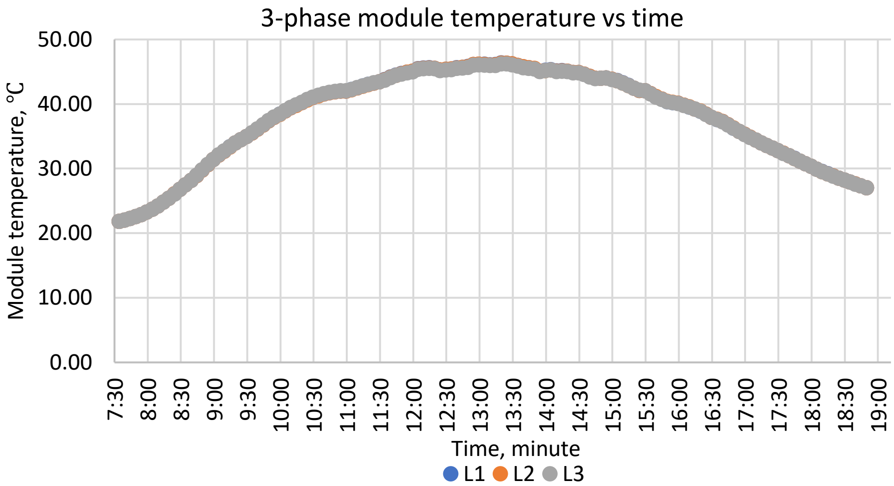


Fig. 11. Daily average of 3-phase module temperature vs time on year 2014

When viewed to the daily average of PV_{ac} pattern on year 2014 in Figure 12, it indicates that the PV solar system of the thin-film is competency to produce high and equivalent output power for a three-phase system with the highest value approximately reached 1380 watt. Based on the figure, it tells that the increment of PV solar module does not make influential much to the PV_{ac} generation since the presence of amorphous material in thin-film PV solar has the potential to withstand at high temperature, thus produce a high value of PV_{ac}. Also, it observed that PV_{ac} is sturdily reliant on irradiance produced by the PV solar system as can be seen from both graphs of PV_{ac} and irradiance has a comparable pattern.

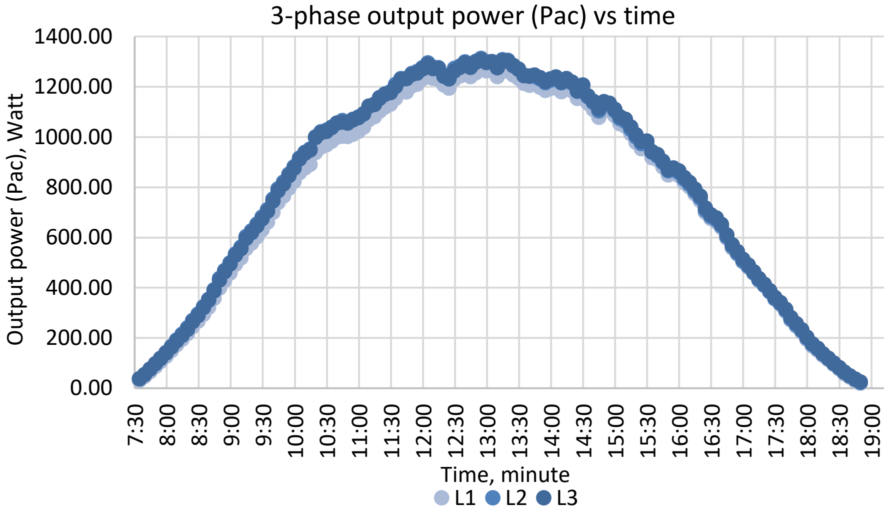


Fig. 12. Daily average of 3-phase P_{ac} vs time on year 2014

To compare the average of trained data from year 2015, Figure 13 tells that the irradiance graph plotted to possess similar irradiance patterns in year 2014. Besides, Malaysia had also experienced constant ambient temperature on a daily basis throughout the year because of having much alike ambient temperature pattern for both year 2014 and 2015 as shown in Figure 14.

