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PHOTOVOLTAIC MODULE TEMPERATURE ESTIMATION MODEL FOR THE ONE-TIME-POINT DAILY ESTIMATION METHOD

KINFATT WONG[1], ROBIAH AHMAD[1*], KUSHSAIRY ABDUL KADIR[2], NORULHUSNA AHMAD[1]

[1]Razak Faculty of Technology and Informatics, University Technology Malaysia, Jalan Sultan Yahya Petra, 54100 Kuala Lumpur, Malaysia
[2]British Malaysian Institute, University Kuala Lumpur, Batu 8, Jalan Sungai Pusu, 53100 Selangor, Malaysia

**Corresponding author: robiahahmad@utm.my*

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ABSTRACT: Based on the hourly solar radiation and ambient temperature, the hourly power estimation work is carried out using the conventional photovoltaic output power (PVOP) estimation model which is used in conjunction with the conventional photovoltaic module temperature (PVMT) estimation model. These hourly data must be processed further before they can be applied to the daily power estimation work. This estimation work is carried out using conventional estimation methods, which are the multiple estimation processes that are complex, time-consuming, and error prone. Therefore, to avoid these shortcomings, one estimation process is designed and used for daily power estimation work. However, this process produces an incorrect daily output power value due to an invalid module temperature value. Thus, a new PVMT estimation model is developed to solve the problem of the invalid value based on a simple linear regression analysis. The performance of the new model has been validated, giving a Normalized Root Mean Squared Error (NRMSE) value of 0.0215 and a Coefficient of Determination (R2) value of 0.9862. The correct daily output power value is produced with a valid module temperature value, giving a NRMSE value of 0.0034 and a R2 value of 0.9999. These results demonstrate the new model's applicability and makes the one estimation process accurate, easy, user-friendly, instantaneous, and direct in daily power estimation work.

ABSTRAK: Berdasarkan sinaran matahari dan suhu persekitaran per jam, kerja-kerja anggaran kuasa setiap jam dijalankan menggunakan model anggaran kuasa dari dapatan fotovolta konvensional (PVOP) yang digunakan bersempena dengan model anggaran suhu modul fotovolta konvensional (PVMT). Data per jam ini perlu diproses dengan lebih lanjut sebelum ia boleh digunakan pada kerja anggaran kuasa harian. Kerja-kerja penganggaran ini dijalankan menggunakan kaedah penganggaran konvensional, iaitu proses penganggaran berganda yang kompleks, memakan masa dan mudah ralat. Oleh itu, bagi mengelakkan kekurangan ini, satu proses anggaran direka bentuk dan diguna bagi kerja anggaran kuasa harian. Namun, proses ini menghasilkan nilai dapatan kuasa harian yang salah disebabkan oleh nilai suhu modul tidak sah. Oleh itu, model anggaran PVMT baharu telah dibina bagi menyelesaikan masalah nilai tidak sah berdasarkan analisis mudah regresi linear. Prestasi model baharu telah disahkan, memberi nilai Ralat Punca Min Kuasa Dua Ternormal (NRMSE) sebanyak 0.0215 dan nilai Pekali Penentuan (R2) sebanyak 0.9862. Nilai dapatan kuasa harian yang betul dihasilkan dengan nilai suhu modul yang sah, iaitu nilai NRMSE 0.0034 dan R2 0.9999. Dapatan ini menunjukkan bahawa kebolehgunaan model baharu menjadikan proses anggaran lebih tepat, mudah, mesra pengguna, serta-merta dan terus dalam kerja anggaran kuasa harian.

KEYWORDS: *Daily module temperature, daily output power, hour-based climatic data, day-based climatic data, estimation method*

1. INTRODUCTION

The conventional PVOP estimation model is used in conjunction with the conventional PVMT estimation model for estimating the possible output power based on the climatic variables of solar radiation and ambient temperature. These conventional PV estimation models are derived based on the PV module performance test under Standard Test Conditions (STC) and Nominal Operating Module Temperature (NOCT). All the relevant data parameters of the models are available from the product specification, as shown in Appendix A [1], except the climatic variable data of solar radiation and ambient temperature. These data can be acquired in hourly, daily, monthly, and yearly data formats from the satellite-based or ground-based climatic measurement centre.

For the conventional PV estimation models, Chang and Zhang [2] stated that it is more suitable to use the hourly climatic data for estimating the hourly output power. In other words, the conventional PV estimation models can be regarded as the hour-based estimation models which estimate the hourly output power using the conventional one-time-point hourly (OTP-H) estimation method. This hourly output power is further used as the primary data to form the daily, monthly, and yearly output power. For instance, Murat Ates and Singh [3] proposed a spreadsheet-based analytical model to simulate the performance of a one-year large-scale rooftop solar PV system based on the daily, monthly, and yearly output power, which are estimated through the sum of the hourly output powers within a day, a month, and a year. Razmjoo *et al.* [4] proposed a techno-economic evaluation of PV-wind-diesel hybrid renewable energies which considered the sum of the PV hourly output powers within a year to estimate the PV yearly output power. As a result, the daily, monthly, and yearly output power estimation method can be considered as the conventional multiple-time-point sum-hourly (MTP-SH) estimation method.

Besides the hourly climatic data, the average hourly climatic data within the sunshine hours of a day, namely the daily hour-average-based climatic data within the sunshine-hours (HAB-SH), is also suitable for the conventional PV estimation models as stated in [5]. Furthermore, Skoplaki and Palyvos [6] provided an overview description of the PV module operating temperature which indicated that the daily HAB-SH climatic data is applicable for the conventional PVMT estimation model to aid in the daily output power estimation. This demonstrates that the daily HAB-SH climatic data has the same function as the hourly data, and hence both can be taken as hour-based climatic data. Since the daily HAB-SH climatic data is exclusively used in the PVMT estimation model, it can be considered as the main hour-based estimation model. Moreover, the estimation method for estimating the daily output power in [6] can be regarded as the conventional multiple-time-point average-hourly (MTP-AH) estimation method, since it deals with the daily HAB-SH climatic data.

