2102531 System Identification

Modeling of Photovoltaic System
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Abstract

Power forecasting of photovoltaic (PV) system using weather data is an important factor for planning the maintanance operations. This project presents nonlinear power prediction model based on a single-diode model with series resistance. The model required irradiance and cell temperature as inputs in order to identify model parameters. The method used to estimate the model parameters is nonlinear least square method with constraints. The initial guess for this optimization problem was obtained from analysis of derived model equation and specification values provided by manufacturer's documentation. The proposed model were compared to two polynomial models and an artificial neural network (ANN) model in terms of mean squared error (MSE). The results indicated that the nonlinear model provided the least MSE compared to other models.

1 Introduction

With the development of photovoltaic (PV) industry, grid-connected PV systems have been expanded around the world in recent years. The monitoring and performance assessment on the grid-connected PV systems is required to ensure reliable power production and thus the modeling of a PV system is necessary.

Many researches focus on modeling of a PV module based on an equivalent circuit model. Most of previous studies aimed to determine the current-voltage characteristic of the model. The identification of model parameters was carried out by using optimization techniques. Some of the researches proposed that the output power model is a polynomial function of environmental data such as irradiance and temperature. In the past few years, many reseaches used artificial neural network (ANN) models to forecast power generation. However, the polynomial models might be not reliable enough due to the lack of derivation of the model equations and physical meanings of the systems cannot be explained by the ANN models.

In order to overcome these problems, this project aims to provide a reliable nonlinear model of a PV module. The nonlinear least square method is used to determine the model parameters. Moreover, the model are compared to the polynomial models and an ANN model in terms of mean squared error.

This paper is organized as follows: the next section gives the background on PV models and reviews of a few literatures. In Section 3, a problem statement is presented, while Section 4 deals with data preprocessing. Experiments and discussion are shown in Section 5. Lastly, Section 6 shows conclusions of this project.

2 Background on Photovoltaic Model

Many researchers have developed PV models using many equivalent circuit models. For example, the PV model can be represented as a ideal equivalent circuit consisting of a diode and a current source connected in parallel as shown in Figure 1.

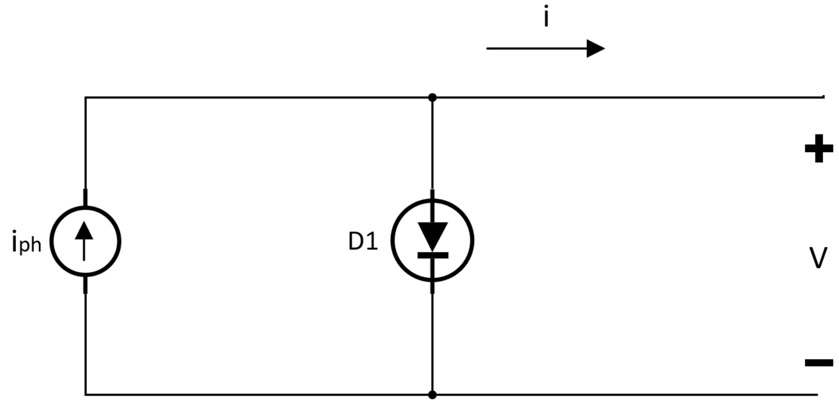


Figure 1: Equivalent circuit of the ideal single-diode model.

However, in order to obtain a better representation of the PV model, the second and third models take account of the ohmic losses represented by only a series resistance R_s and both series resistance R_s and parallel resistance R_p as shown in Figure 2 and Figure 3 respectively.

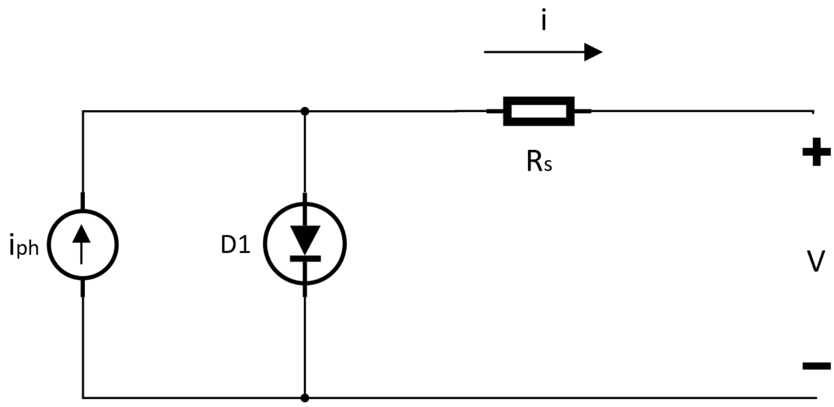


Figure 2: Equivalent circuit of the single-diode model with series resistance.

Moreover, the PV model can be represented as the two-diode model which takes into account the recombination of the minority carriers located both at the surface and within the volume of the material. The two-diode model is shown in Figure 4.

The most common used model in the literature is a single-diode with both series resistance and parallel resistance in Figure 3. For example, The studies [1] and [2] used this single-diode model for modeling PV system. These two studies are reviewed as follows.

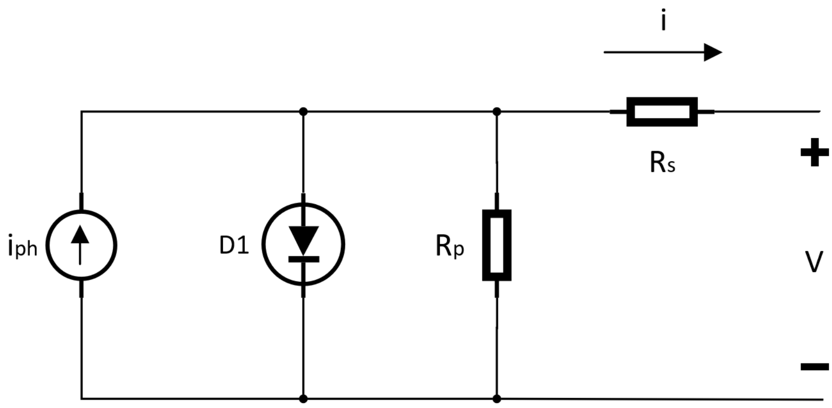


Figure 3: Equivalent circuit of the single-diode model with series resistance and parallel resistance.

