Advancing Solar Power Prediction of p-Si Panel By Considering Temperature and Solar Irradiance Fluctuations

Abdellah Asbayou [1*], *Mohamed Bouzelmad*[1] , *Ismail Isknan*[1] , *Lahoussine Bouhouch*[1] ,*Ahmed Soussi*[1] , and Ahmed Ihlal[1]

[1]EDP Materials and Renewable Energies Faculty Of science, Ibn Zohr University, Agadir, Morocco

Abstract. This article presents a comparative analysis of electrical models for a p-type silicon (p-Si) solar panel, with the objective of improving the accuracy of solar energy prediction under variable environmental conditions. It's important to understand the fluctuations of temperature and solar irradiance on photovoltaic (PV) performance for efficient energy production and grid integration. This article uses a comparative analysis between the simulated and the experimental curve, to understand the interaction between temperature, solar irradiation, and solar panel power output. Furthermore, by taking these factors into consideration in the model, we aim to provide a more accurate long-term prediction of solar power production. The results of this article are expected to contribute significantly to the improvement of solar energy forecasting models, helping energy planners, grid operators and system integrators to optimize the deployment and operation of solar energy systems

1 Introduction

Solar photovoltaic (PV) panels are playing a key role in the global transition to clean and renewable energy. By converting sunlight into electricity, these systems contribute significantly to reshaping how the world produces energy. As the need to fight climate change and reduce dependence on limited fossil fuels grows, solar power offers a sustainable, abundant, and environmentally friendly alternative.

Accurate forecasting of solar energy production is essential for the efficient integration of solar power into the electrical grid [1]. These forecasts are based on models that estimate the output of photovoltaic (PV) systems by considering environmental variables such as solar irradiance, temperature, wind speed, and humidity [2]. Reliable predictions enable grid operators to better manage energy flow, minimize the dependence on expensive backup systems, and enhance the grid's overall reliability [3].

Temperature and solar irradiance are the two primary factors that affect the output of PV panels [4]. As temperature and solar irradiance fluctuate throughout the day, the output of PV panels can also vary, making accurate solar power prediction challenging. However, by incorporating temperature and solar irradiance fluctuations into solar forecasting models, researchers have been able to improve the accuracy of solar power prediction [5]. This approach involves using data-driven machine learning techniques to analyze historical weather data and generate more accurate solar power forecasts [6].

Taking temperature and solar irradiance variations into account when building solar power prediction models plays a key role in improving the efficiency and output of photovoltaic (PV) systems [7][8][9]. Including these environmental factors allows researchers to create more precise forecasting tools, which supports better integration of solar energy into existing power networks [2][10]. This strategy also helps minimize the unpredictability of solar output due to changing weather conditions, making solar power a more stable and dependable renewable energy source [10][11].

The structure of this paper is organized as follows: after the introduction, Section 2 presents the theoretical foundations of the study. Section 3 outlines the experimental setup, and the methodologies applied. Section 4 discusses the results and provides an in-depth analysis. Finally, the paper concludes with a summary of the key findings and suggestions for future research directions.

2 Theoretical Background

There are differents solar cell models that predict electrical behavior as a function of temperature and irradiance. These include the Rs series resistance model, the Rs_Rp double resistance model (the most frequently used model for simulating photovoltaic power generation) [12], and the double diode model. **Fig. 1** shows the equivalent circuit of the various solar cell models

* Corresponding author: a.asbayou@gmail.com

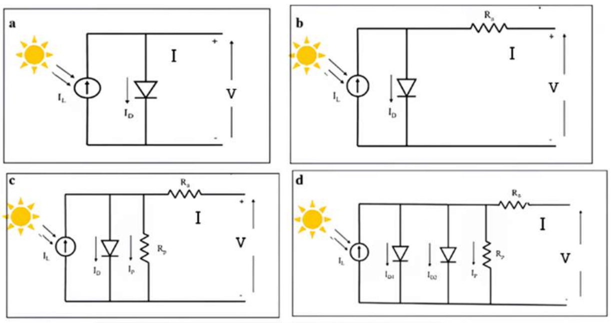

Fig. 1. Equivalent circuit of a PV cell: (a) ideal model, (b) Rs_model, (c) Rs_Rp model, (d) two-diode model.