According to Chang and Zhang [2], the day-based climatic data is unsuitable for use in the conventional PV estimation models for performing the daily power estimation work. To make the day-based climatic data applicable for the daily power estimation work, a new hour-based estimation model, namely a new PVMT estimation model is proposed. This new model is developed by referring to the references of multiple linear regression analyses which describes the relationship between one dependent variable of PVMT and multiple independent climatic variables. For instance, Tamizhmani *et al.* [7] proposed a prediction model to predict the PVMT based on multiple linear regression analysis, which explores the relationship between the measured PVMT and the climatic conditions of ambient temperature, wind speed, wind direction, solar radiation, and relative humidity. The model's efficiency depends on the climatic conditions of the site location and the PV technology type. Kamuyu *et al.* [8] proposed a prediction model of PVMT for a floating PV system based on multiple linear regression analyses, which explores the relationship between the measured PVMT and the effect of ambient temperature, solar radiation, wind speed, and water temperature. By the comparison between the predicted and measured values, it gave the corresponding model error range of between 2% and 4%.

Aside from that, new model development is also referred to the references of simple linear regression analysis which describes the relationship between one dependent climatic variable and one independent climatic variable. For instance, Ibrahim *et al.* [9] proposed a prediction model based on simple linear regression analysis, which explores the relationship between solar radiation and ambient temperature. The results elaborated that their relationship is linear and gave an R2 value of 0.5593. Furthermore, this simple linear regression analysis serves as the foundation for performance validation, which is used to explore the relationship between the same variable that is recorded in two different ways. For instance, Alam *et al.* [10] proposed a dynamic model for a standalone PV distributed power generation system to predict the system's maximum power. The performance of the proposed model is relevant to a simple linear regression analysis, which is used to explore the relationship between the experimental and predicted output power. Li *et al.* [11] proposed a new attenuation hourly solar radiation model based on seasonal and stochastic features. The performance of the proposed model is related to the regression analysis, which explores the relationship between the measured and estimated hourly solar radiation. Cetina-Quiñones *et al.* [12] proposed a machine learning surrogate model of an indirect solar dryer with thermal energy storage. The performance validation was related to the exploration of the relationship between the experimental and predicted temperature.

The new regression coefficients that were used for the new PVMT estimation model are developed based on the climatic variables of solar radiation and ambient temperature. Each of the climatic variables can be recorded in various ways. For instance, Almaktar *et al.* [13] stated that the ambient temperature in their research is recorded as an average of hourly data in 24 hours and within sunshine hours of a day. While the solar radiation is recorded as a sum and average of the hourly data within the sunshine hours of a day. Essentially, this averages of the solar radiation and ambient temperature within the sunshine hours of a day are the uncommon daily climatic variables in the database of NASA [14]. However, Mellit and Pavan [15] specifically mentioned the use of these uncommon daily climatic variables in their research. As a result, these uncommon daily climatic variables, namely daily HAB-SH climatic data, are used as the key climatic variables in this study for developing the new PVMT estimation model, and they are basically the manual-processing hour-based climatic data.

The aim of this study is to develop a new PVMT estimation model based on simple linear regression analysis, which explores the relationship between the hour-based and day-based climatic data to allow the daily power estimation work to be performed with one estimation process, namely the one-time-point daily (OTP-D) estimation method. The following objectives best describe the main contribution of this study:

- To study and analyse the conventional PV estimation models and methods, as well as the ways of recording the climatic variables.
- To develop a new regression coefficient for the new PVMT estimation model to carry out the OTP-D estimation method.

- To validate the new PVMT estimation model with the ground-based climatic dataset using standard statistical indicators, NRMSE and R2.

NRMSE is calculated for the predicted model's degree distributions based on the original, and R2 is used to assess the quality of fit in a linear regression model.

Hence, this new PVMT estimation model is expected to be accurate, easy, user-friendly, instantaneous, and direct for daily power estimation work in the pre-installation phase. The remaining sections of this study are structured as follows: Section 2 discusses the relevant climatic data format. The conventional PV estimation models and methods are presented in section 3. Section 4 describes the research methodology for developing the new PVMT estimation model. The results and discussion for developing the new model are given in Section 5. Section 6 provides the conclusion and recommendations for future development.

2. THE RELEVANT CLIMATIC DATA FORMAT

2.1. Satellite-based Climatic Data

National Aeronautics and Space Administration (NASA) is a well-known satellite-based climatic measurement centre that provides free climatic datasets of hourly, daily, monthly, and yearly data of solar radiation and ambient temperature [13]. These free datasets are used to analyse the conventional PV estimation methods and develop the new PV estimation model in this study. Moreover, the hourly climatic data is used as the primary data to form the daily, monthly, and yearly climatic data as shown in Table 1 [14]. Solar radiation refers to all-sky surface shortwave downward irradiance in NASA, and the total hourly data within the sunshine hours of a day is daily hour-total-based (HTB-SH) data. The average daily HTB-SH data of a month is monthly day-average-based (DAB-SH) data. The average monthly DAB-SH data for a year is yearly month-average-based (MAB-SH) data. Then, the ambient temperature refers to the temperature at 2 meters in NASA, and the average hourly data in 24 hours of a day is daily hour-average-based (HAB-24) data. The average daily HAB-24 data of a month is monthly day-average-based (DAB-24) data. The average monthly DAB-24 data of a year is yearly month-average-based (MAB-24) data.

Table 1: Example of NASA climatic data

Variable	Data Format	Description
Ambient Temperature	Daily HAB-24	Average hourly data in 24 hours of a day
	Monthly DAB-24	Average daily HAB-24 data of a month
	Yearly MAB-24	Average monthly DAB-24 data of a year
Solar Radiation	Daily HTB-SH	Total hourly data within the sunshine hours of a day
	Monthly DAB-SH	Average daily HTB-SH data of a month
	Yearly MAB-SH	Average monthly DAB-SH data for a year

2.2. Ground-based Climatic Data

Ground-based climatic measurement centres are exceedingly expensive to establish; there are not many of them worldwide [13]. Although ground-based data have the same climatic data formats as NASA satellite-based data, they have different measured values. Therefore, the ground-based climatic datasets will be used as the testing datasets in this study for a new estimation model validation. These datasets are measured according to the standard of Typical Meteorological Year Three (TMY3) Dataset [16] at Tasik Banding, Malaysia in 2005, with a Latitude of 5.554 and a Longitude of 101.337 as shown in Fig. 1.