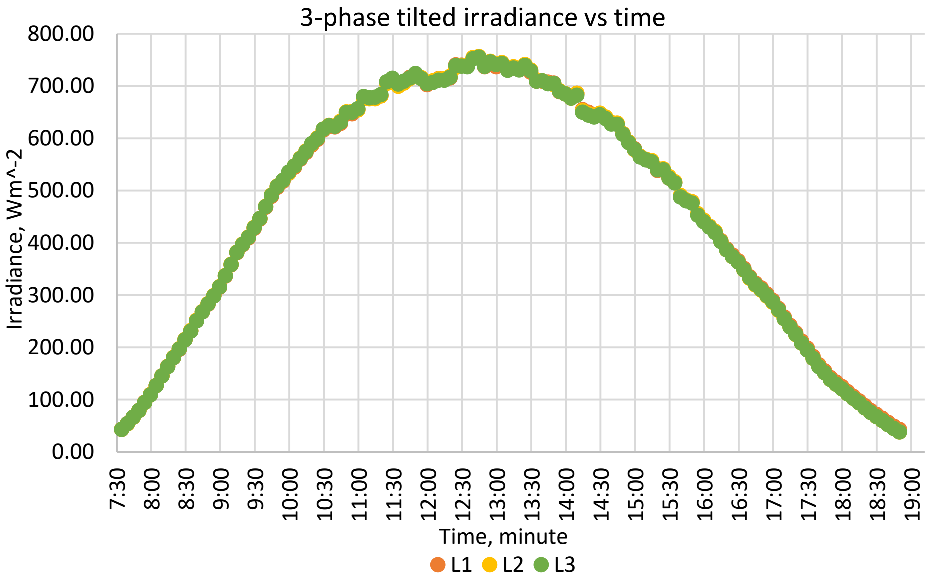


Fig. 13. Daily average of 3-phase tilted irradiance vs time on year 2015

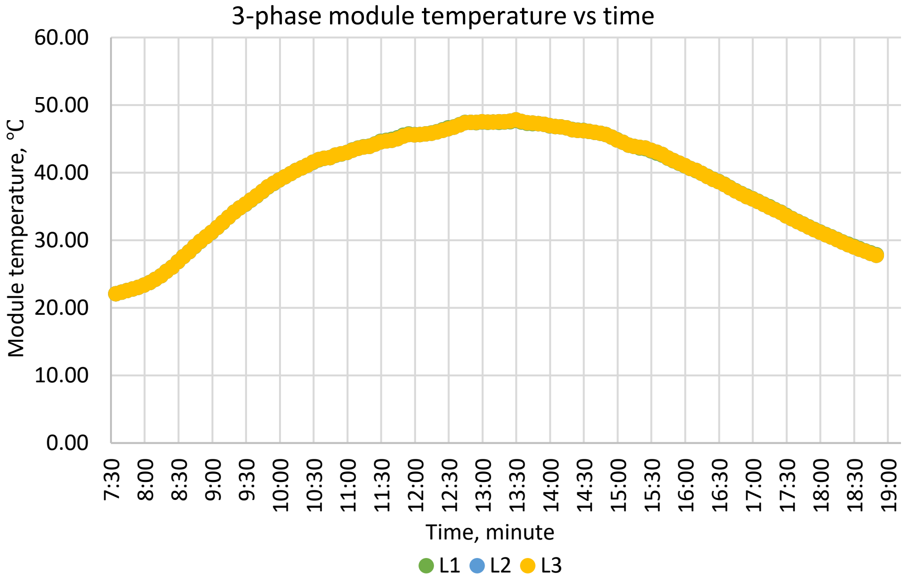


Fig. 14. Daily average of 3-phase ambient temperature vs time on year 2015

Consequently, it gives the same results to module temperature for the year 2015 when compared to data on the year 2014 shown in Figure 15. Due to its constancy for the natural elements; irradiance, module temperature, and ambient temperature, these circumstances indirectly give an analogous outcome pattern of PV_{ac} in the year 2015 that exhibited in Figure 16. It can say that the natural elements are conveniently used as the independent variables for PV solar output forecasting study, as these elements are strongly affected the PV solar output system since PV module generally receives irradiance and produce current and voltage as well when directly exposed to sunlight. Despite can produce high irradiance during hot weather conditions, the high ambient temperature may lead to the increment of module temperature, thus PV_{ac} will diminish.