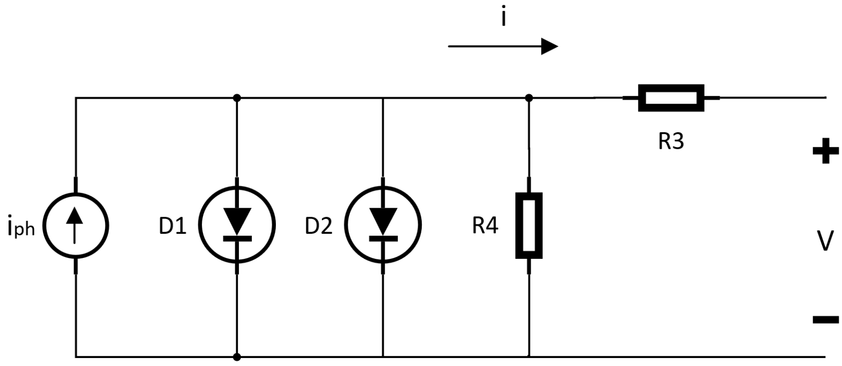


Figure 4: Equivalent circuit of the two diodes model with series resistance and parallel resistance.

2.1 Modeling of Photovoltaic Module from Commercial Specification in Datasheet [1]

The equation which descibes the relationship between the current of PV module and voltage of the PV model in Figure 3 can be derived as

$$i = i_{ph} - i_0\Big(\exp\Big(\frac{V + R_s i}{A}\Big) - 1\Big) - \frac{V + R_s i}{R_p} \tag{1}$$

where i is the current of PV module (A), V is the voltaic of PV module (V), i_{ph} is the photocurrent (A), i_0 is the diode saturation current (A), $A = aN_sV_{\mathrm{th}}$, a is the ideal factor, N_s is number of cells per module, $V_{th} = \frac{kT}{q}$ is the threshold voltage (V), k is the Boltzmann constant (1.38×10^{-23}J·K^{-1}), q is the electronic charge (1.602×10^{-19}C), T is the cell temperature (K), R_s is the series resistance (Ω) and R_p is the parallel resistance (Ω).

Practically, the reason why the commercial datasheet from PV producers cannot lead to an accurate modeling is because the datasheet usually do not provide some specfication parameters, *i.e.* i_0, R_s, R_p and i_{ph}. Thus, the study [1] aims to develop a modeling method based on the given commercial specification in the datasheet. The reviews of this study are divided into 3 parts, Investigation on the model parameters, Environmental factors and Proposed method.

2.1.1 Investigation on the model parameters at reference point

The diode reversed saturation in a module is calculated from the open-circuit condition.

$$i_{0\text{ref}} = \frac{i_{sc}}{\exp\left(\dfrac{V_{oc}}{A_{\text{ref}}}\right) - 1} \tag{2}$$

All parameters (i_{sc}, v_{oc} and A_{ref}) in the right side of (2) are given from the commercial datasheet. This means that it can be straightforwardly calculated.

The series resistance in a module can be calculated by using the diffential of PV module power with respect to PV module voltage at the maximum power point.

$$R_{s\text{ref}} = \frac{V_{\max}}{i_{\max}} - \frac{A_{\text{ref}} R_{p\text{ref}}}{i_{0\text{ref}} R_{p\text{ref}} \exp\left(\dfrac{V_{\max} + i_{\max} R_{s\text{ref}}}{A_{\text{ref}}}\right) + A_{\text{ref}}} \tag{3}$$

However, the parallel resistance (R_p) is still an unknown. By considering (1) at the maximum power point, it can be shown that,

$$R_{p\text{ref}} = \frac{V_{\max} + i_{\max} R_{s\text{ref}}}{i_{ph\text{ref}} - i_{\max} - i_{0\text{ref}} \left[\exp\left(\dfrac{V_{\max} + i_{\max} R_{s\text{ref}}}{A_{\text{ref}}}\right) - 1\right]} \tag{4}$$

This equation has two unknown parameters, which are R_s and i_{ph}

At short circuit condition, the photoelectric current can be approximated by (1) as

$$i_{ph\text{ref}} \approx \frac{R_{p\text{ref}} + R_{s\text{ref}}}{R_{p\text{ref}}} i_{\text{sc}} \tag{5}$$

With (3), (4) and (5) all the three unknown parameters (R_s, R_p and i_{ph}) at the reference point of irradiance and temperature can be calculated.

2.1.2 Envionmental factors affecting the PV module

When the irradiance changes, this change has an impact on two parametersm which are photoelectric current and parallel resistance which can be expressed as

$$i_{\text{ph}} = i_{ph\text{ref}} \left(\frac{I}{I_0}\right) \tag{6}$$

$$R_p = R_{p\text{ref}} \left(\frac{I_0}{I}\right) \tag{7}$$

where I is present irradiation (W/m^2) and I_0 is the reference irradiation from datasheet. (1,000 W/m^2)

The change in temperature has an impact on three parameters, which are photoelectric current, diode reversed saturation current and threshold voltage. The affects can be expressed as

$$i_{ph} = i_{ph\text{ref}} + \alpha(T - T_{\text{ref}}) \tag{8}$$

$$i_0 = \frac{i_{\text{sc}} + \alpha(T - T_{\text{ref}})}{\exp\left(\dfrac{V_{\text{oc}} + \beta(T - T_{\text{ref}})}{A_{\text{ref}}}\right) - 1} \tag{9}$$

$$A = A_{\text{ref}} \left(\frac{T}{T_{\text{ref}}}\right) \tag{10}$$

where T is present temperature (K), T_{ref} is the reference temperature from datasheet. (298 K)

2.1.3 Proposed method

Since the three parameters (R_{sref}, $R_{p\text{ref}}$ and $i_{ph\text{ref}}$) cannot be directly calculated from the equations (3)-(5) due to the nonlinearity, the paper applied minimization principle in order to find the mentioned parameters.

First, the objective function of the minimization problem is defined as a sum of squared errors, that is the minimization problem:

$$\underset{R_s, R_p, i_{\text{ph}}}{\text{minimize}}\, f(R_s, R_p, i_{\text{ph}}) \triangleq e_1^2 + e_2^2 + e_3^2 \tag{11}$$

where e_1, e_2 and e_3 are the error of R_s, R_p and i_{ph} respectively which are defined as follows.

$$e_1 = \frac{V_{\max}}{i_{\max}} - \frac{A_{\text{ref}} R_{p\text{ref}}}{i_{0\text{ref}} R_{p\text{ref}} \exp\left(\dfrac{V_{\max} + i_{\max} R_{\text{sref}}}{A_{\text{ref}}}\right) + A_{\text{ref}}} - R_{\text{sref}} \tag{12}$$

$$e_2 = \frac{V_{\max} + i_{\max} R_{\text{sref}}}{i_{ph\text{ref}} - i_{\max} - i_{0\text{ref}} \left[\exp\left(\dfrac{V_{\max} + i_{\max} R_{\text{sref}}}{A_{\text{ref}}}\right) - 1\right]} - R_{p\text{ref}} \tag{13}$$

$$e_3 = \frac{R_{p\text{ref}} + R_{\text{sref}}}{R_{p\text{ref}}} i_{\text{sc}} - i_{ph\text{ref}} \tag{14}$$

Next, the process of the method is as following.