Fig. 1. Map of Tasik Banding, Malaysia

2.3. Hour-based and Day-based Climatic Data

According to NASA [14], the daily HAB-24 ambient temperature data and daily HTB-SH solar radiation data are the day-based data, and the hourly data of ambient temperature and solar radiation are the hour-based data as shown in Table 2. On the other hand, the uncommon daily HAB-SH ambient temperature and solar radiation data for NASA are the manual-processing data. According to the principle presented in [5] and [6], the manual-processing daily HAB-SH climatic data have the same function as the hourly climatic data and are considered as hour-based climatic data that can be applied into the hour-based estimation model, namely the PVMT estimation model as stated in [2].

Table 2: Hour-based and day-based climatic data

Climatic Variable	Hour-based Data		Day-based Data
	NASA	Manual-processing	NASA
Ambient Temperature	Hourly	Daily HAB-SH	Daily HAB-24
Solar Radiation	Hourly	Daily HAB-SH	Daily HTB-SH

The difference between the manual-processing daily HAB-SH ambient temperature and the NASA daily HAB-24 ambient temperature is that the former does not include the data records during the night-time. While for the manual-processing daily HAB-SH solar radiation and the NASA daily HTB-SH solar radiation, the former does not sum up all the hourly data within the sunshine hours of a day.

3. PV ESTIMATION MODELS AND METHODS

3.1. Conventional PV Estimation Models

One of the conventional PVOP estimation models is given as [4][17]

$$P_{pv} = P_{max}(G/G_{STC})\left[1 + \beta_p\left(T_m - T_{m\_STC}\right)\right] \tag{1}$$

where G is the solar radiation (W/m^2) and the PVMT estimation model, T_m is defined as [17]

$$T_m = T_a + \left(T_{NOCT} - T_{a\_NOCT}\right) G/G_{NOCT} \tag{2}$$

where T_a is the ambient temperature (°C). These conventional estimation models are used in a variety of estimation methods to produce a variety of estimation results for further analysis.

3.2. Conventional PV Estimation Methods

3.2.1. OTP-H Estimation Method

For the conventional OTP-H estimation method, the hourly climatic data of solar radiation, G_h and ambient temperature, T_{a_h}, which are extracted directly from NASA, will be applied into Eq. (2) for estimating the hourly module temperature [18], $T_{m\_h\_1H}$

$$T_{m\_h\_1H} = T_{a\_h} + \left(T_{NOCT} - T_{a\_NOCT}\right) G_h / G_{NOCT} \tag{3}$$

G_h will be further applied into Eq. (1) for estimating the hourly output power [17], $P_{pv\_h\_1H}$

$$P_{pv\_h\_1H} = P_{max}(G_h/G_{STC})\left[1 + \beta_p\left(T_{m\_h\_1H} - T_{m\_STC}\right)\right] \tag{4}$$

3.2.2. Multiple-time-points Daily (MTP-D) Estimation Method

The conventional MTP-D estimation method is referring to the MTP-SH and MTP-AH estimation methods. These estimation methods perform the daily power estimation work based on the hour-based climatic data as shown in Table 3. Moreover, they are the estimation method that involved multiple processes in estimating the daily output power.

Table 3: Conventional MTP-D estimation methods

Estimation Method	Description	Input	Output	Reference
MTP-SH Estimation Method	Sum of hourly output powers	G_h , T_{a_h} , H_s	$P_{pv\_d\_sum}$	[3, 4]
MTP-AH Estimation Method	Average of hourly climatic data	$G_{d\_HAB\_SH}$, H_s $T_{a\_d\_HAB\_SH}$	$T_{m\_h\_avg}$ $P_{pv\_d\_avg}$	[5, 6]

The MTP-SH estimation method sums up each $P_{pv\_h\_1H}$ within the sunshine hours of a day, H_s to produce the daily output power, which is given as [3]

$$P_{pv\_d\_sum} = \sum_{i=1}^{H_s} P_{pv\_h\_1H} \tag{5}$$

H_s is a manual-processing climatic variable as well. It will be used in conjunction with the manual-processing data of daily HAB-SH solar radiation, $G_{d\_HAB\_SH}$ and daily HAB-SH ambient temperature, $T_{a\_d\_HAB\_SH}$ for performing the daily power estimation work with the MTP-AH estimation method. This method is first using $G_{d\_HAB\_SH}$ and $T_{a\_d\_HAB\_SH}$ to produce the daily HAB-SH module temperature, $T_{m\_h\_avg}$, which is defined as [6]

$$T_{m\_h\_avg} = T_{a\_d\_HAB\_SH} + \left(T_{NOCT} - T_{a\_NOCT}\right) G_{d\_HAB\_SH} / G_{NOCT} \tag{6}$$

$T_{m\_h\_avg}$ is an hour-based module temperature since it deals with the hour-based climatic data, namely daily HAB-SH climatic data. Then, it will be applied in conjunction with $G_{d\_HAB\_SH}$ into Eq. (1) to produce the daily HAB-SH output power, $P_{pv\_h\_avg}$

$$P_{pv\_h\_avg} = P_{max}\left(G_{d\_HAB\_SH}/G_{STC}\right)\left[1 + \beta_p\left(T_{m\_h\_avg} - T_{c\_STC}\right)\right] \tag{7}$$

$P_{pv\_h\_avg}$ is also an hour-based output power which is then multiplied by H_s to produce the daily output power, $P_{pv\_d\_avg}$

$$P_{pv\_d\_avg} = P_{pv\_h\_avg} \times H_s \tag{8}$$

The concept of $P_{pv\_d\_avg}$ adheres to the multiplier principle of Peak Sun Hour (PSH) [13].

3.3. Linear Regression Model

The number of independent variables in a simple and multiple linear regression analysis will differ. More than one independent variable will be included in the multiple linear regression analysis. For instance, the regression model includes five independent climatic variables in the proposed model, which is given as [7]

$$T_{m\_MLR\_1} = a_1 G + a_2 T_a + a_3 v_w + a_4 v_{dir} + a_5 RH + a_6 \tag{9}$$

where a_1, a_2, a_3, a_4, a_5 and a_6 are the regression coefficients, v_w is the wind speed (m/s), v_{dir} is the wind direction (°), and RH is the relative humidity (%). Besides, Kamuyu *et al.* propose the regression model with four independent climatic variables, which is defined as [8]

$$T_{m\_MLR\_2} = a_1G + a_2T_a + a_3v_w + a_4T_w + a_5 \tag{10}$$

where T_w is the water temperature (°C).