In the case of two-diode model, (Ipv) is expressed by:

$$I_{pv}(t) = I_{ph}(t) - I_{d1}(t) - I_{d2}(t) - I_{sh}(t) \quad (1)$$

Iph is linearly dependent on solar radiation G by the expression,

$$I_{ph}(t) = (I_{ph,ref} + \alpha_0 \Delta T(t)) \frac{G(t)}{G_{ref}} \quad (2)$$

Under Standard Test Conditions, the expression of $I_{ph,ref}(t)$ is given by:

$$I_{ph,ref} = \left(1 + \frac{R_S}{R_{sh}}\right) I_{sc,ref} \quad \text{, and} \quad (3)$$

$$I_{ph} = \left(\left(1 + \frac{R_S}{R_{sh}}\right) I_{sc,ref} + \alpha_0 \Delta T(t)\right) \frac{G(t)}{G_{ref}} \quad (4)$$

The expression of I_{sh} current can be derived as follows:

$$I_{sh}(t) = \frac{Vpv(t) + R_S\, Ipv(t)}{R_{sh}} \quad (5)$$

The current I_{di} is given by the following expression:

$$I_{d1} = I_{01}\left[\exp\left(\frac{V_{pv}(t)(t) + R_S\, I_{pv}(t)}{n_1\, V_{th}}\right) - 1\right]\text{,and } I_{d2} = I_{02}\left[exp\left(\frac{V_{pv}(t) + R_S\, I_{pv}(t)}{n_2\, V_{th}}\right) - 1\right] \quad (6)$$

with [13]:

$$I_{01} \approx I_{02} = \frac{I_{sc,ref} + \alpha_0 \Delta T}{exp\left(\frac{V_{oc,ref} + \beta_0\, \Delta T}{V_{th}}\right) - 1} \quad (7)$$

The thermal voltage is given by $V_{th} = \frac{k\,T}{q}$

The current, I, supplied by the solar cell in the case of two-diode model is given by:

$$I_{pv}(t) = I_{ph}(t) - I_{01}\left[\exp\left(\frac{V_{pv}(t) + R_S\, I_{pv}(t)}{n_1\, V_{th}}\right) - 1\right] - I_{02}\left[\exp\left(\frac{V_{pv}(t) + R_S\, I(t)}{n_2\, V_{th}}\right) - 1\right] - \frac{V_{pv}(t) + R_S\, I_{pv}(t)}{R_{sh}} \quad (8)$$

The current, *Ipv(t)*, of the PV cell for the Rs_Rp model is given by:

$$I_{pv}(t) = I_{ph}(t) - I_0\left[exp\left(\frac{V_{pv}(t) + R_S\, I_{pv}(t)}{n_1 V_{th}}\right) - 1\right] - \frac{V_{pv}(t) + R_S\, I(t)}{R_{sh}} \quad (9)$$

The electrical current, *Ipv(t)*, of the PV cell for the Rs_ model is given by:

$$I_{pv}(t) = I_{ph}(t) - I_0\left[exp\left(\frac{V_{pv}(t) + R_S\, I_{pv}(t)}{n_1 V_{th}}\right) - 1\right] \quad (10)$$

The electrical current, $I_{pv}(t)$, of the PV cell for the Ideal_ model is given by:

$$I_{pv}(t) = I_{ph}(t) - I_0\left[exp\left(\frac{V_{pv}(t)}{n_1 V_{th}}\right) - 1\right] \quad (11)$$

In this work, we will experimentally test the above-mentioned models power output with the experimental data for the SX 330J solar panel, using our measurement experimental, and as the output power of a solar panel is given by:

$$P_{pv}(t) = I_{pv}(t) * V_{pv}(t) \quad (12)$$

3 Materials and Methods

To obtain the Ppv-Vpv characteristics of a photovoltaic (PV) panel, some researchers have used a variable resistor to adjust current and voltage levels, enabling the extraction of the power-voltage curve, as reported in previous studies [14, 15]. Alternatively, other researchers [16] have implemented a setup involving an Arduino module and a switching system to connect multiple resistors, forming a variable load that allows measurement of both Ipv-Vpv and Ppv-Vpv responses. However, this method based on a switching mechanism tends to have a slower response time compared to other available techniques

Electronic load comprising MOSFET transistors has been developed by researchers [17] to facilitate the acquisition of the I-V characteristics of photovoltaic (PV) modules. In parallel, other approaches have utilized boost converters to trace I-V curves of PV panels [18]. Additionally, studies [19–21] have introduced the use of capacitive loading techniques, where the charging and discharging cycles of capacitors are exploited to automatically vary the load. This enables rapid and efficient plotting of Ipv-Vpv data over a short period.

