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Photovoltaic Panel Parameters Estimation Using Grey Wolf Optimization Technique †

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Abstract: In different photovoltaic PV applications, it is very important to model the PV cell. However, the model parameters are usually unavailable in the datasheet provided by the manufacturers and they change due to degradation. This paper presents a method for identifying the optimal parameters of a PV cell. This method is based on the one diode model using the grey wolf algorithm as well as datasheets. An algorithm is implemented in a SIMULINK simulator for making the I-V and P-V characteristics. This approach is found to be useful for designers due to its simplicity, fastness, and accuracy. The final results are compared to demonstrate the efficiency and accuracy of the proposed method.

Keywords: PV cell; one diode model; model parameters; grey wolf optimization algorithm

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1. Introduction

Among all renewable energy sources, solar energy has acquired the highest growth rate worldwide in recent years. The major application of solar energy is photovoltaic (PV) power generation, which saw growth of more than 22% in 2019 and is predicted to output over 720 TWh [1]. PV systems are easy to install, noise-free, and can directly convert solar energy to electrical energy. For an accurate study in different PV applications, it is very important to model the basic device of the PV cell. However, the model parameters are usually unavailable in the datasheet provided by the manufacturers and their values change over time due to the PV degradation [2]. Thus, how to estimate appropriate parameters is of high importance and has attracted immense interest among researchers.

The one diode model (ODM) is considered the most suitable model used to characterize the solar cells/modules [3–7] in comparison to the double diode model (DDM) and the three-diode model (TDM) as it has a minimum number of parameters and a good level of accuracy. The five electrical parameters of the ODM are: photocurrent (I_{ph}), diode ideality factor (n), reverse saturation current (I_0), shunt resistance (R_{sh}), and series resistance (R_S).

Several methods have been developed to extract the ODM parameters which are classified into three main categories [5,7]:

- Analytical methods [7]
- Numerical methods [3–6]
- Artificial intelligence or optimization methods [8–10]

Numerical methods are widely used in the literature since they provide a good compromise between speed of calculation, simplicity, and accuracy. These numerical methods are utilized to solve a system of a few non-linear equations related with the PV cell.

The objective of this work is to simulate the I-V and P-V characteristics using a one diode model (ODM) associated with a developed algorithm that permits finding the appropriate value of the ideality factor and hence extracting the other needed parameters simply from datasheet information provided by the manufacturer.

2. Photovoltaic Cell

A PV cell is basically a semiconductor diode, as shown in Figure 1. According to the principle theory of photoelectric effect, for any material exposed to light generating charge carriers, when sunlight that is basically photons of different frequencies and energies hits the solar cell surface and is absorbed by a semiconducting material, such as silicon, electrons will be excited from atoms, making them free and ready to move.

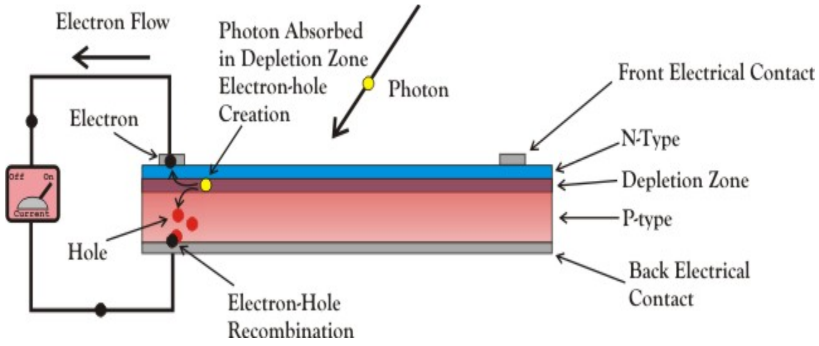


Figure 1. Photo electric effect of PV cell.

Solar cells produce electricity with very small voltage. For the common single junction silicon solar cell, it is approximately 0.5–0.6 volts. They are available in the form of modules or panels to provide sufficient voltage and current for real life applications.