On the other hand, the simple linear regression analysis will include only one independent variable. For instance, Ibrahim *et al.* proposed a model that explores the relationship between two different climatic variables, the model is given as [9]

$$G = mT_a + c \tag{11}$$

where m and c are the regression coefficients of the slope and intercept. Moreover, Alam *et al.* proposed a model that explores the relationship between the same power variables, but recorded per different methods, the model is defined as [10]

$$P_{pv\_measured} = mP_{pv\_estimated} + c \tag{12}$$

where $P_{pv\_measured}$ is the measured output power (W) and $P_{pv\_estimated}$ is the estimated output power (W).

4. RESEARCH METHODOLOGY

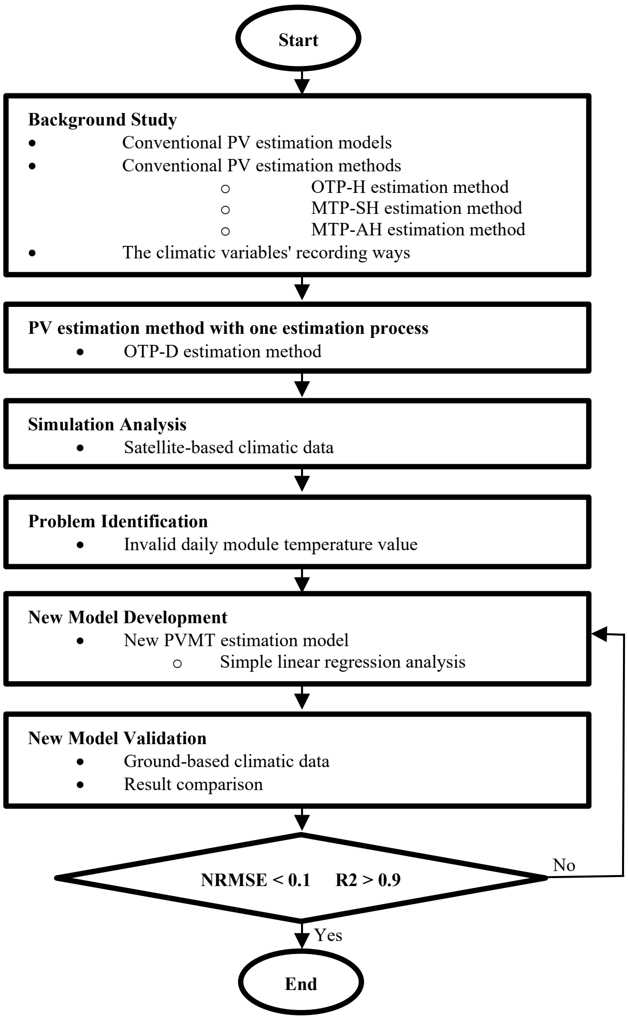

Fig. 2. Research methodology

The flow chart of the research methodology of this study is shown in Fig. 2. The background study focuses on the basic principles of the conventional PV estimation models and methods as well as the ways for recording the climatic variables. According to these studies, the conventional daily power estimation works involve multiple estimation processes in estimating the daily output power. Since the multiple estimation processes is complex, time-consuming, and error-prone, a one estimation process, namely the OTP-D estimation method, is designed and used. This method uses the day-based climatic data directly to perform the daily power estimation work. It is then analysed further in a simulation experiment using satellite-based climatic datasets. However, the experiment results reveal that the problem of the invalid daily module temperature value in the OTP-D estimation method. This is because the day-based climatic data is not suitable to use in the hour-based estimation model, namely the PVMT estimation model. Thus, a new PVMT estimation model is developed based on the simple linear regression analysis to solve the problem of the invalid daily module temperature value. This new model is validated using the same simulation experiment but based on the ground-based climatic datasets. It compares the estimation results that were produced by the MTP-AH estimation method and the OTP-D estimation method with the new PVMT estimation model. The result comparison demonstrates the new model's applicability in the OTP-D estimation method because it gives the NRMSE value less than 0.1 and the R2 value more than 0.9. In other words, the OTP-D estimation method with the new PVMT estimation model is compatible with the conventional MTP-AH estimation method.

4.1. OTP-D Estimation Method

For the OTP-D estimation method, the day-based climatic data, daily HAB-24 ambient temperature data, $T_{a\_d\_HAB\_24}$ and daily HTB-SH solar radiation data, $G_{d\_HTB\_SH}$ which extracted directly from NASA will be applied into Eq. (2) for estimating the daily module temperature, $T_{m\_d\_1D}$

$$T_{m\_d\_1D} = T_{a\_d\_HAB\_24} + \left(T_{NOCT} - T_{a\_NOCT}\right) G_{d\_HTB\_SH} / G_{NOCT} \tag{13}$$

$G_{d\_HTB\_SH}$ will be further applied into Eq. (1) for estimating the daily output power, $P_{pv\_d\_1D}$

$$P_{pv\_d\_1D} = P_{max}\left(G_{d\_HTB\_SH} / G_{STC}\right)\left[1 + \beta_p\left(T_{m\_d\_1D} - T_{m\_STC}\right)\right] \tag{14}$$

However, $T_{a\_d\_HAB\_24}$ and $G_{d\_HTB\_SH}$ in $T_{m\_d\_1D}$ produce an invalid daily module temperature value, resulting in an incorrect daily output power value. This invalid value refers to the value that exceeded the operational module temperature's maximum stated value in the data specification sheet [1], and it differs greatly from the module temperature value estimated by the conventional MTP-AH estimation method.