1. Retrieve input data of PV datasheet which is composed of eight parameters($V_{\text{oc}}, i_{\text{sc}}, \alpha, \beta, N_s, i_0, i_{\text{ph}}, R_s$ and R_p)
2. Compute i_0 using (2)
3. Assume initial value of the three optimization variables
4. Substitute the three optimization variables into (12), (13) and (14).
5. Substitute the value of e_1, e_2 and e_3 into the objective function in (11)
6. Find the value of the three variables which minimize the objective function f
7. Receive the irradiance and temperature data at the moment
8. Update i_{ph}, R_p, i_0 and V_{th} using (6) -(10)

Unfortunately, the optimization method for solving the minimization problem are not detailed in this paper.

2.2 Analysis and Experimental Validation of Various Photovoltaic System Models [2]

In this paper, there are two proposed models, the "one-diode model" and the "polynomial model".

2.2.1 The one-diode model

First, the "one-diode model" is used for modeling the PV system. The equivalent circuit is the same as in Figure 3. The characteristic equation for the PV can then be derived as:

$$i = i_{\text{ph}} - i_d - i_{R_p} \tag{15}$$

where i_d is the polarization current of junction PN or the diode current and i_{R_p} is the current thorough the parallel resistance.

The photocurrent, i_{ph}, is proposed by this study that is directly dependent on both irradiance and temperature, and may be written in the following form:

$$i_{\text{ph}} = k_1 I[1 + k_2(I - I_0) + k_3(T - T_{ref})] \tag{16}$$

where I_0 is the reference irradiance of 1,000 W/m^2 and T_{ref} is the reference temperature of 298 K. k_1, k_2 and k_3 are constant parameters.

The diode current is given by the relationship between current and voltage (I-V curve) of a diode:

$$i_d = i_0 \left[\exp\left(\frac{V + R_s i}{A} \right) - 1 \right] \tag{17}$$

where all parameters are the same as defined in the paper [1].

The saturation current, i_0, can be expressed as a function of temperature as follows [3]:

$$i_0 = k_4 T^3 \exp\left(-\frac{E_g}{kT} \right) \tag{18}$$

where E_g is the gap energy and k_4 is a constant parameter.

Lastly, the current thorough the parallel resistance is:

$$i_{R_p} = \frac{V}{R_p} \tag{19}$$

By substituting (10) and (16) - (19) into (15), the final equation of the model can then be expressed by:

$$\begin{aligned} i &= k_1 I[1 + k_2(I - I_0) + k_3(T - T_{ref})] \\ &\quad - k_4 T^3 \exp\left(-\frac{E_g}{kT} \right) \left[\exp\left(\frac{V + R_s i}{A_{\text{ref}} \left(\frac{T}{T_{\text{ref}}} \right)} \right) - 1 \right] - \frac{V}{R_p} \end{aligned} \tag{20}$$

2.2.2 The polynomial model

The previous model is used to determine the voltage-current characteristic for a given irradiance and temperature. From this basis, it is possible to determine the maximum power supplied by the PV system under a set of given weather conditions.

This paper refers that the characteristic for maximum power indicated by manufacturer's documentation is as following.

$$P_{\max} = k_1 I(1 + k_2(T - T_{\text{ref}})) \tag{21}$$

Then, this paper added a parameter (k_3) to the previous characteristic and proposed a modified maximum power as:

$$P_{\max} = k_1(1 + k_2(T - T_{\text{ref}}))(k_3 + I) \tag{22}$$

Adding k_3 in (22) as a bias term, that is the maximum power $P_{\max}$ can be zero even if irradiance I is not zero, may improve fitting result.

2.2.3 Determination of Parameter Values - Power Analysis

The identification of parameter values has been carried out by means of a binary genetic algorithm (GA) using experimental measurements. For the one-diode model, the identification process was performed using the actual PV power-voltage characteristics $(P^{(k)}, V^{(k)})$.

The objective function is then the sum of the errors committed by the model on the power-voltage characteristics corresponding with the irradiance and temperature of index k:

$$\underset{k_1,k_2,k_3,k_4,R_s,R_p}{\text{minimize}} \sum_{k=1}^{N} \frac{|P^{(k)} - (V^{(k)} i^{(k)}_{\text{model}})|}{P^{(k)}} \tag{23}$$

where i_{model} is obtained by solving the implicit function $i^i_{\text{model}} = f(i^i_{\text{model}}, V^i_{\text{actual}}, I^i, T^i)$ in the equation (20). However, the use of GA techniques for identifying parameter values has to repeat this complex calculation many times. For this reason, i_{model} may be obtained by solving the equation: $i_{\text{model}} = f(i^i_{\text{actual}}, V^i_{\text{model}}, I^i, T^i)$.

For the polynomial model, the optimization step was solely carried out on maximum power values. Thus, the objective function to be minimized is then the sum of the errors between measured power and predicted power values:

$$\underset{k_1,k_2,k_3}{\text{minimize}} \sum_{k=1}^{N} \frac{|P^{(k)} - P^{(k)}_{\text{model}}|}{P^{(k)}} \tag{24}$$

where P^i_{model} is the power in (22).

The results showed that all of the models studied displayed the same level of energy precision. However, the polynomial model did stand out for its simulation speed, *i.e.* for the same computation, the one-diode models took several minutes to yield their results whereas the polynomial model only required in the hundreds of milliseconds.

2.3 Proposed model

In this study, the model used to predict output power generated by PV module is defined as an equivalent circuit using a single-diode circuit model with only series resistance R_s, shown in Figure 2. This model was used in [4] and provided fairly accurate results.