2.1. Characteristics of the PV Cell

Electrical characteristics of PV modules are given by the producers under precise conditions that are known as standard test conditions (STC). Such conditions are defined by the ambient temperature $T_{STC} = 25\ ^\circ C$, irradiation level $G_{STC} = 1000\ W/m^2$, and the air mass value AM = 1.5. However, in the working field, PV modules operate at higher temperatures and somewhat lower insulation conditions. In order to determine the power output of the solar cell, it is important to know the expected operating temperature. The nominal operating cell temperature (NOCT) is defined as the temperature reached by open circuited cells in a module under the conditions: solar irradiance G = 800 w/m^2, air temperature $T_{ambiant}$ = 20 °C, and wind speed = 1 m/s. Then, the cell temperature can be calculated by the following equation:

$$T_{cell} = T_{ambiant} + \left(\frac{NOCT - 20}{800}\right) \times G \tag{1}$$

where G is taken in (w/m^2).

The typical I-V and P-V characteristics of a photovoltaic cell are shown in Figure 2. The main three significant parameters on the photovoltaic characteristics are open circuit voltage (V_{oc}), short circuit current (I_{sc}), and maximum power point at (V_{mpp}, I_{mpp}).

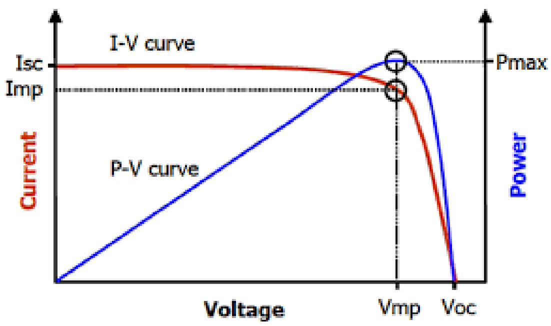


Figure 2. Typical I-V and P-V characteristics of PV cell.

The maximum current in photovoltaic cell is produced when there is a short circuit between its positive and negative terminals and it is denoted as I_{sc}. As $I = I_{sc}$, the voltage in the circuit is zero. The maximum voltage, denoted as V_{oc}, occurs when there is a break in the circuit.

The maximum power achieved from a photovoltaic cell occurs at a point on the bend in the I-V curve known as the maximum power point (MPP), which can be found at voltage and current points designated as V_{mpp} and I_{mpp}.

Generally, these parameters are provided in the datasheet by manufacturers of a particular photovoltaic cell or module. When the PV cell is connected to an external load, the electrical characteristics of the load determine the actual point on the I-V curve at which the photovoltaic cell operates.

2.2. Single Diode Model of PV Cell

To analyze characteristics of solar cells, electrical equivalent circuits are needed and hence modeled using simulation software. Researchers have developed mathematical models to understand and predict the effect of changing conditions on photovoltaic electrical output. The lumped parameter model is one of these models classified based on the number of diodes. It is widely used and has proven to be more successful. The lumped parameter models can take the form of a one diode model, double diode model, or three diode model. Although the accuracy of the characteristics of the model improves as the number of diode increases, the required mathematical expression to obtain the output characteristics become more complex. For simplicity, in this work, the one diode model known as the five parameter model is chosen for the identification of photovoltaic cell parameters.

The complete governing equation for the one diode model is given as [3]:

$$I = I_{ph} - I_s \left[e^{\left(\frac{V + I * R_s}{n * V_t}\right)} - 1 \right] - \frac{V + I \times R_s}{R_{sh}} \tag{2}$$

where V_t is the thermal voltage.

Then, the five parameters of one diode model are: (1) I_s: Diode saturation current (A), (2) n: Diode ideality factor ($1 < n < 2$), (3) R_s: Series resistance (Ω), (4) R_{sh}: Shunt resistance (Ω), and (5) I_{ph}: Photocurrent (A).

The one-diode model takes into account different properties of solar cell: R_s is introduced as to consider the voltage drops and internal losses due to flow of current, and R_{sh} takes into account the leakage current to the ground when the diode is reverse biased. However, this model has neglected the recombination effect of the diode. Therefore, it is still not the most accurate model.

3. Identification of PV Cell Parameters

The current versus voltage relationship of the single diode PV cell model (Figure 3) is presented in Equation (2). It can be noticed that the equation of the I-V curve is nonlinear, which is difficult to solve by the analytical methods. Due to this difficulty, scientists have developed several algorithms in order to solve this equation to determine the parameters of the solar cell. In this work, metaheuristic methods, which can be adapted to solve a wide range of optimization problems, are used. These methods are designed to find a good solution among a large set of feasible solutions with less computational effort than other optimization techniques.