4.2. New Model Development

The problem of the invalid daily module temperature value is solved by developing a new PVMT estimation model for the OTP-D estimation method. This new model is derived from the simple linear regression analysis, which explores the relationship between the hour-based and day-based climatic data, namely the suitable and unsuitable climatic data. The hour-based climatic data refers to the uncommon and manual-processing climatic data, $T_{a\_d\_HAB\_SH}$ and $G_{d\_HAB\_SH}$ as presented in Eq. (6) which are used in the conventional MTP-AH estimation method. While the day-based climatic data refer to the NASA satellite-based climatic data, $T_{a\_d\_HAB\_24}$ and $G_{d\_HTB\_SH}$ as presented in Eq. (13) which are used in the OTP-D estimation method.

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Based on the principle as presented in [10–12], the new regression coefficient for ambient temperature is derived based on the exploration of the relationship between $T_{a\_d\_HAB\_SH}$ and $T_{a\_d\_HAB\_24}$

$$T_{a\_d\_HAB\_SH} = m_T\, T_{a\_d\_HAB\_24} + c_T \tag{15}$$

where m_T and c_T are the regression coefficients of slope and intercept for ambient temperature. While the new regression coefficient for solar radiation is derived based on the exploration of the relationship between $G_{d\_HAB\_DH}$ and $G_{d\_HTB\_DH}$

$$G_{d\_HAB\_SH} = m_G\, G_{d\_HTB\_SH} + c_G \tag{16}$$

where m_G and c_G are the regression coefficients of slope and intercept for solar radiation. Because of these regression coefficients, the day-based climatic data has same function as the hour-based climatic data and is suitable for the PVMT estimation model. Then, the new PVMT estimation model, $T_{m\_d\_1D\_new}$ is proposed as

$$T_{m\_d\_1D\_new} = \left(m_T\, T_{a\_d\_HAB\_24} + c_T\right) + \left(T_{NOCT} - T_{a\_NOCT}\right)\left(m_G\, G_{d\_HTB\_SH} + c_G\right)/G_{NOCT} \tag{17}$$

to aid in the daily output power estimation.

4.2.1. Simple Linear Regression Analysis

The new regression coefficients, m_T and c_T, m_G and c_G are not derived from the simple linear regression analysis rather than the multiple linear regression analysis. This is due to the problem of invalid values, which is caused solely by the unsuitable climatic data format. So, the simple linear regression analysis explores the relationship between the same climatic variable but recorded in two different ways, referring to the suitable and unsuitable climatic variables. This analysis is carried out in accordance with the principle stated in [10–12]. These regression coefficients can lead to the main structure of the PVMT estimation model to remain constant, with no significant impact on future development. Therefore, the new PVMT estimation model is a combination model to some extent, where the conventional PVMT estimation model and regression model are combined.

4.2.2. Regression Coefficient

For the OTP-D estimation method, the PVMT estimation model, as presented in Eq. (13), needs the regression coefficients for $T_{a\_d\_HAB\_24}$ and $G_{d\_HTB\_SH}$ to avoid the problem of the invalid daily module temperature value. However, $G_{d\_HTB\_SH}$ in the PVOP estimation model, as presented in Eq. (14), is not required. This is because $G_{d\_HTB\_SH}$ adheres to the multiplier principle of Peak Sun Hour (PSH), which makes Eq. (14) the same as Eq. (7), the principle is given as [13]

$$G_{d\_HTB\_SH} = G_{d\_HAB\_SH} \times H_s \tag{18}$$

In other words, multiplying H_s in Eq. (8) by $G_{d\_HAB\_SH}$ in Eq. (7) will make Eq. (7) become Eq. (14). Furthermore, when both are given the same daily module temperature value, they will produce the same daily output power value.

4.3. Model validation

In this study, the one-year NASA satellite-based climatic datasets are used for analysing the conventional PV estimation methods. Moreover, they are also used as the training dataset for developing the new PVMT estimation model for the OTP-D estimation method. While the one-year ground-based climatic datasets are used as the testing datasets for the validation of the new PVMT estimation model. Although the ground-based and satellite-based climatic data have the same data format, they have different measured values. Furthermore, the length of one year dataset in this study is set according to the standard data length of a long-term experiment [19], which is acceptable for PV performance planning, managing, and monitoring. Based on the ground-based climatic datasets, the performance of the new PVMT estimation model, as presented in Eq. (17), for the OTP-D estimation method is validated by the standard statistical indicators as follows.

The Root Mean Squared Error (RMSE) is the typically used standard deviation of the estimation errors, which is defined as [2]

$$RMSE = \sqrt{\sum_{i=1}^{N}(OTP_i - MTP_i)^2/N} \tag{19}$$

where OTP_i is the estimated value which produced based on the OTP-D estimation method with the new PVMT estimation model, MTP_i is the estimated value which produced based on the conventional MTP-AH estimation method, N is the total number of days per year. It can be further interpreted as NRMSE, in which it will provide the normalized value from zero to one, which is given as [11]

$$NRMSE = RMSE/MTP_{mean} \tag{20}$$

where MTP_{mean} is the mean value of MTP_i. When the proposed model is with better performance, the NRMSE value is closer to zero but not more than 0.1 [20]. R2 is used to measure the relationship between two datasets which also provides the value from zero to one, which is expressed as [20]

$$R^2 = 1 - \sum_{i=1}^{N}(MTP_i - OTP_i)^2/\sum_{i=1}^{N}(MTP_i - MTP_{mean})^2 \tag{21}$$

When the proposed model is more efficient, the R2 value is closer to one [20].

5. Result and Discussion

Based on the NASA hour-based climatic data, the conventional MTP-SH and MTP-AH estimation methods produce the daily output power, $P_{pv\_d\_sum}$ and $P_{pv\_d\_avg}$ which are approximately equal, as shown in Fig. 3. Since all the values differ between $P_{pv\_d\_sum}$ and $P_{pv\_d\_avg}$ their range isfrom 0.3135% to 3.6379%.