The current-voltage $(i - V)$ relation of a photovoltaic cell is given by:

$$i = i_{\text{ph}} - i_0 \left(\exp\Big(\frac{V + R_s i}{A}\Big) - 1 \right) \tag{25}$$

where i_{ph} is the photocurrent (A)
i_0 is the diode saturation current (A)
$A = aN_s kT/q$
a is the diode ideality factor
k is the Boltzmann constant $(1.38 \times 10^{-23} \text{J} \cdot \text{K}^{-1})$
q is the electronic charge $(1.602 \times 10^{-19} \text{C})$
T is the cell temperature (K)
R_s is the series resistance (Ω)

The reference values of these parameters are usually provided by manufacturers of PV modules for specified operating point such as STC(Standard Test Conditions: irradiance $I_{\text{ref}} = 1000$ W/m^2 and temperature $T_{\text{ref}} = 25°$C). These values are not accurate enough for real operating conditions in which the irradiance and the cell temperature are not at STC. However, by assuming R_s is constant, the values of the other parameters at any condition of irradiance and temperature are given by [5],[6]:

$$i_{\text{ph}} = \frac{I}{I_0}[i_{ph\text{ref}} + \alpha(T - T_{\text{ref}})] \tag{26}$$

$$i_0 = i_{0\text{ref}} \Big(\frac{T}{T_{\text{ref}}}\Big)^3 \exp\Big(\frac{E_g N_s}{A_{\text{ref}}}(1 - \frac{T_{\text{ref}}}{T})\Big) \tag{27}$$

$$A = A_{\text{ref}} \Big(\frac{T}{T_{\text{ref}}}\Big) \tag{28}$$

where I is the solar irradiance (W/m^2), α is the temperature coefficient $(\text{A} \cdot \text{K}^{-1})$, E_g is the band gap energy of the semiconductor, N_s is the number of solar cells connected in series and the subscript $_{\text{ref}}$ refers to the reference value. Note that i_{ph} in (26) is proposed equation but i_0 and A in (27) and (28) can be derived by principles in [3].

By rewriting (26), (27) and (28), the equations which describe i_{ph}, i_0 and A as a function of I and T are as following:

$$i_{\text{ph}} = k_1 I + k_2 IT \tag{29}$$

$$i_0 = k_3 T^3 \exp\left(\frac{k_4}{T}\right) \tag{30}$$

$$A = k_5 T \tag{31}$$

where k_1, k_2, k_3, k_4 and k_5 are constants.

Typically, the PV systems are connected to the loads by the electronic equipment which are designed to follow the Maximum Power Point (MPP). In this case, the current of the MPP at arbitary conditions of irradiance and temperature can be considered to scale proportinally with the irradiance and linearly with the temperaure and is proposed in [7] as:

$$i_m = i_{m\text{ref}} \frac{I}{I_0} + \alpha(T - T_{\text{ref}})$$

or

$$i_m = k_6 I + k_7 T + k_8 \tag{32}$$

where k_6, k_7 and k_8 are constants.

Next, by assuming that $\exp\left(\frac{V+R_s i}{A}\right) >> 1$, (25) is considered at MPP (i_m, V_m) and rearranged as

$$V_m = A \log\left(\frac{i_{\text{ph}} - i_m}{i_0}\right) - i_m R_s \tag{33}$$

Thus, the maximum power output can be expressed as:

$$\begin{aligned} P_m &= V_m i_m \\ &= A i_m \log\left(\frac{i_{\text{ph}} - i_m}{i_0}\right) - i_m^2 R_s \end{aligned} \tag{34}$$

Substitute (29), (30), (31) and (32) into (34) and then simplify the equation. The simplified maximum power output model as a function of irradiance and temperature can be expressed as follows.

$$P_m = (k_5 T)(k_6 I + k_7 T + k_8) \log\left(\frac{k_1 I + k_2 IT - k_6 I - k_7 T - k_8}{k_3 T^3 \exp\left(\frac{k_4}{T}\right)}\right) - (k_6 I + k_7 T + k_8)^2 R_s$$

$$P_m = (c_1 IT + c_2 T^2 + c_3 T) \log\left(c_4 \frac{I}{T^3} + c_5 \frac{I}{T^2} + \frac{c_6}{T^2} + \frac{c_7}{T^3}\right) + (c_8 I^2 + c_9 T^2 + c_{10} IT + c_{11} I + c_{12} T + c_{13}) \tag{35}$$

3 Problem statement

In this section, the models used for generated power prediction are described, which are the nonlinear model and the two polynomial models. The parameter estimation methods used can be expressed as optimization problems with constraints. The constraints and initial guess for the optimization problems are obtained from Section 4.

3.1 Nonlinear Model

In matrix form, the nonlinear model for generated power prediction are given by the formula:

$$\hat{P} = f(X, \theta) \tag{36}$$

where

- $\hat{P}$ is an N-by-1 vector of prediction power.
- X is a N-by-2 matrix which each row contains each sample of I and T.
- $\theta \triangleq (c_1, c_2, ..., c_{13})$ is a 13-by-1 vector of coefficients.
- f is a vector-valued function of X and θ which maps each sample of I and T to each prediction output by using (37)

The prediction output at k^{th} sample of irradiance and temperature can be calculated from:

$$\begin{aligned}\hat{P_1}^{(k)} &= (c_1 I^{(k)} T^{(k)} + c_2 (T^{(k)})^2 + c_3 T^{(k)}) \log\left(c_4 \frac{I^{(k)}}{(T^{(k)})^3} + c_5 \frac{I^{(k)}}{(T^{(k)})^2} + \frac{c_6}{(T^{(k)})^2} + \frac{c_7}{(T^{(k)})^3}\right) \\ &+ (c_8 (I^{(k)})^2 + c_9 (T^{(k)})^2 + c_{10} I^{(k)} T^{(k)} + c_{11} I^{(k)} + c_{12} T^{(k)} + c_{13}) \end{aligned} \tag{37}$$

Thus, the measured power $P^{(k)}$ and the prediction power $\hat{P}^{(k)}$ can be expressed in vector forms as $P = [P^{(1)} \; P^{(2)} \; \cdots \; P^{(N)}]^T$ and $\hat{P} = [\hat{P}^{(1)} \; \hat{P}^{(2)} \; \cdots \; \hat{P}^{(N)}]^T$ where N is the number of samples, the generated power $P^{(k)}$, solar irradiance $I^{(k)}$ and temperature $T^{(k)}$ are measurable variables and the constants c_1,...,c_{13} are unknown parameters.