The experimental platform used in this study, depicted in Fig. 2, enables real-time monitoring and characterization of PV panel performance. Central to the setup is an Arduino UNO microcontroller, which manages data collection, control, and communication of current (Ipv) and voltage (Vpv) readings to a computer through the PLX-DAQ interface. The system uses dedicated Arduino-compatible sensors to measure voltage and current independently. A thermocouple is employed to monitor panel temperature, while solar irradiance is assessed using the FI 109SM solarimeter, as outlined in reference [15].

The variable-resistor load used in this work is a MOSFET IRF740, controlled by DC-DC Booster

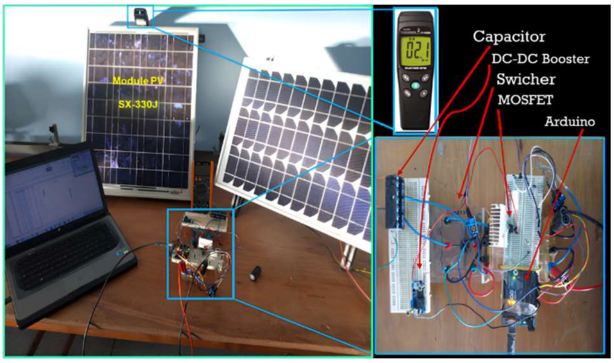

Fig. 2. Test bench for PV data acquisition

The electrical characteristics of the SX330J solar panel used in this work, namely: maximum power Pmax, short-circuit current Isc, open-circuit voltage Voc, maximum voltage Vmax, maximum current Imax, are presented in the following table.

Table 1. Electrical characteristics of the PV Module SX330 at STC (1000 W/m2 and 25 °C)

Parametre	Symbol	Value
Maximum power	P_{max}	30 W
Voltage at P_{max}	V_{mp}	16.8 V
Current at P_{max}	I_{mp}	1.78 A
Warranted minimum P_{max}	P_{min}	27 W
Short-circuit current	I_{sc}	1.94 A
Open-circuit voltage	V_{oc}	21.0 V

In this article, we carried out simulations with MATLAB/Simulink using the Newton–Raphson algorithm [22, 23] to resolve the complex nonlinear equation of the Ppv-Vpv curve (Fig. 3).

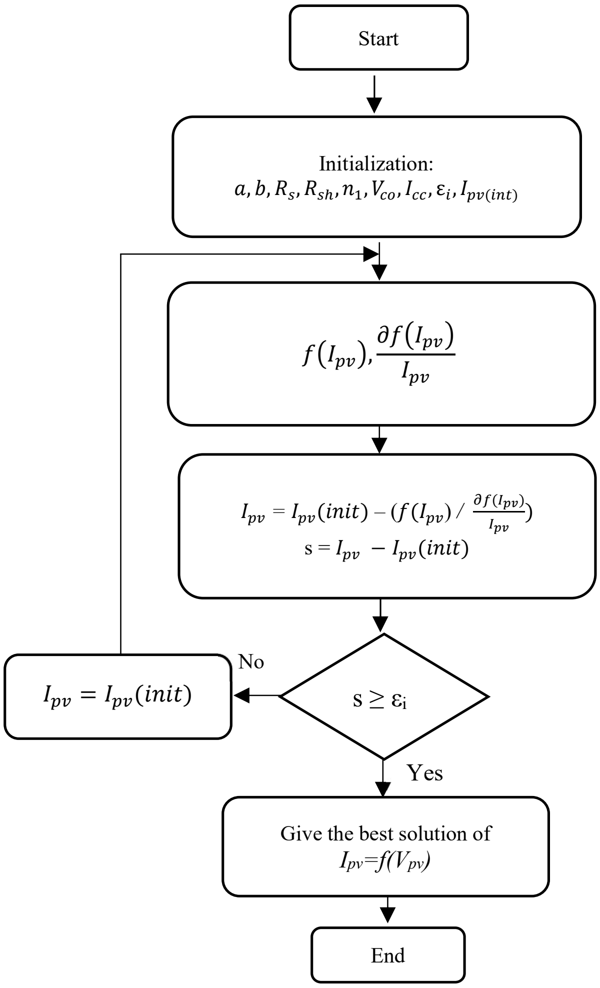

Fig. 3. Flow chart of the Newton–Raphson algorithm

The main goal of this study was to identify the most accurate model for predicting the electrical performance of the solar panel. This objectif was achieved through a detailed comparison between simulated and experimental results under specific conditions: temperatures of 25 °C, 50 °C, and 60 °C, and irradiance levels of 1 kW/m² and 820 W/m².