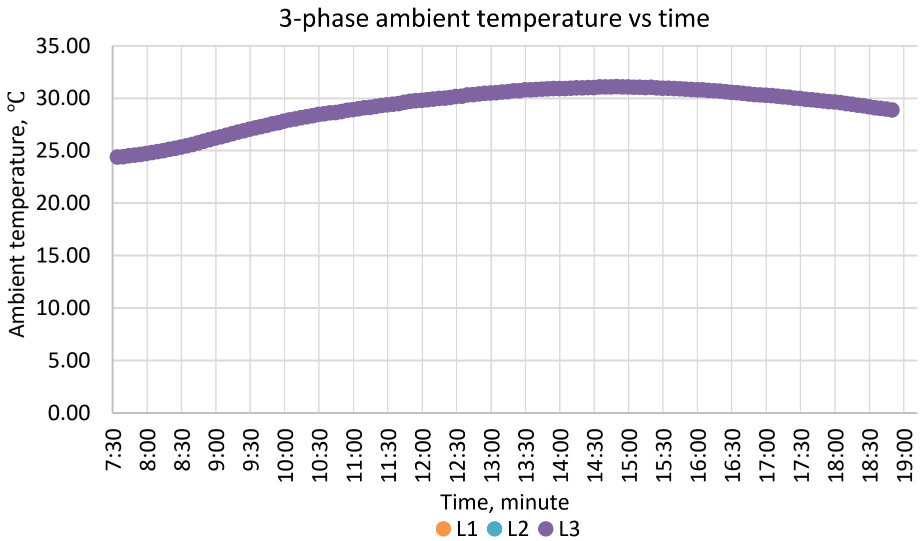


Fig. 15. Daily average of 3-phase module temperature vs time on year 2015

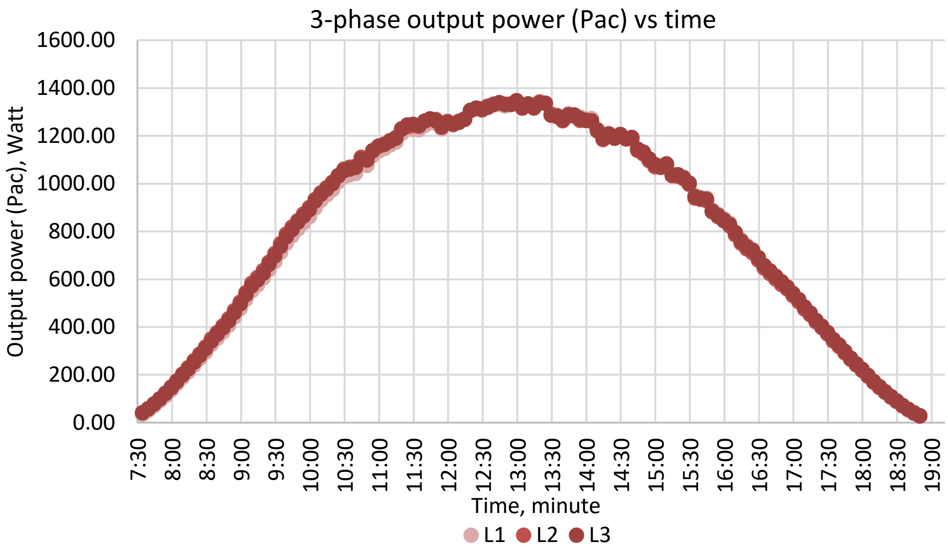


Fig. 16. Daily average of 3-phase P_{ac} vs time in year 2015

To perceive validity, Response Surface Methodology (RSM) model is used to forecast the PV solar PV_{ac} by observing its interaction between three independent variable elements; irradiance, module temperature, and ambient temperature. Therefore, R^2 is used to explain the variation of the RSM model; MLR, interaction, pure quadratic and full quadratic. The accuracy of RSM model to forecast the response in the year 2014 in order to forecast the yearly solar PV output system in the year 2015 is valid and acceptable when any value of $R^2 > 0.75$. For that, the processed data from 2014 was trained in MATLAB to produce the RSM equation. Then, the equation was applied to the real data in 2015 for validation. During the training process, each RSM model produced a beta equation, *b* to achieve the optimum accuracy for forecasting model respectively. As the results, the *b* equation for RSM model of MLR, interaction, pure quadratic and full quadratic is expressed in Table 6.

