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# Photovoltaic Panel Parameters Estimation Using an Opposition Based Initialization Particle Swarm Optimization †

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**Abstract:** A photovoltaic (PV) cell is generally used as renewable energy source. For an accurate study of various PV applications, modeling this basic device in a PV generator is essential. However, the manufacturers do not usually provide the model parameters and their values vary over time due to PV degradation and the change in weather conditions. Thus, finding an optimal technique for estimating the appropriate parameters is crucial. This problem can be solved by metaheuristic optimization algorithms, namely particle swarm optimization (PSO). However, early convergence is the main defect of PSO. This work presents an enhancement in the optimization method (PSO) for identifying the optimal parameters of a PV generating unit. In this method, the identification of parameters of the single diode model is based on an opposition-based initialization particle swarm optimization technique. The optimization algorithm is implemented in MATLAB which gives good results.

**Keywords:** photovoltaic (PV) cell; opposition-based particle swarm optimization algorithm; one diode model parameters



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## 1. Introduction

Solar Energy is considered as the most promising alternative to conventional energy sources. Its main application is the photovoltaic (PV) power generation that was predicted to be over 1000 TWh in 2021 [1]. PV systems convert solar energy into electrical energy. They can be installed easily, and they are noise-free. For an accurate study of various PV applications, modeling the basic device in a PV generator is essential. However, the manufacturers do not usually provide the model parameters and their values vary over time due to PV degradation [2] and the change in weather conditions. Thus, finding an optimal method for estimating appropriate parameters is critical.

The single diode model (ODM) is regarded as the most suitable model used to characterize the PV generator [3–7] compared to the two-diode model (DDM) and the three-diode model (TDM) as it has the least number of parameters and a good accuracy. The ODM has five electrical parameters that are: photocurrent ($I_{ph}$), reverse saturation current (Is), diode ideality factor (n), series resistance (Rs), and parallel resistance ($R_{sh}$).

Different techniques have been developed to identify ODM parameters, which can be classified in three categories [5,7]:

- Analytical methods [7],
- Numerical methods [3–6],
- Optimization methods based on artificial intelligence [8–11].

Although numerical methods are widely used in the literature due to their speed of calculation, simplicity, and accuracy, they cannot be used to solve PV model complex non-linear equations. This problem can be solved using optimization techniques based on artificial intelligence. Particle swarm optimization (PSO) is a popular metaheuristic optimization algorithm. However, the main defect of PSO that does not let it provide high-quality solutions in multimodal problems, such as PV panels parameters estimation, is its early convergence. This work presents an enhancement in the optimization method (PSO) for extracting the optimal parameters of a PV generating unit. The purpose of this work is to simulate the I-V and P-V characteristics based on the single diode model (ODM) using an opposition-based initialization particle swarm optimization algorithm that allows finding the optimal values of the needed parameters. The optimization algorithm is implemented in MATLAB for obtaining these model parameters and hence, I-V and P-V characteristics. The analysis is performed on various PV modules under different environmental conditions. The obtained results are compared and discussed to prove the efficiency and accuracy of the suggested optimization technique.

## 2. Photovoltaic Cell

A PV cell is an electronic device that permits the conversion of solar energy into electrical energy based on the photovoltaic effect, as shown in Figure 1. Solar cell produces electricity with poor voltage, which is approximately about 0.5 to 0.6 volts for the common single junction silicon PV cell. Thus, PV cells are coordinated in the form of modules or panels to produce electricity with high voltage and to provide adequate voltage and current for life applications.

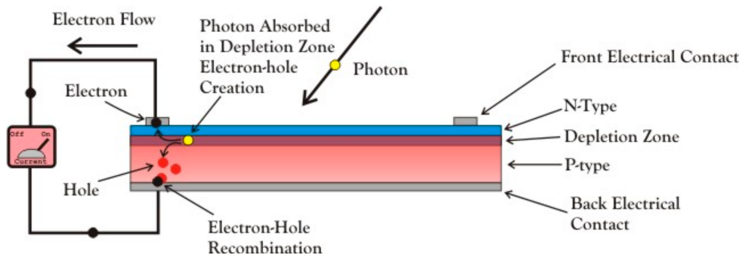


**Figure 1.** The photovoltaic effect in a PV cell.

### 2.1. Characteristics of the PV Cell

The electrical characteristics of a PV generator are mainly provided by the manufacturers under standard test conditions (STC) that are specified 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 panels operate at varying temperatures and at lower insulation levels. In order to define the power output of the solar generator, it is essential to find the expected operating temperature of the PV panel. The nominal operating cell temperature (NOCT) is set as the temperature reached by open circuited cells in a PV panel under the conditions: ambient temperature $T_{ambient} = 20\ ^\circ C$, solar irradiance $G = 800\ w/m^2$, and wind speed = 1 m/s. Hence, the PV cell temperature can be calculated as follows:

