Prediction Model for the Performance of Different PV Modules Using Artificial Neural Networks

Mahmoud Jaber 1, Ag Sufiyan Abd Hamid 2,* , Kamaruzzaman Sopian 1, Ahmad Fazlizan 1 and Adnan Ibrahim 1,*

1 Solar Energy Research Institute, Universiti Kebangsaan Malaysia, Bangi 43600, Selangor, Malaysia; p104798@siswa.ukm.edu.my (M.J.); ksopian@ukm.edu.my (K.S.); a.fazlizan@ukm.edu.my (A.F.)
2 Faculty of Science and Natural Resources, Universiti Malaysia Sabah, Kota Kinabalu 88400, Sabah, Malaysia
* Correspondence: pian@ums.edu.my (A.S.A.H.); iadnan@ukm.edu.my (A.I.)

Abstract: This study presents a prediction model for comparing the performance of six different photovoltaic (PV) modules using artificial neural networks (ANNs), with simple inputs for the model. Cell temperature (Tc), irradiance, fill factor (FF), short circuit current (Isc), open-circuit voltage (Voc), maximum power (Pm), and the product of Voc and Isc are the inputs of the neural networks’ processes. A Prova 1011 solar system analyzer was used to extract the datasets of IV curves for six different PV modules under test conditions. As for the result, the highest FF was the mono-crystalline with an average of 0.737, while the lowest was the CIGS module with an average of 0.66. As for efficiency, the most efficient was the mono-crystalline module with an average of 10.32%, while the least was the thin-film module with an average of 7.65%. It is noted that the thin-film and flexible mono-modules have similar performances. The results from the proposed model give a clear idea about the best and worst performances of the PV modules under test conditions. Comparing the prediction process with the real dataset for the PV modules, the prediction accuracy for the model has a mean absolute percentage error (MAPE) of 0.874%, with an average root mean square error (RMSE) and mean absolute deviation (MAD) of, respectively, 0.0638 A and 0.237 A. The accuracy of the proposed model proved its efficiency for predicting the performance of the six PV modules.

Keywords: photovoltaic; IV curve; efficiency; fill factor; ANN

1. Introduction

Solar energy has become one of the world’s most essential resources in the last decade, leading to the development of photovoltaic (PV) cells. The photovoltaic (PV) system contains many components such as cells, wires, inverters, structures, and mechanical connections. The output power from this system is measured by the peak kilowatt, which indicates the amount of electrical power delivered when the sun is at its highest point [1]. With the number of advantages of the PV system, many different applications have started to depend on it, such as solar systems in homes, pumps, PV and thermal collector systems, and building-integrated photovoltaic (BIPV) systems [2-6]. PV performance is influenced by environmental factors such as wind, temperature, dust pollution, and installation factors such as the tilt angle and area [1,7,8]. Many previous studies have focused on the result of dust on PV systems. The position of PV cells, the type of PV cells, the type of dust product (ash, carbon, cement, and limestone), and the type of investigated parameters (IV curve, power, and efficiency) were the main aspects of these studies [9,10].

Many studies have compared different types of PV cells and examined how each type will perform under different conditions from the STC. Mirzaei and Mohiabadi [11] studied the changes for two different PV modules types. The highest monthly average efficiency for the monocrystalline module was 15.2% in winter, while the lowest was 13.2% in summer. Meanwhile, the polycrystalline module’s highest monthly average efficiency
was 12.97% in summer and 11.44% in winter. Silvestre et al. [12] calculated the performance of monocrystalline, polycrystalline, and HiT modules. This research used the performance ratio (PR) and fill factor (FF) to compare the PV modules. The PV module with the highest PR and FF was the HiT module, and the lowest was the polycrystalline module.