4 Results and Discussion

As illustrated in Fig. 4, the results indicate that at a lower temperature of 25 °C and irradiance levels of 1 kW/m² and 820 W/m², the experimental data closely align with the predictions of the double-diode model. In contrast, at elevated temperatures of 50 °C and 60 °C—representing typical operating conditions for PV panels—the experimental outcomes correspond more closely with those generated by the single-diode model at the same irradiance levels.

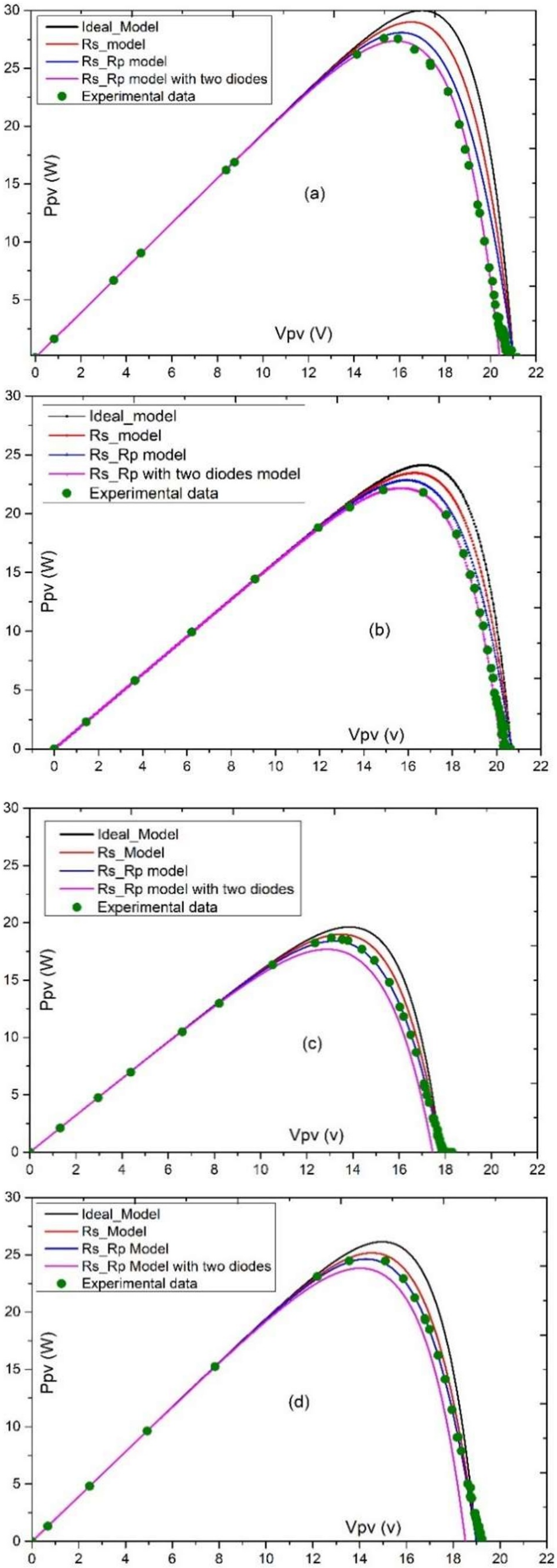

Fig. 4. Comparison of simulated and experimental Ppv-Vpv curves for the SX330J panel under various conditions: (a) at 25 °C with 1 kW/m² irradiance, (b) at 25 °C with 820 W/m², (c) at 60 °C and 820 W/m², and (d) at 50 °C with 1 kW/m² irradiance.

We can see from Fig. 4 that the ideal_model and Rs_model can't explain the electrical behaviour of our SX330J solar panel, as it's a very simplified model,

But on the other hand, the Rs_Rp model, and Rs_Rp model with the two-diodes, which is generally the most used, can explain and monitor variations of electrical performance of the solar panel in relation to a variation of irradiance and temperature.