The parameter estimation method used in this study is non-linear least square method. Thus, the optimization problem can be expressed as:

$$\begin{array}{lll} \underset{c_1,...,c_{13}}{\text{minimize}} & \frac{1}{N}\sum_{k=1}^{N}(P^{(k)} - \hat{P_1}^{(k)})^2 & \\ \text{subject to} & c_1, c_2, c_5, c_7 & \geq 0 \\ & c_3, c_6, c_8, c_9, c_{10}, c_{13} & \leq 0 \end{array} \tag{38}$$

where $\hat{P_1}^{(k)}$ is expressed in (37)

This non-linear least square estimation can be solved by the trust-region algorithm which is described in [8].

3.2 Polynomial Models

The polynomial model are used to compare results in terms of complexity and accuracy with the nonlinear model. The polynomial models used are expressed in (21) and (22) and thus can be rewritten as:

$$\hat{P_2}^{(k)} = d_1 I^{(k)} + d_2 I^{(k)} T^{(k)} \tag{39}$$

$$\hat{P_3}^{(k)} = d_3 + d_4 I^{(k)} + d_5 T^{(k)} + d_4 I^{(k)} T^{(k)} \tag{40}$$

where d_1, d_2, d_3, d_4 and d_5 are constant parameters which can be determined by solving linear least square problems:

$$\begin{array}{ll} \underset{d_1,d_2}{\text{minimize}} & \frac{1}{N}\sum_{k=1}^{N}(P^{(k)} - \hat{P_2}^{(k)})^2 \\ \text{subject to} & d_1 \geq 0, d_2 \leq 0 \end{array} \tag{41}$$

$$\begin{array}{ll} \underset{d_3,d_4,d_5,d_6}{\text{minimize}} & \frac{1}{N}\sum_{k=1}^{N}(P^{(k)} - \hat{P_3}^{(k)})^2 \\ \text{subject to} & d_4 \geq 0, d_6 \leq 0 \end{array} \tag{42}$$

4 Data Preprocessing

4.1 Measurement Data

The measured data used to train and verify the models are generated energy from 8 kW PV module located at EE building(Wh), temperature (°C) and irradiance (W/m^2) which are accessed from CUBEMS. The sample periods for these data are 1 minute, 3 minutes and 3 minutes respectively. Therefore, The generated energy data has to be converted into average generated power by using 15-min sample period. Moreover, the irradiance and temperature data are also averaged by using 15-min sample period. An example of the time series plots of these data are shown in Fig 5. In this study, the data are considered only from 6.00 AM to 19.00 PM for each day and are collected from January 2017 to April 2017.

4.2 Initial values for solving optimization

Since choosing an initial guess is important for solving optimization problems, the initial values in this study are chose based on manufacturer's documentation. The specification values of the PV module provided by the manufacturer's documentation which can be derived for guessing initial values of $k_1, ..., k_8$ in (29)-(32) are shown in Table 1. For the parameters $i_{0\text{ref}}$ and E_g, their initial values are chose to be 10^{-6} A and 1.6×10^{-19} V respectively which are in the ranges of their typical values, that is μA and eV respectively.

parameter	value
i_{phref}	2.20 A
$i_{m\text{ref}}$	1.91 A
α	0.01 %/K
N_s	50

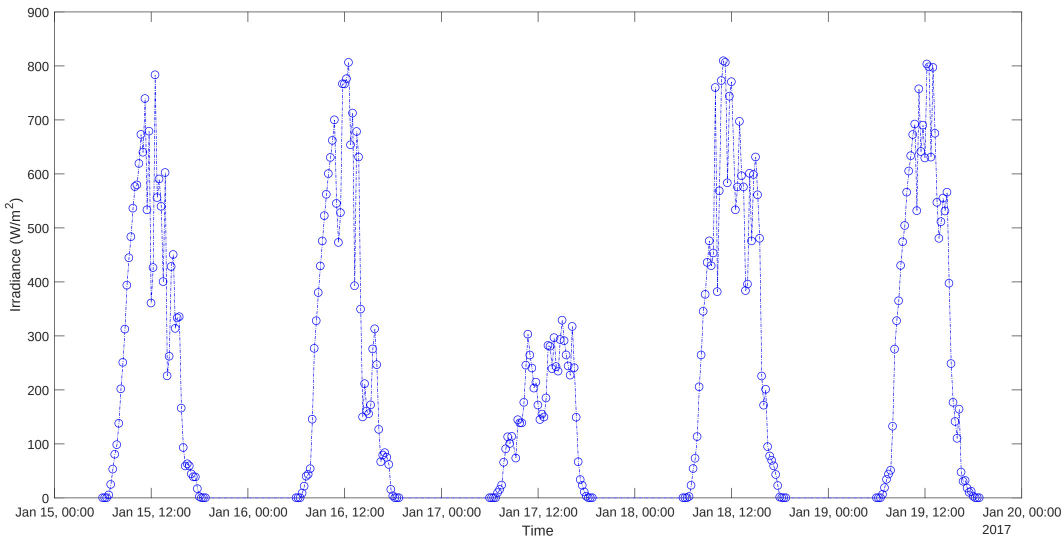
Table 1: the specification values of the PV module

Therefore, the initial values of the parameters $c_1, ..., c_{13}$ in the nonlinear model and their sign which are derived from the parameters $k_1, ..., k_8$ are shown in Table 2.

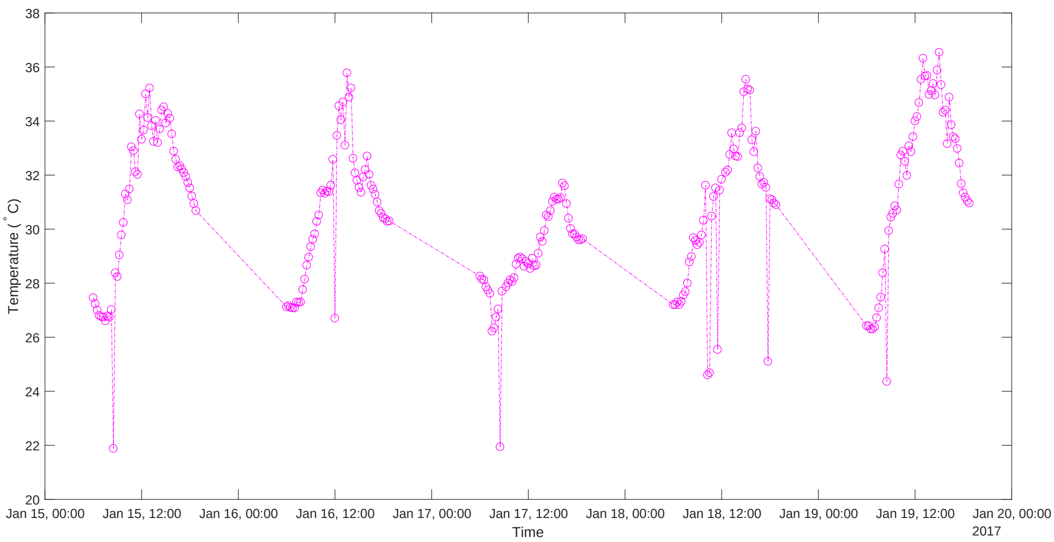
parameter	value	sign
c_1	6.51×10^{-6}	positive
c_2	4.31×10^{-5}	positive
c_3	-1.29×10^{-2}	negative
c_4	-6.06×10^{10}	unknown
c_5	2.65×10^{8}	positive
c_6	-2.65×10^{11}	negative
c_7	7.88×10^{13}	positive
c_8	-4.56×10^{-7}	negative
c_9	2.00×10^{-5}	negative
c_{10}	-6.04×10^{-6}	negative
c_{11}	1.80×10^{-3}	unknown
c_{12}	1.19×10^{-2}	unknown
c_{13}	-1.78	negative