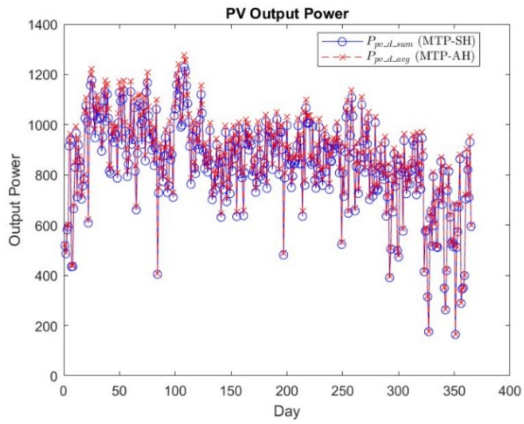

Fig. 3. Daily output power in 2005: MTP-SH and MTP-AH estimation methods

However, when $P_{pv\_d\_sum}$ and $P_{pv\_d\_avg}$ are compared to the daily output power, $P_{pv\_d\_1D}$, produced using the NASA day-based climatic data and OTP-D estimation method, all $P_{pv\_d\_1D}$ in a year are given a lower output power value as shown in Fig. 4. According to the values

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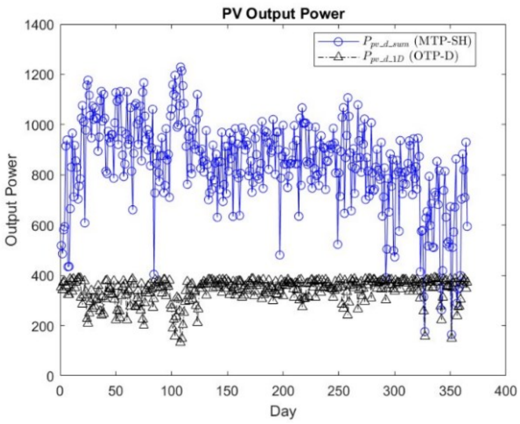
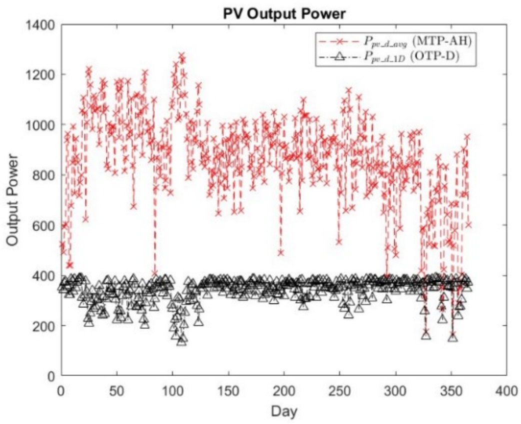
comparison, all the values of $P_{pv\_d\_1D}$ range from 9.4809% to 89.329% lower than $P_{pv\_d\_sum}$ and range from 9.814% to 89.7172% lower than $P_{pv\_d\_avg}$. This is due to the PVMT estimation model for the OTP-D estimation method produces an extremely high value of the daily module temperature, $T_{m\_d\_1D}$, which can far exceed the maximum stated value of the operational module temperature, 85 °C and has a different module temperature value than the conventional MTP-AH estimation method, $T_{m\_h\_avg}$ as shown in Fig. 5. Based on the values comparison, all the values of $T_{m\_d\_1D}$ range from 48.3953% to 82.4163% higher than $T_{m\_h\_avg}$. In other words, $T_{m\_d\_1D}$ value is clearly an invalid daily module temperature value resulting in an incorrect $P_{pv\_d\_1D}$ value.



(a)



(b)

Fig. 4. Daily output power in 2005: (a) MTP-SH and OTP-D estimation methods. (b) MTP-AH and OTP-D estimation methods.

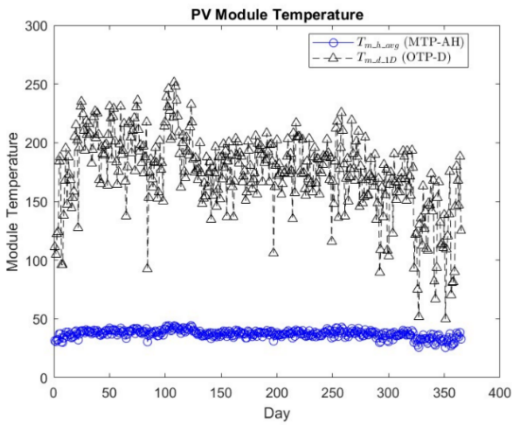


Fig. 5. Daily module temperature in 2005: MTP-AH and OTP-D estimation methods

The problem of the invalid $T_{m\_d\_1D}$ value for the OTP-D estimation method is solved by developing a new PVMT estimation model based on the simple linear regression analysis. This analysis explores the relationship between the climatic variables of the solar radiation, $G_{d\_HAB\_DH}$ and $G_{d\_HTB\_DH}$, as well as between the ambient temperature variables, $T_{a\_d\_HAB\_SH}$ and $T_{a\_d\_HAB\_24}$ as shown in Fig. 6. The developed regression coefficients are derived based on the training datasets from NASA. These datasets are the satellite-based climatic datasets with different measured values from the ground-based climatic datasets, as shown in Fig. 7. In terms of solar radiation and ambient temperature data, the ground-based climatic data mostly have higher measured values than the NASA satellite-based climatic data. Thus, the ground-based