To enhance understanding of the performance of the SX330J PV panel under different irradiance and temperature conditions, the following key insights can be drawn from the analysis:

- The Rs_Rp model proves to be the most suitable choice, particularly for testing under real outdoor conditions.
- Its simplicity and effectiveness in representing the electrical behavior of most PV cells make the Rs_Rp model a practical and widely applicable solution for solar cell modeling.
- However, under standard test conditions (STC), the two-diode model offers superior accuracy and performance, making it the preferred option in such controlled environments.

To predict the power output of our SX330J solar panel, as a function of the daily variation in solar irradiation and panel temperature, based on experimental data measured on 02/06/2022 at Ibn Zohr university, Agadir Morocco.

the following figures (Fig. 5 and Fig. 6) shows solar irradiance and temperature as a function of time.

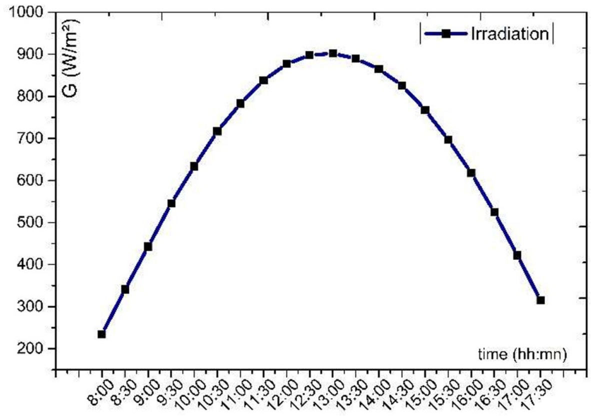

Fig. 5. Solar irradiation on 02/06/2022 from 8AM to 5:30PM

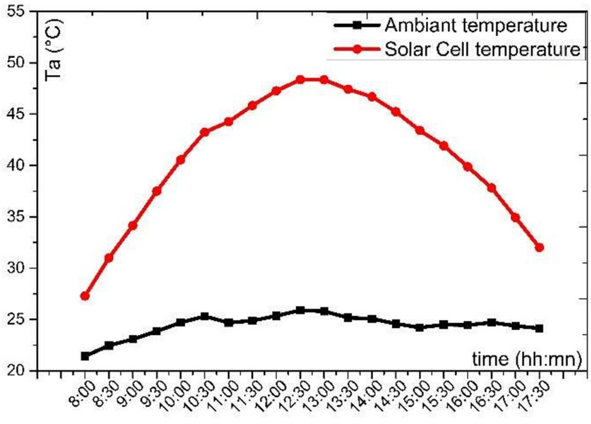

Fig. 6. Temperature on 02/06/2022 from 8AM to 5:30PM

We can notice also that the ideal_model, Rs_model can't explain the electrical behaviour of the SX330J solar panel, as it's a very simplified model.

The Fig. 7 represents a comparative study between the predicted power of SX330J Rs_model, Rs_Rp with one diode model, and two-diode model versus the experimental measurement of power under the same conditions.

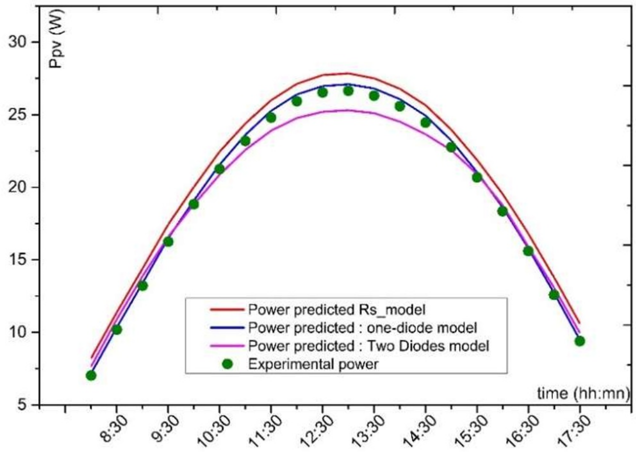

Fig. 7. Power predicted by model's vs experimental power measured on 02/06/2022 from 8AM to 5:30PM

We find that the experimental results for output power prediction agree with the Rs_Rp one diode model than with the other models, namely the Rs_model and Two-diode model.