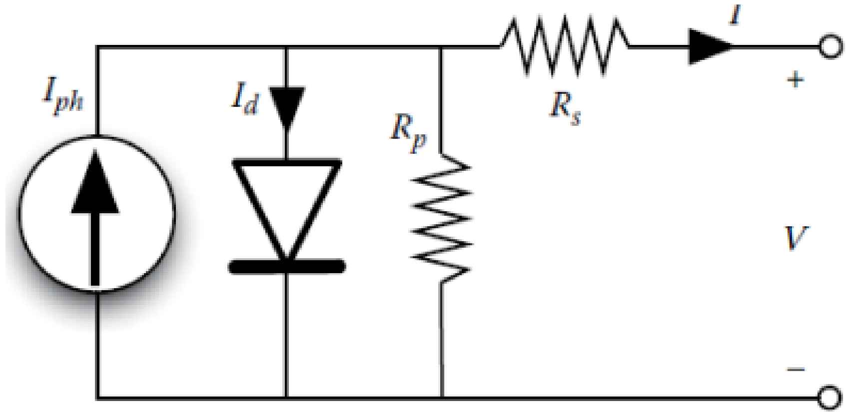


Figure 3. One-diode Model of PV cell.

3.1. Grey Wolf Optimization Technique

Grey wolf optimization (GWO) is a population-based meta-heuristic optimization method inspired by grey wolves (Canis lupus). The GWO algorithm mimics the leadership hierarchy and hunting mechanism of grey wolves in nature. The pack is classified into four groups, alpha, beta, delta, and omega, for simulating the leadership hierarchy. Alpha is the first level and is the leader of the pack. Beta is the second level on the hierarchy of wolves, as they help alpha wolves to make a decision. Delta represents the third level in the pack, as members have to succumb to alpha and beta, however they dominate omega. Omega wolves have the lowest position in the pack, having to succumb to all other dominant wolves. Figure 4 shows the grey wolf social hierarchy [11,12].

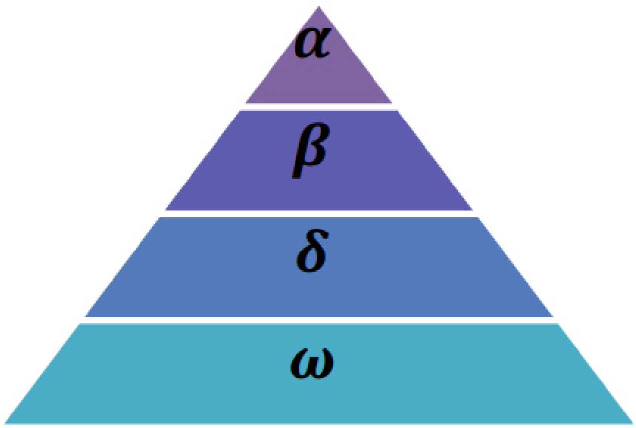


Figure 4. Hierarchy of grey wolf.

In addition to the social hierarchy of wolves, group hunting is another interesting social behavior of grey wolves. According to Muro et al. [13], the main phases of grey wolf hunting are as follows:

- Tracking, chasing, and approaching the prey.
- Following, encircling, and harassing the prey until it stops moving.
- Attacking the target.

Wolves encircle the target during the chase. The encircling is modeled by the Equations (7) and (8) [13]:

$$\vec{D} = |\vec{C}\,\vec{X}_p(t) - \vec{X}(t)| \tag{3}$$

$$\vec{X}(t+1) = \vec{X}_p(t)\vec{A}.\vec{D} \tag{4}$$

where t represents the current iteration, $\vec{A}$, $\vec{C}$, and $\vec{D}$ are coefficient vectors, $\vec{X}_p$ is the position vector of the victim, and $\vec{X}$ is the position vector of a grey wolf $\vec{A}$ and $\vec{C}$, as computed through these two equations:

$$\vec{A} = 2\vec{a}\,\vec{r}_1 - \vec{a} \tag{5}$$

$$\vec{C} = 2\,\vec{r}_2 \tag{6}$$

Components of $\vec{a}$ linearly reduce from 2 to 0 through the iterations and $\vec{r}_1$ and $\vec{r}_2$ as random vectors in [0, 1].