Table 2: the initial values and signs of the model parameters

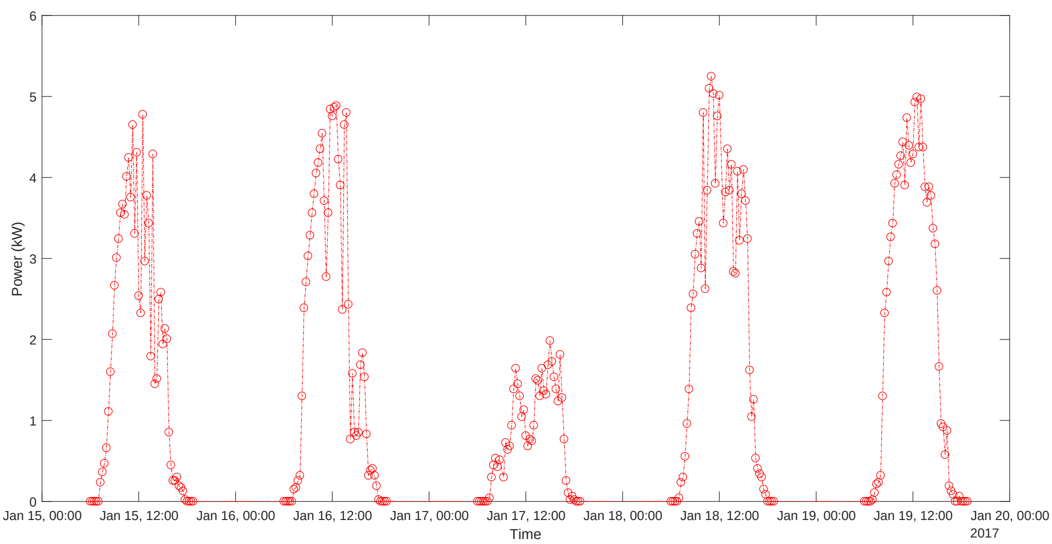
In the case of the polynomial model, by assuming that the output power changes in the same direction as irradiance changes. Thus k_1 in (21) is positive. Moreover, according to the manufacturer's documentation, the temperature coefficient of output power *i.e.* k_2 in (21) is negative.



(a) Irradiance data



(b) Temperature data



(c) Generated power data

Figure 5: Time series plots of the averaged data from January 15 to January 19

Therefore the sign of the parameters d_1 and d_4 are positive and the sign of the parameters d_2 and d_6 negative. Note that the signs of the parameters are used to determine lower bounds and upper bounds of the parameters for the optimization with constrains.

5 Experimental Results and Discussion

In this study, the method used to test the models is described as follows. First, the total data of 5531 samples were randomly divided into training data of 4975 samples (90% of the total data) and validation data of 556 samples (10% of the total data). Then the training data were used to estimate the parameters in the nonlinear model and polynomial model. The averaged estimation parameters of the models are shown in Table 3.

Nonlinear model $\hat{P}_1$		Polynomial model $\hat{P}_2$	
c_1	3.42×10^{-6}		
c_2	17.29×10^{-6}		
c_3	-5.42×10^{-3}		
c_4	-60.6×10^{9}		
c_5	264.5×10^{6}		
c_6	-264.5×10^{9}		
c_7	$78.8 \times 10^{1}2$		
c_8	-3.24×10^{-6}		
c_9	-618×10^{-6}		
c_{10}	-62.5×10^{-6}	d_2	-46.7×10^{-6}
c_{11}	13.7×10^{-3}	d_1	19.8×10^{-3}
c_{12}	315.3×10^{-3}		
c_{13}	-38.3		

Table 3: Estimation parameters of the models

Because of the nonlinearity of the nonlinear model, it will be interesting to apply Artificial-Neural-Network (ANN) to train and compare results with the nonlinear model. The ANN used in this study has one hidden layer with 100 nodes. The same training data of 4975 samples are used to train the ANN model. The features used as inputs to train the ANN model are expressed in term of $[I, T, IT, I^2, T^2, \log I, \log T]$.

Next, the models were tested with the validation data of 556 samples. Thus, The objective function, mean squared error, of the models are shown in Table 4.

Model	Mean Squared Error	
	Traning	Validation
Nonlinear model	0.0072	0.0226
Unbiased-polynomial model	0.0073	0.0232
Biased-polynomial model	0.0073	0.0233
ANN model	0.0078	0.0241

Table 4: Mean squared error of the models

Table 4 supports the fact that the polynomial models are nested model of the nonlinear model and thus the residual norm of the nonlinear model is always less than the polynomial model. In addition, according to Table 3, the parameters c_{10} and c_{11} in (37) are in the same order as d_2 and d_1 in (39) respectively because they are parameters corresponding to the features IT and I respectively.