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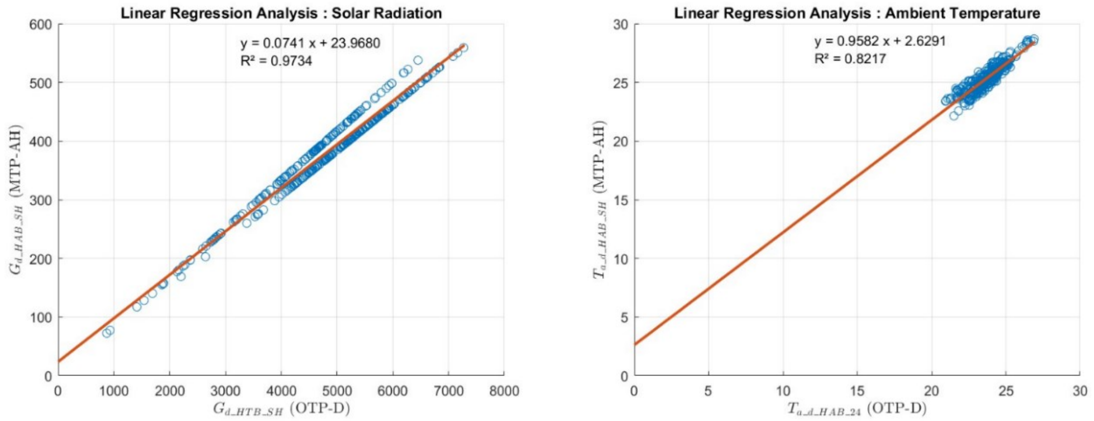
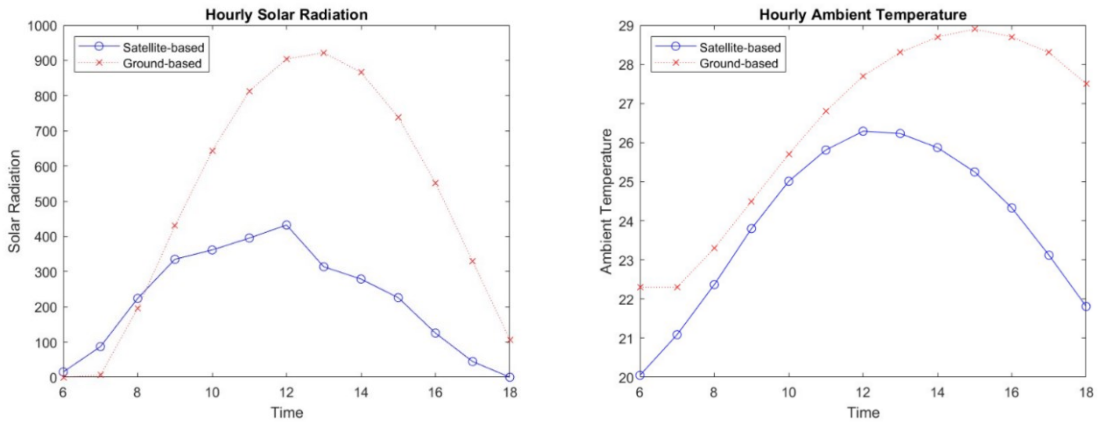
datasets can be used as the testing datasets for new model validation. Since all the values difference between $G_{d\_HAB\_DH}$ and $G_{d\_HTB\_DH}$ range from 0.0453% to 88.2497%, while for $T_{a\_d\_HAB\_SH}$ and $T_{a\_d\_HAB\_24}$ range from 0.0364% to 26.5204%.



(a) (b)

Fig. 6. Linear regression Analysis: (a) Solar radiation. (b) Ambient temperature.

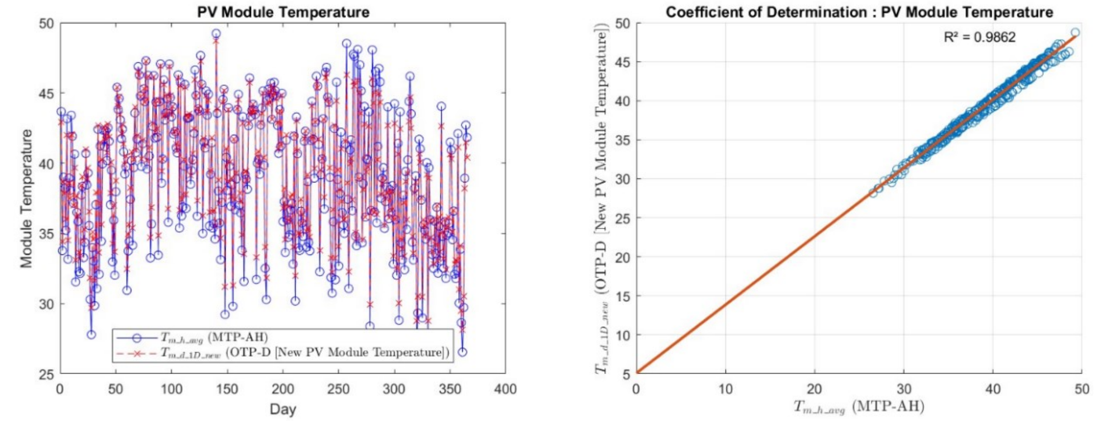


(a) (b)

Fig. 7. Example of satellite-based and ground-based climatic data on 1/1/2005: (a) Solar radiation. (b) Ambient temperature.

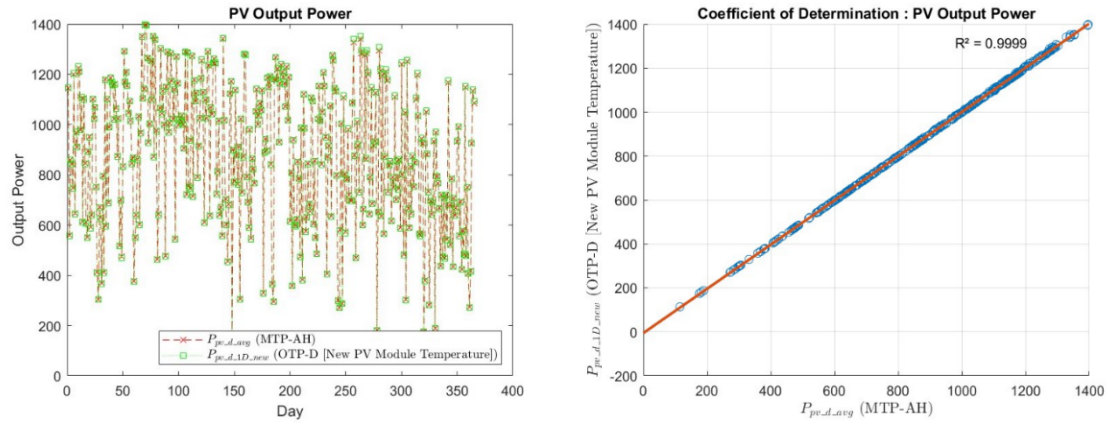
Based on the ground-based data of solar radiation and ambient temperature, the day-based data are used in the OTP-D estimation method with the new PVMT estimation model, while the hour-based data are used in the conventional MTP-AH estimation method for further results comparison. According to the results comparison, all the value differences between $T_{m\_d\_1D\_new}$ and $T_{m\_h\_avg}$ range from 0.0024% to 4.6061%, as shown in Fig. 8. The NRMSE value is 0.0215 and R2 value is 0.9862 as shown in Table 4. When $T_{m\_d\_1D\_new}$ returns the valid daily module temperature value, $P_{pv\_d\_1D}$ returns the correct daily output power value. Consequently, all the values difference between $P_{pv\_d\_1D}$ and $P_{pv\_d\_avg}$ range from 0.0002% to 0.8057% as shown in Fig. 9. The NRMSE value is 0.0034 and R2 value is 0.9999.