Table 6
Beta equation of RSM model simulated in MATLAB

Beta, *b*	Equation			
	MLR	Interaction	Pure quadratic	Full quadratic
b_0	-5.58×10^2	3.39×10^3	5.85×10^3	-4.83×10^2
b_1	1.08×10^0	5.19×10^0	1.35×10^0	6.48×10^0
b_2	2.27×10^1	-1.42×10^2	2.04×10^1	-2.66×10^2
b_3	-6.56×10^1	-1.40×10^2	-4.66×10^2	2.74×10^2
b_4	-	-3.15×10^{-3}	-1.00×10^{-4}	3.56×10^{-2}
b_5	-	-1.37×10^{-1}	-6.21×10^{-2}	-2.38×10^{-1}
b_6	-	5.75×10^0	8.49×10^0	1.46×10^1
b_7	-	-	-	6.55×10^{-5}
b_8	-	-	-	-1.93×10^0
b_9	-	-	-	-1.22×10^1

After completion of the training process, each beta of the RSM model contributed to the different value of R^2 results as described in Figure 17. The result indicates that all RSM models; MLR, interactions, pure quadratic and full quadratic was acceptable to forecast the output response of PV solar since all have respectively high accuracy value, which is $R^2 > 0.75$. For the best forecasting model, the full quadratic was in the first place with a value of 0.9981 for R^2. It then followed by a pure quadratic model and interactions that contribute an equivalent R^2 value of 0.998 that slightly varies by 0.0001 to be compared with a full quadratic model. Next, the MLR model also provides a good result of R^2 which is 0.9941 despite having the least accuracy, yet approximately close to 1, where it is referred as the exact response of PV_{ac} PV solar.

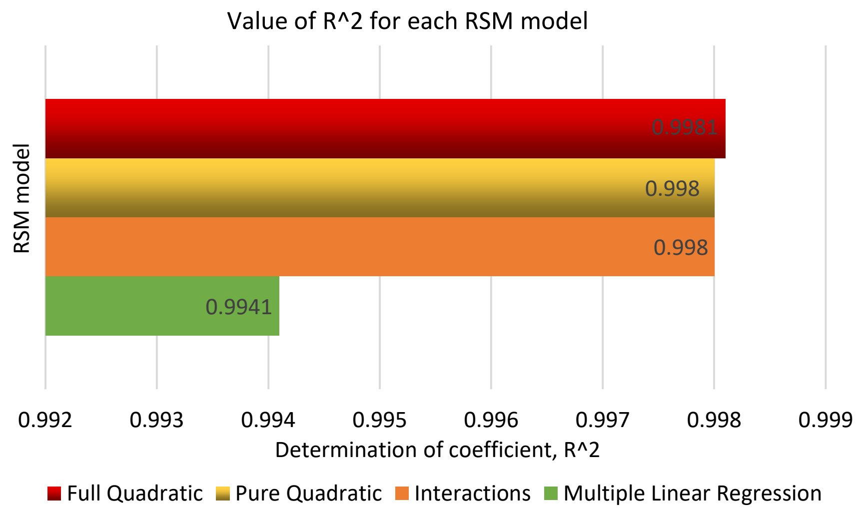


Fig. 17. R^2 value of respective RSM model from trained data on the year 2014

In terms of root mean square error (RMSE) shown in Figure 18, a full quadratic still precedes by having the least value of 18.74. Further, it should be noted that the interactions model has better RMSE value by produce 18.76 compared to pure quadratic that provide 18.96 which significantly differentiates 0.2. Since interactions model performs as a screening method, it shows that there is no curvature found in the real PV_{ac} response, thus produce lower correlation than pure quadratic that is more convenient when there is a presence of curvature surface on response data though it has similar precision as interactions model in terms of R^2 value. For the MLR model, it shows weak correlation by the given immense amount of RMSE with a value of 32.50. This is due to b_1 in this model would only interpret as the unique irradiance effect towards output power response, PV_{ac} and similar condition go to another variable input; module temperature and ambient temperature.