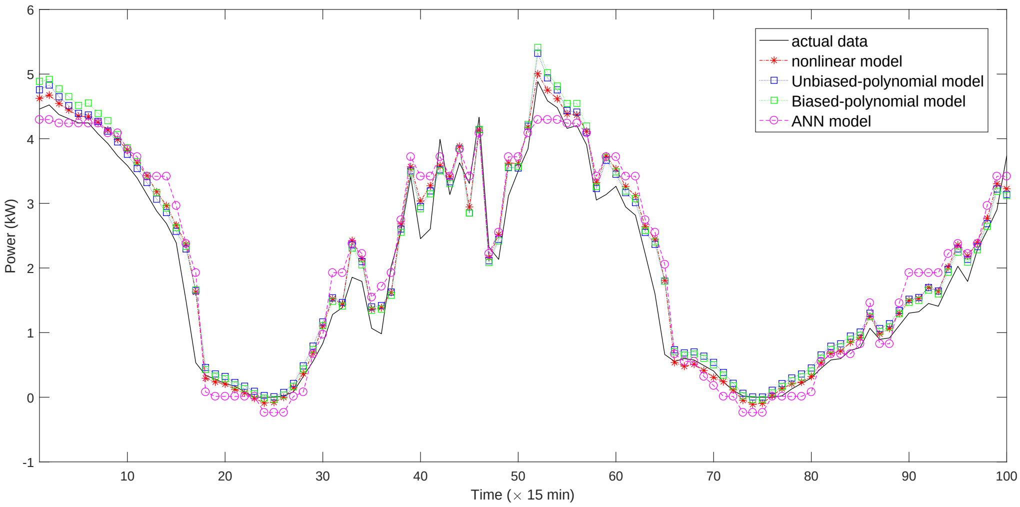


Figure 6: An example of fitting for all models

Figure 6 shows an example of time-series fitting of the nonlinear model, polynomial models and ANN model. The fitting curves obviously indicated that the nonlinear model can estimate the output power better than other models. Even thought the results showed that the ANN model were likely to be the worst model for the prediction, the performance of the ANN model could be improved by adding more number of hidden layers.

6 Conclusions

This project has proposed the nonlinear model which was derived from the single-diode equivalent circuit model with series resistance. The model parameters were determined by solving the nonlinear optimization problem. The nonlinear model were compared to the polynomial models and ANN model and the results showed that the nonlinear model gave the least mean squared error. This could be due to the fact that the polynomial models are nested models of the nonlinear model.

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Appendix A MATLAB Code

```matlab
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%% MATLAB CODE FOR PARAMETER ESTIMATION AND FITTING RESULTS %%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%% the nonlinear function for the prediction as shown in (37) %%
fun = @(x,xdata) (x(1).*xdata(:,1).*xdata(:,2)+x(2).*xdata(:,2).^2+x(3).*xdata(:,2)).*real(log(x(4).*xdata(:,1)./xdata(:,2).^3+x(5).*xdata(:,1)./xdata(:,2).^2+x(6)./xdata(:,2).^2+x(7)./xdata(:,2).^3))+x(8).*xdata(:,1).^2+x(9).*xdata(:,2).^2+x(10).*xdata(:,1).*xdata(:,2)+x(11).*xdata(:,1)+x(12).*xdata(:,2)+x(13);
%% the initial guess as shown in Table 2 %%
x0 = [c1,c2,c3,c4,c5,c6,c7,c8,c9,c10,c11,c12,c13];
%% the constraints for solving the nonlinear model %%
lb_nonli = [0,0,-Inf,-Inf,0,-Inf,0,-Inf,-Inf,-Inf,-Inf,-Inf,-Inf];
ub_nonli = [Inf,Inf,0,Inf,Inf,0,Inf,0,0,0,Inf,Inf,0];
%% the constraints for solving the unbiased-polynomial model %%
lb_polyunbiased = [0;-Inf];
ub_polyunbiased = [Inf;0];
%% the constraints for solving the biased-polynomial model %%
lb_polybiased = [-Inf;0;-Inf;-Inf];
ub_polybiased = [Inf;Inf;Inf;0];
%% use the data only when irradiance I > 0 %%
ydata = ydata(xdata(:,1)>0,:);
xdata = xdata(xdata(:,1)>0,:);
%% define the matrix A for solving linear least square problems of the polynomial models %%
A_unbiased = [xdata(:,1) xdata(:,1).*xdata(:,2)]; %A=[I IT]
A_biased   = [ones(length(xdata),1) xdata(:,1) xdata(:,2) xdata(:,1).*xdata(:,2)]; %A=[1 I T IT]
%% split the data into training data and validation data %%
indices = crossvalind('Kfold',ydata,10); % training data 90% and validation data 10%
test  = (indices==1);
train = ~test;
xtest = xdata(test,:);
xtrain= xdata(train,:);
ytest = ydata(test,:);
ytrain= ydata(train,:);
Atrain_unbiased = A_unbiased(train,:);
Atest_unbiased  = A_unbiased(test,:);
Atrain_biased = A_biased(train,:);
Atest_biased  = A_biased(test,:);
```

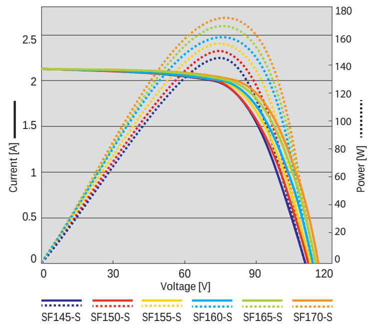
```
%% estimate the model parameters using linear and nonlinear least square optimization %%
xpoly_unbiased = lsqlin(Atrain_unbiased,ytrain,[],[],[],[],lb_polyunbiased,ub_polyunbiased);
xpoly_biased = lsqlin(Atrain_biased,ytrain,[],[],[],[],lb_polybiased,ub_polybiased);
xnonli = lsqcurvefit(fun,x0,xtrain,ytrain,lb_nonli,ub_nonli);
%% Results (MSE) of training data %%
ypred_nonli_train = fun(xnonli,xtrain);
ypred_polyunbiased_train  = Atrain_unbiased*xpoly_unbiased;
ypred_polybiased_train  = Atrain_biased*xpoly_biased;
X1 = xtrain(:,1);
X2 = xtrain(:,2);
X_fit = [X1,X2,X1.*X2,X1.^2,X2.^2,log(X1),log(X2)]; % define the features for the ANN model
ypred_ANN_train = predict(Theta1, Theta2, X_fit);
resnormpolyunbiased_train = norm(ytrain - ypred_polyunbiased_train)/length(ytrain);
resnormpolybiased_train = norm(ytrain - ypred_polybiased_train)/length(ytrain);
resnormnonli_train= norm(ytrain - ypred_nonli_train)/length(ytrain);
resnormANN_train  = norm(ytrain - ypred_ANN_train)/length(ytrain);
result_train = [resnormnonli_train resnormpolyunbiased_train resnormpolybiased_train resnormANN_train];
%% Results (MSE) of validation data %%
ypred_nonli_test = fun(xnonli,xtest);
ypred_polyunbiased_test  = Atest_unbiased*xpoly_unbiased;
ypred_polybiased_test  = Atest_biased*xpoly_biased;
X1 = xtest(:,1);
X2 = xtest(:,2);
X_fit = [X1,X2,X1.*X2,X1.^2,X2.^2,log(X1),log(X2)];
ypred_ANN_test = predict(Theta1, Theta2, X_fit);
resnormnonli_test= norm(ytest - ypred_nonli_test)/length(ytest);
resnormpolyunbiased_test = norm(ytest - ypred_polyunbiased_test)/length(ytest);
resnormpolybiased_test = norm(ytest - ypred_polybiased_test)/length(ytest);
resnormANN_test  = norm(ytest - ypred_ANN_test)/length(ytest);
result_test = [resnormnonli_test resnormpolyunbiased_test resnormpolybiased_test resnormANN_test];

%% Plot of fitting results of the prediction models %%
r = randi([1 length(xdata)-100],1); % randomly display the fitting results
yfit_nonli  = fun(xnonli,xdata(r:r+100,:));
yfit_polyunbiased   = A_unbiased(r:r+100,:)*xpoly_unbiased;
yfit_polybiased   = A_biased(r:r+100,:)*xpoly_biased;
X1 = xdata(r:r+100,1);
X2 = xdata(r:r+100,2);
X_fit = [X1,X2,X1.*X2,X1.^2,X2.^2,log(X1),log(X2)];
y_ANN = predict(Theta1, Theta2, X_fit);
figure
plot(ydata(r:r+100),'k');
```

```
hold on
plot(yfit_nonli,'-.r*');
plot(yfit_polyunbiased,':bs');
plot(yfit_polybiased,':gs');
plot(y_ANN,'--mo');
hold off
```