these results make a crucial contribution to improving the performance of PV panels in the context of changing environmental parameters such as temperature, solar irradiance. In Fig. 8 we have represents the power predicted with solar power temperature

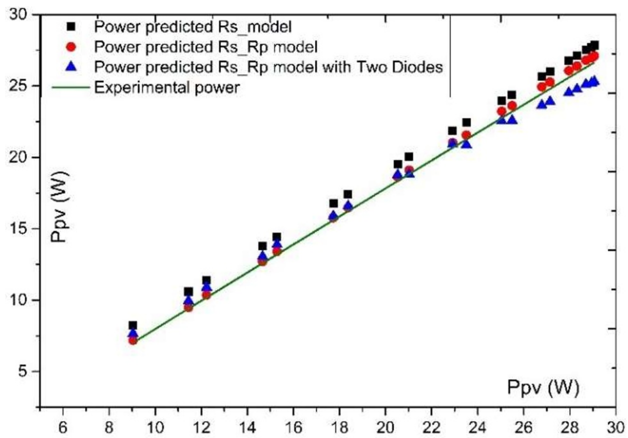

Fig. 8. Power predicted by model's vs experimental power measured on 02/06/2022 from 8AM to 5:30PM, with solar power temperature of SX330J.

From Fig.8 the experimental data of power output P_{pv} are in agreement with the simulated data of Rs-Rp one diode model, however we have observed a difference between the simulated data with two diodes or only with the Rs model in comparison with the experimental data which are the reference.

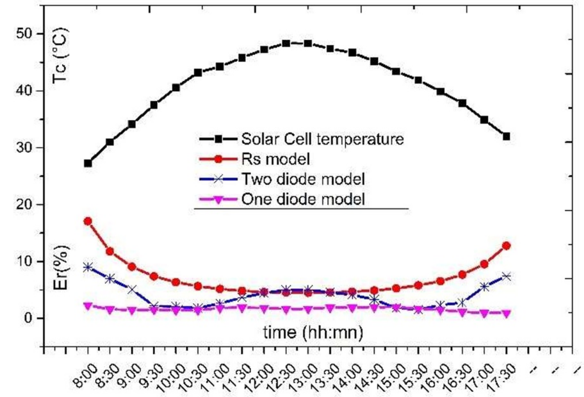

Fig. 9. Relative error Er (%) between experimental data and simulated on 02/06/2022 from 8AM to 5:30PM, with solar power temperature of SX330J.

We also note from Fig. 9 that at low temperatures the experimental results coincide with the simulations of the models; Rs_Rp model and Rs_Rp model with two diodes. So we can say that the temperature and irradiance received by a solar panel, are very important factors that determine the exact model on which the output prediction as a function of time will be correct.

5 Conclusion

In this work we have shown experimentally that the single diode model with Rs_Rp resistors is the most adequate model to describe the performance and the prediction of the output power of a polycrystalline PV solar panel under normal operating conditions, basing on a comparison between Matlab/Simulink simulations and experimental data, Moreover we have found that the daily prediction of the output power of the SX330J solar panel during a day 02/06/2022 from 8AM to 5: 30PM is consistent with the prediction of the Rs_Rp model.

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Nomenclature

G Solar irradiance on the module PV (W/m^2)
G_{ref} Reference solar irradiance (G_{ref} = 10^3 W/m^2)
I_{ph} Photo-generated current (A)
Ipv Solar cell terminal output current (A)
I_{SC} Short circuit current (A)
I_0 Reverse saturation current (A)
I_{0i} *Reverse* saturation current of diode in the conventional model (A)
n_i Diode ideality factor
N_S Cell number connected in series
N_{sh} Cell number connected in shunt
PV Photovoltaic
Ppv Power (W)
R_S Series resistance (Ω)
R_{sh} Shunt resistance (Ω)
STC Standard Test Conditions (G_{ref} = 1000 W/m^2, T_0 = 25 °C, and AM = 1.5)
T Cell or Module operating temperature (°C)
T_a Ambient temperature (°C)
ΔT Temperature difference: = T - T_0 (°C)
V_{OC} Solar cell open-circuit voltage (V)
Vpv Solar PV terminal output voltage (V)
E_g Bandgap energy
α Temperature correction coefficient for current
β Temperature correction coefficient for voltage
PLX-DAQ tool: Parallax Data Acquisition tool

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