The IV curve plays a significant role in this research. This curve provides a lot of information and important characteristics that could be useful for testing, measuring, and modeling the performance of the system, such as the short-circuit current ($I_{sc}$), the open-circuit voltage ($V_{oc}$), and the maximum power ($P_{m}$) [13]. There are two types of measurement of the IV curve: online and offline methods. The first type of method uses elements such as capacitors, resistors, and switches to measure the specifications of the PV cell. The advantage of this type of measurement is the ability to extract the IV curve and diagnose any faults in the system.

However, these methods have some drawbacks, such as their accuracy, time constraints, and the ability to use them in large-scale systems. Malik et al. [14] increased the value of the resistor manually, step by step, and then calculated current and voltage using digital multimeters in each step. In addition, Van Dyk et al. [15] measured the IV curve for monocrystalline and polycrystalline modules using variable resistors. A high-quality capacitor with low losses is recommended for this experiment, in order to extract the IV curve with high accuracy. Lorenzo et al. [16] used the capacitive load. The author avoided some of the drawbacks of the previous research, but the limitation of the power size is still considered a major problem. Forero et al. [17] presented a system that could monitor the performance of PV solar cells with an IV curve using several transistors in a cascade. The system obtained the IV curve with a short testing time, avoiding some problems encountered during previous research. Kuai et al. [18] extracted the IV characteristic curve while avoiding problems related to time constraints and the method’s use in large-scale systems. Durán et al. [19] proposed new buck–boost converters for the same purpose. Compared to the other online methods, flexibility and the ability to trace the IV curve in both directions are the advantages of this research.

In comparison, this converter cannot trace the points close to $I_{sc}$ and $V_{oc}$. Khatib et al. [20] suggested extracting the IV curve using a DC–DC boost converter. Using no external devices is the major advantage of this research. The disadvantage of this method is the low accuracy. The performance of the proposed model is 63%. Considering the significant drawbacks of these methods, many researchers have discussed new offline methods.

Offline methods are mainly based on genetic algorithms (GA) and artificial intelligence (AI) techniques. The major drawback of some of the offline methods is the ability to detect unusual conditions for the solar cell system. Some researchers have discussed this issue in their research. Bai et al. [21] used the five-parameter model, while Ma et al. [22] used the Levenberg–Marquardt method. These studies proved their high accuracy and lower testing time than online methods. Much research, such as that of Navabi et al. [23], used numerical techniques. However, these studies faced different challenges, such as complex calculations and the relationship between accuracy and initial conditions. Due to the drawbacks of some offline methods, a variety of methods, including genetic algorithms (GA) [24,25] and hybridized evolutionary methods [26,27], were used to solve them. These methods (called “evolutionary algorithms”) extract the IV curve with different approaches and concepts. Table 1 highlights the accuracy of these methods.

Researchers used some AI technologies, such as artificial neural networks (ANNs), to predict different parameters related to PV performance. One of the parameters is solar radiation. Solar radiation in tropical regions such as Malaysia is unique because it is stable and does not change throughout the year [28,29]. Khatib et al. [30] created a method for predicting it in Malaysia using ANNs. The technique that was proposed had a low percentage error compared to the previous process. In addition, El-kenawy [31] investigated the potential for the ANN with ant colony optimization (ACO) to predict received solar radiation. Sivanesan et al. [32] proposed a model to improve solar forecasting using ANNs with fuzzy logic. The model had a lower MAPE compared to models with no fuzzy
logic. Khatib et al. [33] used ANNs to predict the IV curve. The proposed method had a high percentage of errors in predicting the IV curve. Zhang et al. [34] predicted the IV characteristic curve using ANNs with an explicit analytical model (EAM). Mittal et al. [35] predicted the IV parameters (V_{oc}, I_{sc}, maximum current (I_m), maximum voltage (V_m), and P_m) using ANNs for different types of PV modules, while Ibrahim et al. [36] predicted the IV curve using the random forest method. Some researchers used ANNs to predict the output power of the PV system. Theocharides [37] predicted the output power using ANNs. Meanwhile, Jung et al. [38] used a recurrent neural network (RNN) to predict the output power; the mean absolute percentage error for the method was about 10.805%. Moreover, Khandakar et al. [39] indicated the output power in Qatar using ANNs in two different techniques.