Appendix B PV Specification

SOLAR FRONTIER

I-V Curve



STC Characteristics

		SF145-S	SF150-S	SF155-S	SF160-S	SF165-S	SF170-S
Nominal power	Pmax	145 W	150 W	155 W	160 W	165 W	170 W
Module efficiency	%	11.8 %	12.2 %	12.6 %	13.0 %	13.4 %	13.8 %
Power tolerance		+5 W/ 0 W					
Open circuit voltage	Voc	107.0 V	108.0 V	109.0 V	110.0 V	110.0 V	112.0 V
Short circuit current	Isc	2.20 A	2.20 A	2.20 A	2.20 A	2.20 A	2.20 A
Voltage at nominal power	Vmpp	81.0 V	81.5 V	82.5 V	84.0 V	85.5 V	87.5 V
Current at nominal power	Impp	1.80 A	1.85 A	1.88 A	1.91 A	1.93 A	1.95 A

Standard Test Conditions (STC): 1,000 W/m² irradiance, module temperature 25 °C, air mass 1.5. Isc and Voc are ±10 % tolerance of STC rated values. Module output may rise due to the Light Soaking Effect. Subject to simulator measurement uncertainty (using best-in-class AAA solar simulator and applying Solar Frontier preconditioning requirements): +10 %/ -5 %.

Certificates and Guarantee

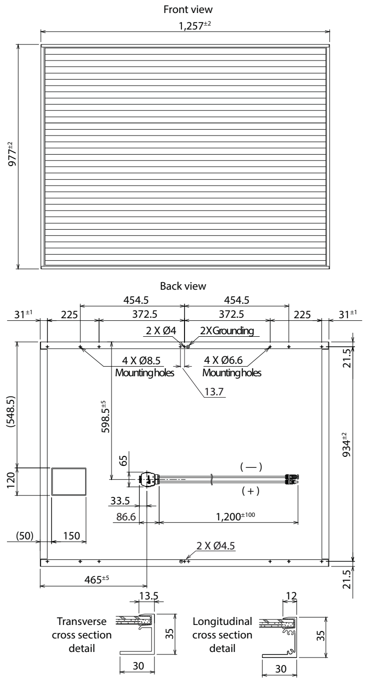
All new product classes are subject to immediate certification
Product guarantee: 5 years (extended garantee upon request)
Power output guarantee: 90 % for 10 years, 80 % for 25 years

NOCT Characteristics

		SF145-S	SF150-S	SF155-S	SF160-S	SF165-S	SF170-S
Nominal power	Pmax	108 W	111 W	115 W	119 W	123 W	126 W
Open circuit voltage	Voc	97.4 V	98.3 V	99.2 V	100.0 V	100.0 V	102.0 V
Short circuit current	Isc	1.76 A	1.76 A	1.76 A	1.76 A	1.76 A	1.76 A
Voltage at nominal power	Vmpp	76.0 V	76.4 V	77.4 V	78.8 V	80.2 V	82.1 V
Current at nominal power	Impp	1.43 A	1.47 A	1.49 A	1.51 A	1.53 A	1.55 A

Nominal Operating Cell Temperature Conditions: Module operating temperature at 800 W/m² irradiance, air temperature 20 °C, wind speed 1 m/s and open circuit condition.

Module Drawing



Performance at Low Irradiance

Efficiency reduction of maximum power from an irradiance of 1,000 W/m² to 200 W/m² at 25 °C is typically 2.0 %. The standard deviation for the reduction of efficiency is 1.9 %.

Temperature Characteristics

NOCT		47 °C
Temperature coefficient of Isc	α	+0.01 %/K
Temperature coefficient of Voc	β	-0.30 %/K
Temperature coefficient of Pmax	δ	-0.31 %/K

Mechanical Characteristics

Dimensions (L x W x H)	1,257 x 977 x 35 mm (49.5 x 38.5 x 1.4 in.)
Weight	20 kg (44.1 lbs)
Application class (IEC 61730)	Class A
Fire rating (IEC 61730)	Class C
Safety class (IEC 61140)	II
Snow/wind load*	2,400 Pa (IEC 61646) / 1,600 Pa design load (UL 1703)
Cell type	CIS glass substrate (cadmium free)
Front cover	Clear tempered glass, 3.2 mm
Encapsulant	EVA
Back sheet	Weatherproof plastic film (color: black & silver)
Frame	Anodized aluminum alloy (color: black)
Edge sealant	Butyl rubber
Junction box	Protection rating: IP67 (with bypass diode)
Adhesive	Silicone
Output cables (conductor)	2.5 mm² / AWG14 (halogen free)
Cable lengths (symmetrical)	1,200 mm (47.2 in.)
Connectors	MC4 compatible
Packing information	25 modules/pallet • 36 pallets/40' container (900 modules)

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