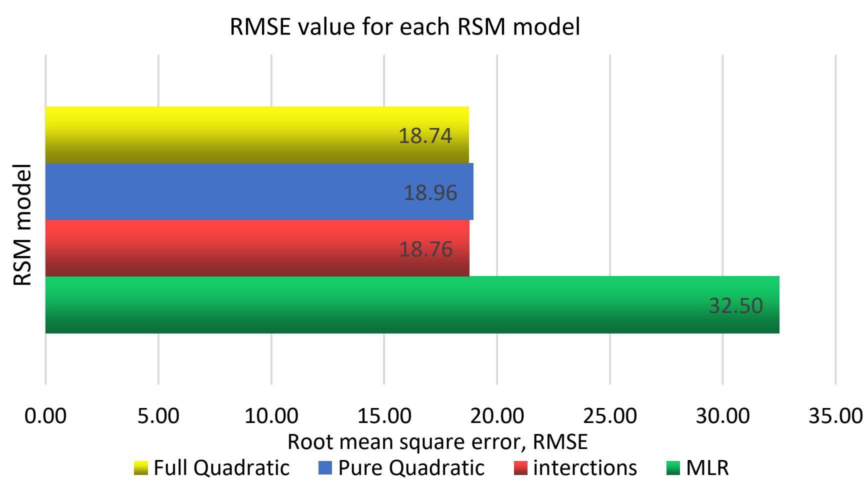


Fig. 18. RMSE value of RSM model

Due to the data on year 2014 was averaged to 5 minutes of sampling data according to the target data of PV_{ac}, thus slightly affected producing of huge RMSE. Nevertheless, full quadratic model still proved that the model is the most veracious and it is selected to be used to test the input data on the year 2015 in order to verify forecast PV_{ac} RSM results against the real P_{ac} data on the year 2015, since it produces the highest R^2 and RMSE result which is 0.9981 and 18.74. As a result, Figure 19 explains that the full quadratic does clearly created a high R^2 value of 0.9931.

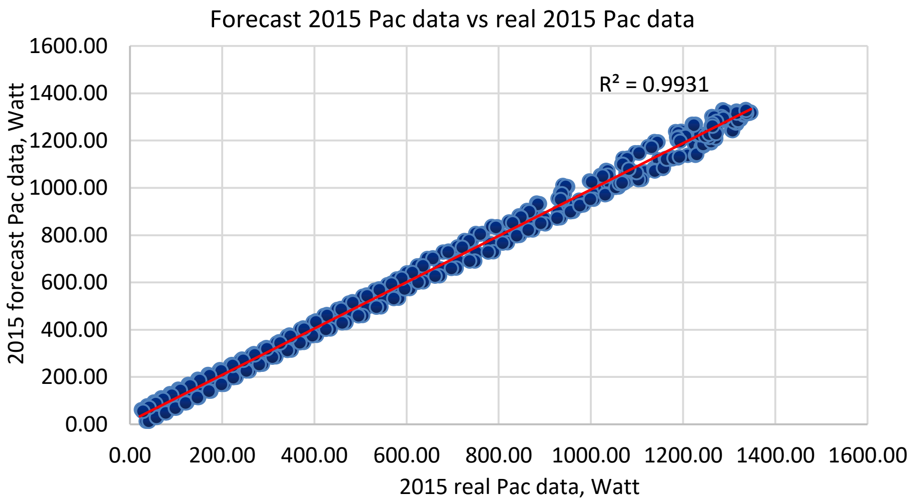


Fig. 19. Validation result of R^2 forecast data vs real data for year 2015

To compare the RMSE value of validation data on year 2015 with the RMSE value of trained data on the year 2014 as shown in Figure 20, seemly that value of RMSE on the year 2015 resulted of a considerable amount which is 36.48 compared to RMSE of trained data on the year 2014 gives the value of 18.74. In fact, the value of RMSE would be increased due to the full quadratic beta equation is originally produced specifically using of 2014 processed data, and since R^2> 0.75, thus it still proved that full quadratic gives excellent results to perform forecasting of thin-film PV_{ac} solar three-phase system, whereby the results of forecast PV_{ac} for the system can be seen in Figure 21.