Table 1. The accuracy of some of the methods that extracted the IV curve or output power.

| Name of Author       | Type of Method                        | Accuracy (%) |
|----------------------|---------------------------------------|--------------|
| Malik et al. [14]    | Online—Variable Resistor              | 69           |
| Van Dyk et al. [15]  |                                       | 78           |
| Lorenzo et al. [16]  | Online—Capacitive load                | 80           |
| Kuai et al. [18]     | Online—Electronic load                | 91.6         |
| Khatib et al. [20]   | Online—DC-DC converter                | 63           |
| Navabi et al. [23]   | Offline—Numerical models              | 90.5–99      |
| Ismail et al. [24]   | Offline—Evolutionary algorithms       | 78–98.6      |
| Dizqah et al. [25]   | Offline—Artificial neural networks    | 98.5         |
| Khatib et al. [33]   | Offline—Artificial neural networks    | 99           |
| Zhang et al. [34]    |                                       | 99           |
| Mittal et al. [35]   |                                       | 99           |
| Jung et al. [38]     | Offline—recurrent neural networks     | 90           |

The main objective of this study is to compare the predicting performance (FF, efficiency, and IV curve) for six different types of PV module (a CIGS module, a flexible monomodule, a thin-film module, a monocrystalline module, a polycrystalline module, and a flexible back-contact monomodule) under test conditions (solar radiation and ambient temperature) in Malaysia using GRNNs. The proposed model uses simple inputs for both networks, such as I_{sc}, V_{oc}, P_m, T_c, and irradiance, which could be extracted by any IV analyzer devices, and achieves this with higher accuracy than the online and offline methods represented in Table 1.

2. Experimental Setup and Major Parameters of the PV Module

During this research, six different types of PV panels were used to collect data using a Prova 1011 solar system analyzer, namely, a polycrystalline panel (100 W), a monocrystalline panel (100 W), a flexible mono-panel (100 W), a thin-film amorphous panel (100 W), a CIGS solar panel (90 W), and a flexible back-contact mono-panel (30 W). Figure 1 shows the six PV modules’ visual images while collecting the dataset.

The Prova 1011 solar system analyzer was used to measure the PV module performance (IV curve), FF, P_m (V_m and I_m), and efficiency under different test conditions. The instrument connects with a wireless irradiance meter and thermometer to collect the irradiance and cell temperature under the test conditions for the PV modules, as shown in Figure 2. Moreover, the device can calculate the efficiencies and the maximum power under test conditions by saving the specification of the PV module (area, V_{oc}, and I_{sc}) by connecting the device with a special software program for the device. After that, a considerable number of IV curves at different irradiance and temperature for the six PV modules are extracted from the device, and the software is used during the MATLAB program’s training process.
Figure 1. (a) Polycrystalline panel, (b) monocrystalline panel, (c) flexible mono-panel, (d) thin-film amorphous panel, (e) CIGS solar panel, and (f) flexible back-contact mono-panel.

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Figure 2. Set-up for extracting IV curves by Prova 1011 solar system analyzer.

An IV curve can represent the relationship between the current (the vertical axis of the curve) and voltage (the horizontal axis of the curve) at a specific irradiance and temperature, as shown in Figure 3. Analyzing the figure shows several essential points in the IV curve. As shown in Equation (1), the $Isc$ represents the highest current produced when the voltage is zero.

$$I (at \ V = 0) = I_s$$  \hspace{1cm} (1)

Secondly, as shown in Equation (2), $Voc$ represents the highest voltage produced when the current is zero.

$$V (at \ I = 0) = V_o$$  \hspace{1cm} (2)