The pursuit is habitually directed by the leader alpha (α) followed by beta (β) and delta (δ) which can sometimes contribute in chasing. (δ) and (ω) look after the injured wolves in the group. Alpha (α) is considered the best result owing to the best information of the place of the target, while beta (β) and delta (δ) are the second and the third best solutions respectively in designing GWO. (ω) is the last best. Therefore, the first three best solutions obtained so far are saved and the other search agents (including ω) are obliged to update their positions according to the position of the best search agent. When the prey stops moving, the wolves terminates the chase by attacking it, as shown in Figure 5.

Figure 5. Hunting conduct of grey wolves: (**A**) approaching and pursuing target, (**B**–**D**) following, encircling and disturb the target, (**E**) attacking the target [13].

In this regard, the following formulas are applied:

$$\begin{cases} \vec{D}_\alpha = |\vec{C}_1 \cdot \vec{X}_\alpha(t) - \vec{X}(t)| \\ \vec{X}_1 = \vec{X}_\alpha(t) - \vec{A}_1 \cdot \vec{D}_\alpha \end{cases} \tag{7}$$

$$\begin{cases} \vec{D}_\beta = |\vec{C}_2 \cdot \vec{X}_\beta(t) - \vec{X}(t)| \\ \vec{X}_2 = \vec{X}_\beta(t) - \vec{A}_2 . \vec{D}_\beta \end{cases} \tag{8}$$

$$\begin{cases} \vec{D}_\delta = |\vec{C}_3 \cdot \vec{X}_\delta(t) - \vec{X}(t)| \\ \vec{X}_3 = \vec{X}_\delta(t) - \vec{A}_3 \cdot \vec{D}_\delta \end{cases} \tag{9}$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{10}$$

3.2. ODM Parameters Extraction Using a GWO Method

The proposed five-parameter estimation method is based on the three points that characterize the I-V curve, which are the maximum power point (V_{mpp} , I_{mpp}), short circuit point (0, I_{sc}), and open circuit point (V_{oc} , 0). These data can be provided in the datasheet or extracted from the experiments.

Like any optimization algorithm, an objective function F(X) should first be set. F(X) is based on the one diode Equation (2). For the identification of PV module parameters, the number of series connected cells N_s is considered. Thus, the objective function is:

$$\begin{cases} F(X) = I - I_{ph} - I_s \left[e^{\left(\frac{V+I\times R_s}{n\times N_s\times V_t} \right)} - 1 \right] - \frac{V+I\times R_s}{R_{sh}} \\ X = \left\{ I_{ph}, I_s, R_s, n, R_{sh} \right\} \end{cases} \quad (11)$$

The fitness function that needs to be minimized in order to quantify the error is the root main square error (RMSE) between the approximated values in the datasheet I_{mpp}, I_{sc} and I = 0 at open circuit condition and the calculated ones.

$$\text{Fitness} = \text{RMSE} = \sqrt{\frac{1}{3} \sum_{1}^{3} \left(I_{Datasheet} - I_{calculated} \right)^2} \quad (12)$$

Then, the NRMSE error is calculated as follows:

$$\text{NRMSE} = \frac{\text{RMSE}}{\sqrt{\frac{1}{3} \times \sum_1^3 {I_{Datasheet}}^2}} \times 100 \quad (13)$$

The pseudo code of the proposed algorithm is presented in Algorithm 1.

Algorithm 1 GWO

Input: T, N_s, V_{mpp}, I_{mpp}, V_{oc}, I_{sc}
Output: X_α
Initialize the grey wolf population Xi (i = 1, 2, ... n)
Initialize a, A, and C
Calculate the fitness of each search agent by Equation (12)
X_α = the best search agent
X_β = the second best search agent
X_δ = the third best search agent
while (t < Max number of iterations)
for each search agent
X_δ = the third best search agent
while (t < Max number of iterations)
for each search agent
Update the position of current search agent by Equation (10)
end for
Update a, A, and C
Calculate the fitness of all search agents by Equation (12)
Update X_α, X_β and X_δ
t = t + 1
end while
return X_α
Calculate NRMSE using Equation (13)
end procedure

4. Test Results and Discussion

The proposed algorithm GWO is used to extract the parameters of the ODM based on curve fitting method. The algorithm is tested on two PV modules and compared with other algorithms to prove its effectiveness. The simulator is developed using MATLAB R2016a and executed on a PC with Intel® Core™ i5-2450M CPU processor @ 2.50 GHz, 4 GB RAM, under Windows 10 64-bit OS.