$$T_{cell} = T_{ambient} + \left(\frac{NOCT - 20}{800}\right) * G \quad (1)$$

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

The maximum current $I_{sc}$ in the photovoltaic cell is generated when a short circuit occurs between its terminals, while the maximum voltage $V_{oc}$ can be measured when there is an open 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). The voltage and current at those points are designated as $V_{mpp}$ and $I_{mpp}$.

Generally, manufacturers provide these parameters in the datasheet under STC. When the PV panel is connected to an external load, the actual point on the I-V curve at which the photovoltaic cell operates is determined based on the electrical characteristics of the load.

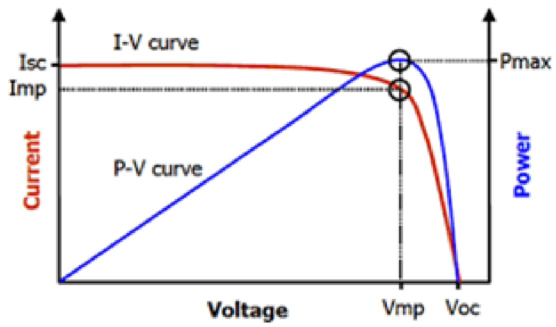


**Figure 2.** Typical I-V and P-V characteristics of PV cell.

### 2.2. One Diode Model of PV Cell

In order to analyze solar cells characteristics, this latter is modeled as electrical equivalent circuits using simulation software. Researchers have developed mathematical models to understand and study the effect of different weather conditions on photovoltaic electrical output. One of these models that is widely used is the lumped parameter model. This model is classified based on the number of diodes used and it has proven to be the most successful.

Although the model characteristics accuracy improves as the number of diodes increases, the model mathematical equation becomes more complex. In this work, the single diode model that is shown in Figure 3 is used for the identification of the PV generator parameters due to its simplicity compared to other lumped models and its good accuracy.

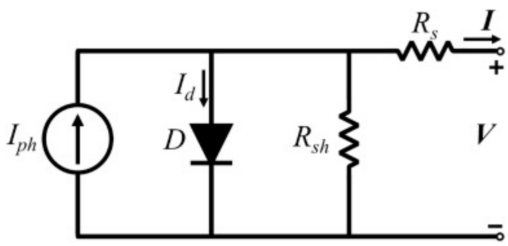


**Figure 3.** One diode model of PV cell.

The ODM governing equation is given as:

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

Such that, $V_t$ is the thermal voltage.

The model's five parameters are:

$I_{ph}$: Photocurrent (A); $I_s$: Diode saturation current (A); n: Diode ideality factor; $R_{sh}$: Parallel resistance (Ω); $R_s$: Series resistance (Ω).

The single diode model considers various properties of the solar cell such as: the shunt resistance that considers the leakage current to the ground when the diode is in reverse biased, and the series resistance that takes into account the voltage drops and internal losses due to the flow of current. However, this model is still not the most accurate model as it has neglected the recombination effect of the diode.

## 3. Identification of PV Cell Parameters Using Optimization algorithms

### *3.1. Optimization Algorithms*

It can be noticed that the I-V relationship of the one diode model, which is given in Equation (2) and hence the current voltage curve, is complex and highly nonlinear. Thus, it is difficult to solve it using analytical methods. Consequently, metaheuristic optimization methods based on artificial intelligence have been developed by scientists for solving these kinds of equations and determine the needed parameters. These techniques are developed to find a good solution among a large set of feasible solutions with less computational effort than other optimization techniques.

### *3.2. Opposition Based Initialization Particle Swarm Optimization Technique*

Particle Swarm Optimization is a population-based metaheuristic global optimization method inspired by the motion of schooling fish and bird flocks. The PSO algorithm examines the space of an objective function by adjusting the trajectories of individual agents, named particles. A population of these particles flies through the search space such that each particle i is attracted toward the position of the current global best $g^*$ and its own best location $x^i$ in history, simultaneously, it has a tendency to move randomly. Initially, the particles are placed randomly in the search space. The objective function is evaluated for all the particles. When a particle i finds a position that is better than any previously found locations, it updates it as the new current best location $x^i$ by updating the velocity, first depending on movement inertia, self-cognition, and social interaction using Equation (3), then updating its position through Equation (4) at each iteration. Thus, all n particles have a current best position at any time t during iterations. The purpose is to find the global best among all the current best solutions until the objective no longer improves or after a specified number of iterations. The motion of particles is schematically represented in Figure 4. Where $g^* = \{(x^i)\}$ for (i = 1, 2, … n) is the current global best and $x_i^*$ is the current best for particle i [8,12].