Other essential points and parameters for this research include the maximum power point (MPPT). This represents the point in the IV curve where the rectangle area below the IV curve is the maximum. At the same time, the efficiency is the ratio between $P_m$ and the input power ($P_{in}$). $P_{in}$ is the product of the solar cell irradiation of the incident light. Lastly, the $FF$ is the ratio between $P_m$ and the product of $I_{sc}$ and $V_{oc}$. These important parameters can be given by Equations (3)–(5) [40,41]:

$$P_m = I_m \cdot V_m$$  \hspace{1cm} (3)

$$\eta = \frac{P_m}{P_{in}}$$  \hspace{1cm} (4)

$$FF = \frac{P_m}{I_{sc} \cdot V_{oc}}$$  \hspace{1cm} (5)
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3. Proposed ANNs Model for Predicting the Performance of the Six PV Modules

Artificial neural networks (ANNs) are non-algorithm information-processing systems that use previously collected data to train the networks to predict specific variables such as current, efficiency, output power, and solar radiation [42]. Every network, in general, has three types of layers, input, hidden, and output layers [42,43].

There are two generalized regression neural networks (GRNNs) that predict the IV curve. The output for the first GRNN is used as an input variable in the second GRNN; the second network predicts the current of one of the six PV modules at specific conditions. The architecture, and the number of neurons in the input, hidden, and output layers, are the
same for both networks. Moreover, each training dataset has one neuron for every input with different values and weights. The input neurons in this proposed model feed their values to the neurons in the hidden layer. After multiplying the values with a target, the final value is transferred to the neurons in the pattern layer. In this layer, the final values are added by weights from each hidden neuron, and the result is used as the predicted value [30]. In this research, the mechanism recorded IV curves for the proposed ANNs method using a Prova 1011 Solar System Analyzer. The device extracted a considerable number of IV curves at different irradiances and temperatures for the six PV modules. Most of these IV curve data were sent for the training process for the proposed ANNs method. Simultaneously, some of them were used during the testing process of the method.

In the proposed model, the first GRNN is trained by IV curve data for six different types of PV modules at different irradiances and cell temperatures, with FF, $P_{\text{max}}$, $I_{sc}$, $V_{oc}$, voltage, current, and the product of $I_{sc}$ and $V_{oc}$. These factors are used as input for the training process in the first network. The output for the first GRNN represents the relation between current and voltage. The training method’s inputs contain specialized information for one of the six PV modules covered by the device. Figure 4 shows the first proposed GRNN used in the model.

![Figure 4](image-url)  
**Figure 4.** The first proposed GRNN flowchart to predict the relation between the X and Y axes.

The testing process for the first GRNN starts by obtaining the current and voltage for the PV module by stepping their highest value down. These parameters are used as an input for the testing process with irradiance, cell temperature ($T_c$), FF, $P_{\text{max}}$, a product of $I_{sc}$ and $V_{oc}$, $I_{sc}$, and $V_{oc}$ to predict a parameter representing the relation between the $x$-axis and the $y$-axis. Meanwhile, the second GRNN predicts the current for one of the six types of modules at specific irradiance and temperature. The inputs for the training process are irradiance, $T_{cr}$, voltage, a product of $I_{sc}$ and $V_{oc}$, FF, $P_{\text{max}}$, $I_{sc}$, $V_{oc}$, and the output parameter from the first GRNN. The inputs for the testing process for the network are the same as the training process. Figure 5 shows the second GRNN proposed in this model. The proposed model starts by entering the name of the PV module with the specifications of the module. A “for loop” is used to upload the training dataset for the same PV module, depending on the type of PV module chosen. After this, the test conditions for the PV module (irradiance and $T_c$) should be specified. Then, the datasheet for the PV module is used to calculate $I_{oc}$ and $V_{oc}$ under test conditions using Equations (6) and (7) as below [42]:

$$V_{oc-T} = V_{oc-stc} - ((T_{c} - T_{a})) \times 0.123$$

(6)
\[ I_{sc-T} = I_{sc-STC} \times \left( \frac{\text{Irradiance at the test condition}}{\text{Irradiance at STC}} \right) \]  

Figure 5. The second proposed GRNN flowchart to predict the real current.