The search ranges used in the optimization of the five parameters are given Table 1. However, the GWO parameters are given in Table 2. The datasheet parameters of used PV modules are presented in Table 3.

Table 1. ODM parameter search ranges.

Parameter	Search Range
I_{ph}	$[0.95 \times I_{sc},\ 1.05 \times I_{sc}]$
I_s	$[1\ \mu A, 5\ \mu A]$
n	[1, 2]
R_{sh}	$\left[\frac{V_{mpp}}{I_{sc}-I_{mpp}},\ 1500\ \Omega\right]$
R_s	$\left[0,\ \frac{V_{mpp}-V_{oc}}{I_{mpp}}\right]$

Table 2. GWO parameters.

Parameters	Value
Random values r1, r2	[0, 1]
No. of search agents	30
Maximum iteration	1000

Table 3. Datasheet Parameters under STC (T = 25 °C, G = 1000 W/m^2).

Module	Type	Parameters				
		V_{mpp}[V]	I_{mpp}[A]	V_{oc}[V]	I_{sc}[A]	N_s
STP050D-12/MEA	Poly-crystalline	17.4	2.93	21.8	3.13	36

Case Study #1: KC200GT

The polycrystalline module KC200GT ODM parameters are extracted to draw the I-V and P-V characteristics using the developed PV simulator, as shown in Figure 6. The results obtained at STC are presented in Table 4. The GWO results for the KC200GT module are compared with other published optimization methods results to prove its efficiency.

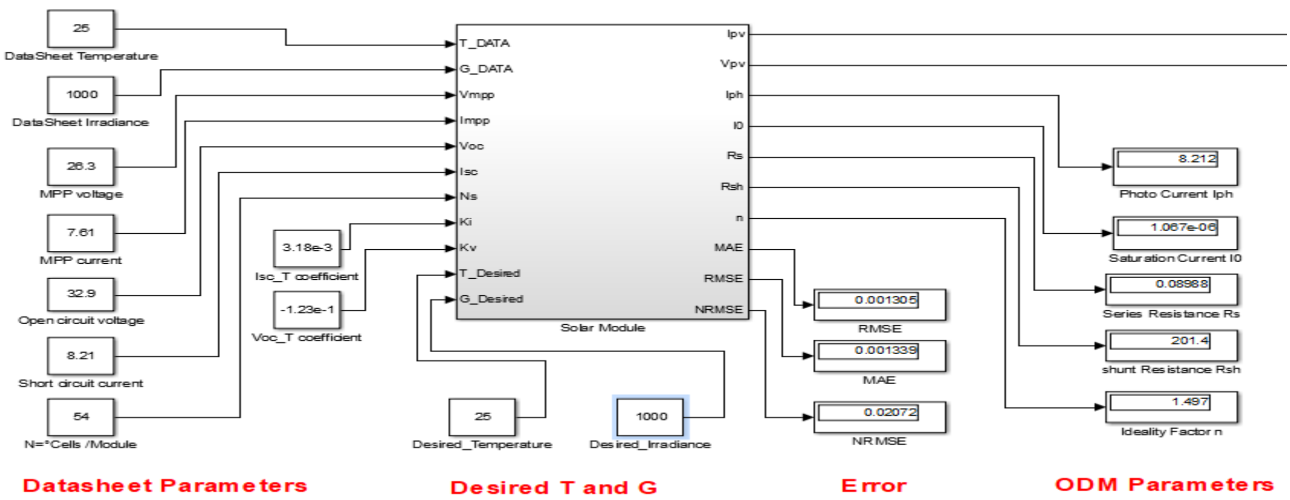


Figure 6. GWO based ODM PV simulator.

Table 4. KC200GT parameters at STC achieved by different methods.