Aside from that, when the results of the OTP-D estimation method which with the new PVMT estimation model are compared to the MTP-SH estimation method, all the value differences between $P_{pv\_d\_1D}$ and $P_{pv\_d\_sum}$ range from 0.0914% to 4.0206%, as shown in Fig. 10. The NRMSE value is 0.0318 and R2 value is 0.9997. Due to development of the new PVMT estimation model, the OTP-D estimation method can produce the daily module temperature value that are approximately equal to the MTP-AH and MTP-SH estimation methods.



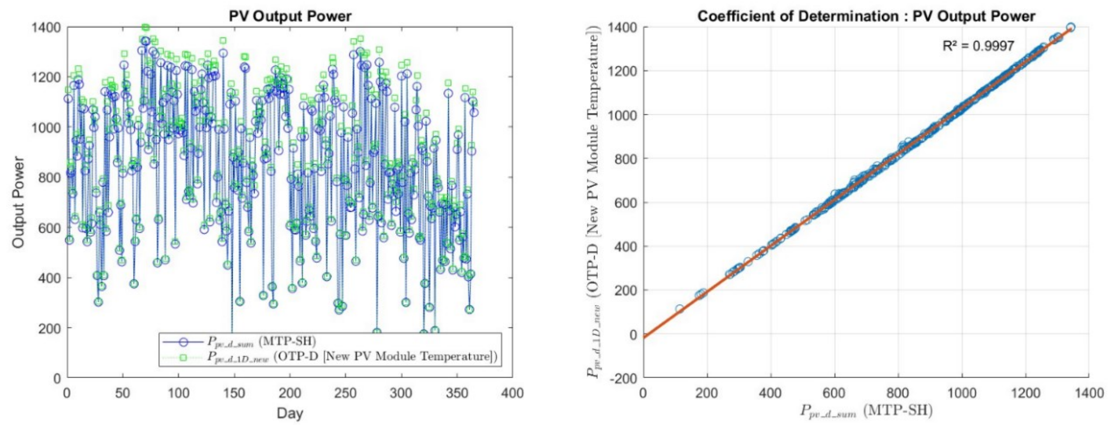
(a) (b)

Fig. 8. PVMT comparison of MTP-AH and OTP-D (with the new PVMT estimation model): (a) Linear plot graph. (b) Scatter plot graph.



(a) (b)

Fig. 9. PVOP comparison of MTP-AH and OTP-D (with the new PVMT estimation model): (a) Linear plot graph. (b) Scatter plot graph.



(a) (b)

Fig. 10. PVOP comparison of the MTP-SH and OTP-D (with the new PVMT estimation model): (a) Linear plot graph. (b) Scatter plot graph.

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Table 4: New model validation

Standard Indicator	PVMT (MTP-AH)	PVOP (MTP-AH)	PVOP (MTP-SH)
RMSE	0.8389	2.9834	27.134
NRMSE	0.0215	0.0034	0.0318
R2	0.9862	0.9999	0.9997

6. CONCLUSION AND RECOMMENDATION

The conventional PVOP estimation model and PVMT estimation model are the hour-based estimation models derived from the PV module performance test under STC and NOCT. In the OTP-H estimation method, the PVOP estimation model is used in conjunction with the PVMT estimation model to estimate the hourly output power based on the hourly solar radiation and hourly ambient temperature. The hourly output power is then used to estimate the daily output power using the conventional MTP-SH estimation method. While the hourly solar radiation and hourly ambient temperature are processed before being used in the conventional MTP-AH estimation method to estimate the daily output power. Since both MTP-SH and MTP-AH estimation methods involve multiple estimation processes in the hourly data, producing the daily output power becomes complex, time-consuming, and error-prone. Therefore, to avoid these shortcomings, a one estimation process is designed and used to reduce the process of estimating the daily output power. This process directly uses the day-based climatic data to perform the daily power estimation work, but it resulted in an incorrect daily output power value due to an invalid module temperature value. Thus, a new PVMT estimation model for the OTP-D estimation method is developed to solve the problem of invalid values. This new model is derived from the simple linear regression, which explores the relationship between the hour-based and day-based climatic data to develop a new regression coefficient for daily solar radiation and daily ambient temperature. The performance of the new model in the OTP-D estimation method is validated using the one-year ground-based climatic data, which has higher measured values than the NASA satellite-based climatic data. When the new and conventional PVMT estimation models' results are compared, the NRMSE value is 0.0215 and the R2 value is 0.9862. With the valid module temperature, the daily output powers produced by the OTP-D estimation method are compared to the MTP-AH estimation method, and the NRMSE value of 0.0034 and the R2 value of 0.9999 are obtained. The comparison of the results shows that the new model's applicability makes the OTP-D estimation method accurate, easy, user-friendly, instantaneous, and direct in daily power estimation work. The next step is to develop a new regression coefficient for the month-based and year-based climatic data to perform the monthly and yearly power estimation work.

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APPENDIX

Appendix A: Example of product specification [1]

Data Type	Parameter	Value
Electrical Data	Peak Power, P_{max}	190 W
	Module Efficiency, η_{pv}	14.9 %
Temperature Ratings	Nominal Operating Module Temperature, T_{NOCT}	45 ℃
	Temperature Coefficient of Power, β_p	-0.4 %/℃
Mechanical Data	Module Dimensions	1581 × 809 × 35 mm
Maximum Ratings	Operational Module Temperature	$-40 \sim 85$ ℃
Standard Test Conditions (STC)	Reference Solar Radiation, G_{STC}	1000 $\mathrm{W/m^2}$
	Reference Module Temperature, T_{m_STC}	25 ℃
	Reference Air Mass, AM_{STC}	1.5
Nominal Operating Module Temperature (NOCT)	Reference Solar Radiation, G_{NOCT}	800 $\mathrm{W/m^2}$
	Reference Ambient Temperature, T_{a_NOCT}	20 ℃
	Reference Wind Speed, v_{NOCT}	1 m/s