Before the testing process, another “for loop” is used to create the testing data input. The inputs are the same as those used during the training process. The last two inputs are calculated by stepping down \( I_{sc} \) and \( V_{oc} \). As shown in Figure 5, the first GRNN is utilized as an input for the second GRNN, which predicts the relationship between the \( x \)-axis and \( y \)-axis in the IV curve. The second GRNN, as shown in Figure 5, predicts the current and extracts the IV and PV curves. Finally, after repeating the same process with the same test conditions for the six different PV modules, the output data from each test condition are used to calculate the efficiency and FF to compare how each PV module performs under the same test conditions in Malaysia. Figure 6 shows the flowchart of the proposed model process.

Figure 6. Flowchart of the proposed model process.
For this research, the accuracy of the predicted performance was evaluated by using three types of errors: first, the mean absolute deviation (MAD). This error is an indication to measure the dispersal of a specific set of data and is calculated using Equation (8):

$$ \text{MAD} = \frac{1}{n} \sum_{i=1}^{r} |x_p - m(X)| $$

where $r$ is the number of the value, $x_i$ is the predicted value from the proposed model, and $m(X)$ is the dataset’s average. Secondly, the mean absolute percentage error (MAPE) was used, which can be given by Equation (9):

$$ \text{MAPE} = \frac{\text{Experimental Value} - \text{Predicted Value}}{\text{Experimental Value}} \times 100\% $$

This is usually used for calculating the accuracy of the new value (predicted value). Lastly, the root mean square error (RMSE) was used, which indicates the short-term performance and is calculated by using Equation (10):

$$ \text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{r} (x_p - x_e)^2} $$

where $x_e$ is the experimental value. MAPE was used to calculate the percentage of error of the predicting result to the experimental result. However, the results of the MAPE cannot always indicate the real error if the value of the prediction is too small. Therefore, types of errors such as RMSE and MAD are useful for this research.

4. Result and Discussion

In this research, six different types of PV modules were used to collect datasets for the training and testing process of the ANN by a Prova 1011 solar system analyzer. The technical characteristics of the PV modules at STC are described in Table 2.

| Types of PV Module | $P_m$ | $V_{oc}$ | $I_{sc}$ | $V_m$ | $I_m$ |
|--------------------|-------|----------|----------|-------|-------|
| CIGS               | 90 W  | 26.4 V   | 5.1 A    | 21 V  | 4.5 A |
| Thin film          | 100 W | 20 V     | 5.6 A    | 18 V  | 5.1 A |
| Flexible mono      | 100 W | 19.2 V   | 5.68 A   | 16 V  | 5.15 A|
| Polycrystalline    | 100 W | 21.42 V  | 5.76 A   | 18.59 V| 5.38 A|
| Monocrystalline    | 100 W | 21.97 V  | 6.07 A   | 17.46 V| 5.73 A|
| Flexible back-contact Mono | 30 W | 21.97 V | 1.75 A   | 18.31 V| 1.64 A|

There are 37,144 records for 247 IV curves that have been collected from the six PV modules, 40 IV curves from the flexible back-contact mono-module, 50 curves from the CIGS module, 42 curves from the thin-film module, 40 IV curves from the flexible mono-module, 35 curves from monocrystalline module, and 40 curves from polycrystalline module. Each record has a value for voltage, current, $V_{oc}$, $I_{sc}$, FF, a product of $I_{sc}$ and $V_{oc}$, irradiance, $T_c$, and $P_{max}$. A total of 7.69% of the dataset was used for the testing process, while the remaining data were used during the training process.