Methods	Parameters					Error	
	I_{ph}[A]	I_s[μA]	n	R_s[Ω]	R_{sh}[Ω]	RMSE [A]	NRMSE [%]
Villalva [3]	8.193	0.08520	1.300	0.13870	466.0	2.3×10^{-1}	3.02
Accarino [3]	8.193	0.00200	1.079	0.23630	204.0	1.1×10^{-1}	1.49
Stornelli [3]	8.220	0.00514	1.120	0.26560	144.9	1.2×10^{-1}	1.53
GWO *	8.212	1.06700	1.497	0.08988	201.4	1.305×10^{-4}	2.072×10^{-2}

* Proposed method.

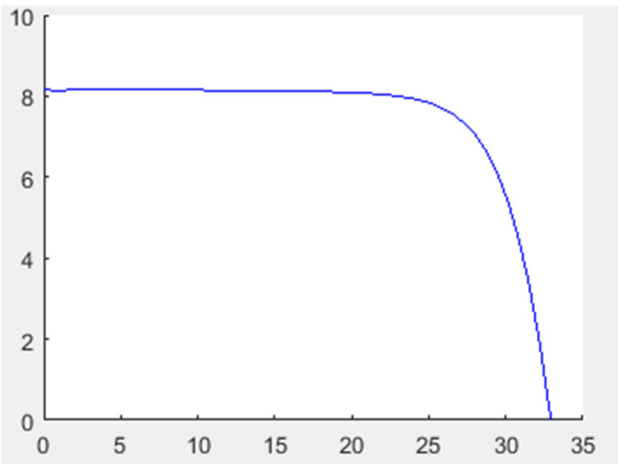
As given in Table 4, the normalized mean absolute error NRMSE obtained by the proposed method (0.02072%) is the lowest, which proves the effectiveness of this technique in extracting the unknown PV parameters. Moreover, the convergence using this method is very fast, where the simulation execution time is less than 7 s.

Case Study #2: STP050D-12/MEA

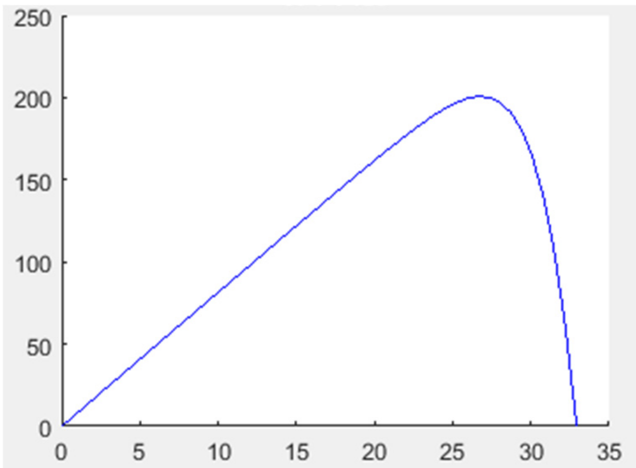
The PV characteristics of the poly-crystalline STP050D-12/MEA module are simulated at T = 45.57 °C and G = 632 w/m^2 using the GWO based ODM PV simulator as shown in Figure 6. The obtained results are given in Table 5 and Figure 7. The computed errors are: RMSE = 1.327×10^{-3} and NRMSE = 7.282×10^{-2}. The simulated characteristics are compared with the module's experimental data obtained in our research laboratory [14]. The comparison results are presented in Figure 8 and Table 6.

Table 5. STP050D-12/MEA extracted parameters.

T [°C]	G [w/m^2]	Parameters				
		I_{ph}[A]	I_s[A]	n	R_s[Ω]	R_{sh}[Ω]
45.57	632	1.986	1.326	1.497	0.1024	1497



(a)



(b)

Figure 7. (**a**) I-V and (**b**) P-V characteristics of KC200GT at STC.