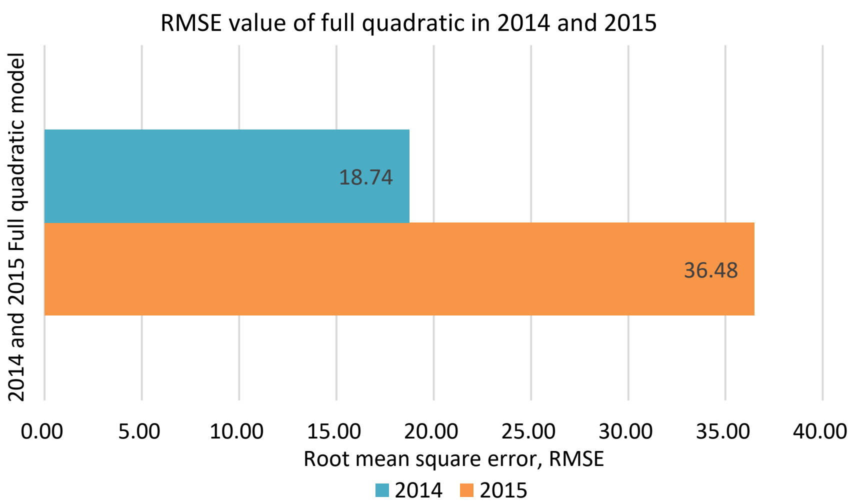


Fig. 20. Comparison of RSME value from trained data on year 2014 with RMSE validation result data on year 2015

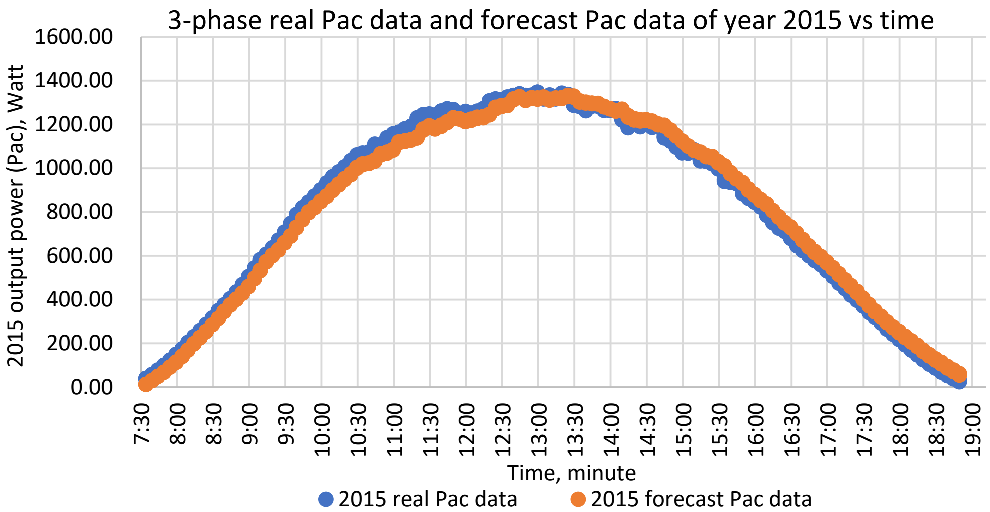


Fig. 21. Comparison of 3-phase real Pac data and forecast Pac data of year 2015 vs time

5. Conclusions

This study is to explore the potential of RSM model to perform forecasting three-phase of 6kW Thin-Film GCPV System that using of MATLAB RStool comprises four models; MLR, interactions, pure quadratic and full quadratic. The 5 minutes of sampling data of three natural elements; irradiance, module temperature and ambient temperature, as well as the real output power (*PVac*) of 6kW thin-film from the year 2014, was collected from PVSG Lab Weather Station, UTeM and used as the training data. While another 5 minutes of sampling data from the year 2015 was used for test and validation. This study has employed the determination of coefficient (R^2) and root mean square error (RMSE) for determining the most accurate forecasting model of RSM. As the results, it shows that the full quadratic model provides the best prediction model among other RSM models by producing the topmost value of R^2> 0.75 and RMSE. This study is conducted to observe the potential of the 6kW thin-film GCPV three-phase system to forecast the output power using the RSM method and it is hoped that the forecasting method introduced in this experiment is practicable for any thin-film PV system installer at different area in an equatorial climate. To determine the PV solar viability, more systems of PV solar will be used and for future study by comparing the presents forecasting model with other forecasting approaches such as machine learning models.

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