For the prediction process, the proposed model predicted the IV curve for the six different PV modules by entering the name of the PV module and the specific desired test conditions, as explained in Figure 6. To test the accuracy of the proposed model under different test conditions, each predicted IV curve has a different solar radiation level and ambient temperature for each PV module. Figures 7–12 show the predicted IV curves with the experimental IV curves for the six modules that were extracted. For each predicted IV curve, the proposed model starts the process of training and predicting from the start, as shown in the flowchart in Figure 6.
Figure 7. Predicted and experimental IV curves for CIGS module at 601 W/m² and 323 K Tc.

Figure 8. Predicted and experimental IV curves for thin module at 586 W/m² and 312 K Tc.

Figure 9. Predicted and experimental IV curves for flexible mono-module at 864 W/m² and 314 K Tc.
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Figure 10. Predicted and experimental IV curves for polycrystalline module at 410 W/m² and 316 K Tc.

Figure 11. Predicted and experimental IV curves for monocrystalline module at 640 W/m² and 324 K Tc.

Figure 12. Predicted and experimental IV curves for flexible back-contact mono-module at 865 W/m² and 312 K Tc.
After this, to compare the prediction performance of the six PV modules under test conditions and how each PV module will perform under the same test conditions, the proposed model predicted the IV and PV curves for the six different types of PV modules under the same test conditions, as explained in Figure 6. Figures 13–16 compare and show the predicted IV and PV curves for the six modules under the same test conditions. All the graphs were created using the MATLAB program.

![IV curves for six different types of PV modules at 650 W/m² and 315K Tc](image1)

**Figure 13.** Predicted IV curves for the six PV modules at 650 W/m² and 315K Tc.

![IV curves for six different types of PV module at 500 W/m² and 310K Tc](image2)

**Figure 14.** Predicted IV curves for the six PV modules at 500 W/m² and 310K Tc.

From Figures 13–16, FF efficiency for the six modules under the same test conditions were calculated, as shown in Table 3. The highest FF is the monocrystalline module, with an average of 0.737, while the lowest FF is the CIGS module, with an average of 0.66. For efficiency, the highest is the monocrystalline module, with an average of 10.32%, while the lowest is the thin-film module, with an average of 7.65%. Both thin-film and flexible mono-modules have similar performances.
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Table 3. FF and efficiency for the six PV modules under the same test conditions.

| Type of PV Module | Cell Temperature (K) | Irradiance (W/m²) | FF | Efficiency (%) |
|------------------|-----------------------|-------------------|----|----------------|
| CIGS             | 315                   | 650               | 0.667845 | 9.6274 |
|                  | 310                   | 500               | 0.65454  | 8.7328 |
| Thin film        | 315                   | 650               | 0.676499 | 8.083  |

From Table 4, by using Equations (8)–(10), the overall prediction accuracy of the proposed model was shown to have an average root mean square error (RMSE) and mean absolute deviation (MAD) of 0.0638 A and 0.237 A, respectively, while the average accuracy of the mean absolute percentage error (MAPE) is 0.874%. The accuracy of the proposed model proved its efficiency compared to the previous models presented in Table 1.

From the results in Tables 3 and 4, the proposed model predicted and compared the performance of the six different PV modules under test conditions with an accuracy of 99.126%, which is higher than of the all offline and online methods represented in Table 1. The model needs less than 30 s after entering the specific test conditions to predict the performance of the PV module by using and asking for simple parameters such as irradiance, \( V_{oc} \), and \( I_{sc} \) of the PV module.
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|-------------------|----------------------|-------------------|--------|----------------|
| CIGS              | 315                  | 650               | 0.667845 | 9.6274        |
|                   | 310                  | 500               | 0.65454  | 8.7328        |
| Thin film         | 315                  | 650               | 0.676499 | 8.083         |
|                   | 310                  | 500               | 0.685678 | 7.223         |
| Flexible mono     | 315                  | 650               | 0.677629 | 8.0899        |
|                   | 310                  | 500               | 0.698835 | 7.323         |
| Polycrystalline   | 315                  | 650               | 0.696921 | 10.9832       |
|                   | 310                  | 500               | 0.702558 | 8.4353        |
| Monocrystalline   | 315                  | 650               | 0.73124  | 11.2789       |
|                   | 310                  | 500               | 0.742875 | 9.3722        |
| Flexible back-contact mono | 315          | 650               | 0.71744  | 8.828         |
|                   | 310                  | 500               | 0.725462 | 7.2522        |