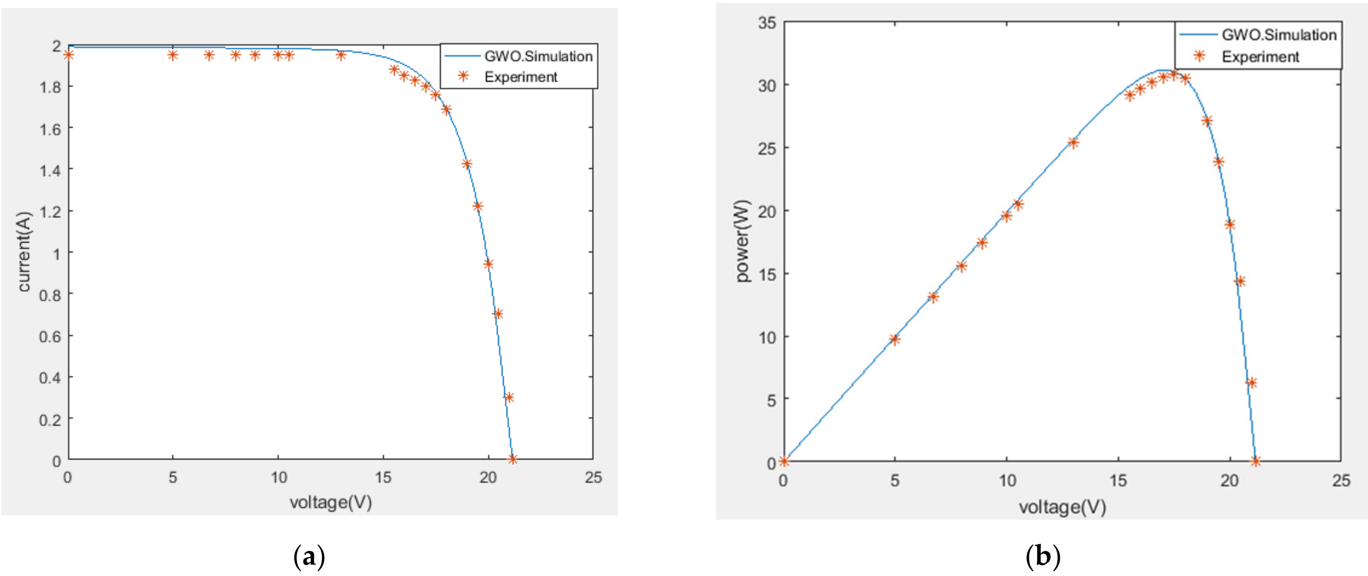


Figure 8. (**a**) Experimental versus Simulation I-V and, (**b**) Experimental versus Simulation P-V characteristics of STP050D-12/MEA at T = 45.57 °C and G = 632 w/m^2.

Table 6. Comparison of Experimental and simulation model values.

Parameters	Experimental Data	Simulation Data	Relative Error (%)
V_{mpp}[V]	17.591	17.16	2.450116537
I_{mpp}[A]	1.76824	1.8138	2.576573316
P_{max}[W]	31.1052	31.1242	0.06108303435
V_{oc}[V]	21.1435	21.15	0.03074230851
I_{sc}[A]	1.94817	1.9926	2.280601796

It can be noticed that the measured data points obtained in our laboratory for the STP050D-12/MEA module highly agreed with the simulated curves. Thus, the obtained I-V and P-V characteristics for the STP050D-12/MEA module based only on the datasheet information using the GWO based ODM PV simulator gives good results.

5. Conclusions

PV cell characterization is a hot research topic in the field of renewable energy. Obtaining the most accurate I-V and P-V characteristics has been the main purpose of this research work. This was attempted by finding an efficient method based on the one diode model using the information provided by the manufacturers. However, not all (five) parameters are available in the datasheet. Thus, the simulation has been associated with the developed algorithm that permits finding the appropriate value of the needed parameters. Grey wolf optimization (GWO) has been implemented using SIMULINK for extracting the five parameters based only on the three critical I-V points information provided in the datasheet, namely the open circuit point (0, V_{oc}), the short circuit point (I_{sc}, 0), and the maximum power point (I_{mpp} , V_{mpp}). Furthermore, this method has been enhanced to provide the parameters under different environmental conditions. The developed ODM-GWO simulation was tested for various PV modules, under different temperatures and irradiances. The obtained I-V and P-V curves were compared to the characteristics provided in the datasheet. Moreover, the BP MSX 120 multi-crystalline module simulated curves were compared to the experimental I-V data. The measured data points conformed to the obtained curves. Thus, the good accuracy of the developed PV simulator was demonstrated.

Adding to the fact that these proposed algorithms have provided optimal results with an acceptable accuracy, the time taken by the ODM-GWO simulation execution is less than 10 s.

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