Table 4. Values of MAD, MAPE, and RMSE under different test conditions for the six PV modules.

| Type of PV Module | Irradiance (W/m²) | Tc (K) | MAD  | MAPE (%) | RMSE |
|-------------------|-------------------|--------|------|----------|------|
| Flexible back-contact mono | 547              | 312    | 0.112 | 0.532    | 0.026|
| CIGS              | 716               | 321    | 0.263 | 0.517    | 0.080|
| Polycrystalline   | 550               | 310    | 0.393 | 1.173    | 0.092|
| Flexible back-contact mono | 695              | 308    | 0.154 | 0.347    | 0.034|
| Thin film         | 401               | 310    | 0.198 | 0.872    | 0.052|
| Flexible mono     | 395               | 314    | 0.232 | 0.985    | 0.064|
| Flexible back-contact mono | 865              | 315    | 0.196 | 1.069    | 0.035|
| Monocrystalline   | 750               | 327    | 0.34  | 1.186    | 0.098|
| CIGS              | 840               | 315    | 0.237 | 0.953    | 0.075|
| Polycrystalline   | 473               | 311    | 0.248 | 1.065    | 0.082|
| Thin film         | 570               | 313    | 0.174 | 0.775    | 0.041|
| Monocrystalline   | 380               | 308    | 0.291 | 1.024    | 0.087|

5. Conclusions

This research proposed a model for comparing the prediction performance (IV curves, efficiency, and FF) of six different PV modules using an ANN. The ANN that is used for this model is a generalized regression neural network (GRNN). The model inputs for the ANN are irradiance, Tc, a product of Isc and Voc, FF, and the technical characteristics of the six PV modules. In this research, 37,144 records for 247 IV curves were collected from the six PV modules under different test conditions. The MATLAB program was used to train and test the data that were extracted from the device. Under the test conditions in Malaysia (solar radiation and ambient temperature), the monocrystalline module had the highest FF and efficiency, while the CIGS module had the lowest FF. As for efficiency, the lowest was the thin-film module. The overall prediction accuracy for the proposed model has an RMSE and MAD of 0.0638 A and 0.237 A, respectively. At the same time, the accuracy of the MAPE is 0.874%. In future, a different device with a higher accuracy for collecting training data sets and more variation in the training data and test conditions could improve the accuracy of the proposed model. These results proved the accuracy of the model for predicting the performance of the six PV modules.
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Abbreviations

PV Photovoltaic
IV Current–voltage
BIPV Building-integrated photovoltaic
I_sc Short-circuit current
V_oc Open-circuit voltage
T_c Cell temperature
FF Fill factor
PR Performance ratio
MPPT Maximum power point
P_m Maximum power
I_m Maximum current
V_m Maximum voltage
P_in Input power
\eta Efficiency
ANNs Artificial neural networks
AI Artificial intelligence
GA Genetic algorithm
RNN Recurrent neural network
GRNN Generalized regression neural network
V_{oc,T} Open-circuit voltage under test conditions
V_{oc,STC} Open-circuit voltage under standard test conditions
T_a Ambient temperature
I_{sc,T} Short-circuit current under test conditions
I_{sc,STC} Short-circuit current under standard test conditions
MAPE Mean absolute percentage error
r Number of the value
x_i Predicted value
m(X) Dataset’s average
RMSE Root mean square error
MAD Mean absolute deviation
x_e Experimental value

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