$$v_{n+1}^{i} = w\, v_n^i + c_1 r_1 \left[p_n^i - x_n^i\right] + c_2 r_2 \left[p_n^g - x_n^i\right] \tag{3}$$

$$x_{n+1}^{i} = x_n^i + v_{n+1}^{i} \tag{4}$$

Such that:
$x^i$ is the position of the ith particle in the search space;
$v^i$ is the velocity of the ith particle;
w is particle inertia;
$c_1$ is the cognitive acceleration constant;
$c_2$ is the social acceleration constant;
$p^i$ is the particle's best-known position;
$p^g$ is the global best position;
$r_1$, $r_2$ are random numbers that vary between 0 and 1.

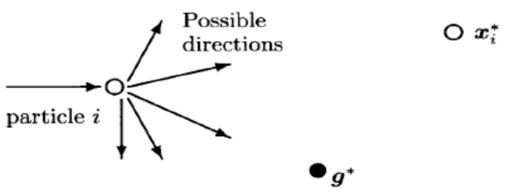


**Figure 4.** Schematic representation of the motion of a particle in PSO.

The starting points in PSO are randomly given. If these latter are close to the optimal point, convergence speed would be faster. Thus, to get better results, a better and careful initialization based on priori information is needed. The proposed method for an improved PSO algorithm is an opposition-based initialization of the swarm. This approach consists of initializing the PSO population and its opposite population, as shown in Figure 5. The fitness function is evaluated for both populations and only the fitter particles are selected to form a new population for the PSO.

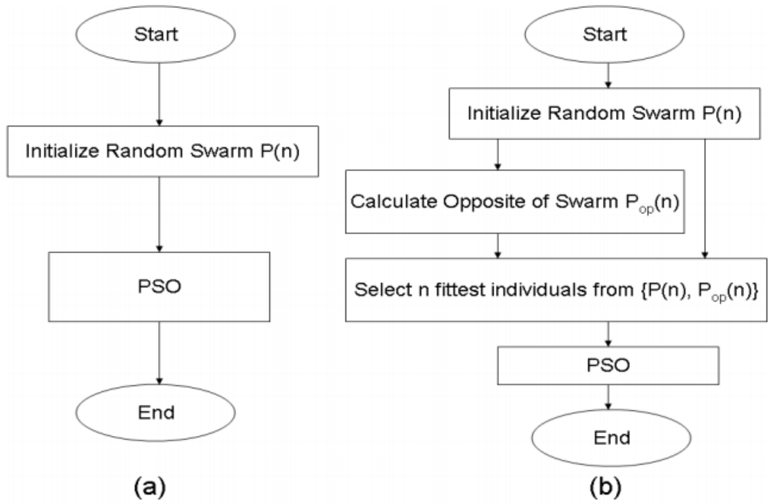


**Figure 5.** PSO with (**a**) Random population initialization and (**b**) Opposition based population initialization.

The concept used is described below.
Particle: a swarm particle $p^i$ is defined as:
$i \in [a, b]$ such that, $i = 1, 2, \ldots, D$ and $a, b \in R$;
D represents dimensions, and R represents real numbers.
Opposite particle: every particle $p^i$ has a unique opposite ${p^i}_{op}$ defined as:

$$ {p^i}_{op} = a + b - p^i \text{ such that, } i = 1,\ 2,\ \ldots\ D \text{ and } a,\ b\ \in\ R \tag{5} $$

*3.3. ODM Parameters Extraction Using an IOB-PSO*

The following objective function is used,

$$ \begin{cases} F(X) = I - I_{ph} + I_s\left[e^{\left(\frac{V+I*R_s}{n*N_s*V_t}\right)} - 1\right] + \frac{V+I*R_s}{R_{sh}} \\ X = \left\{I_{ph}, I_s, R_s, n, R_{sh}\right\} \end{cases} \tag{6} $$

The fitness function used to quantify the error between the simulated and measured data is the root mean square error (RMSE),

$$ \text{Fitness} = \sqrt{\frac{1}{N}\sum_{1}^{N} F(X)^2} \tag{7} $$

The pseudo code of the IBPSO method is given in Algorithm 1 and its corresponding flowchart is shown in Figure 6.

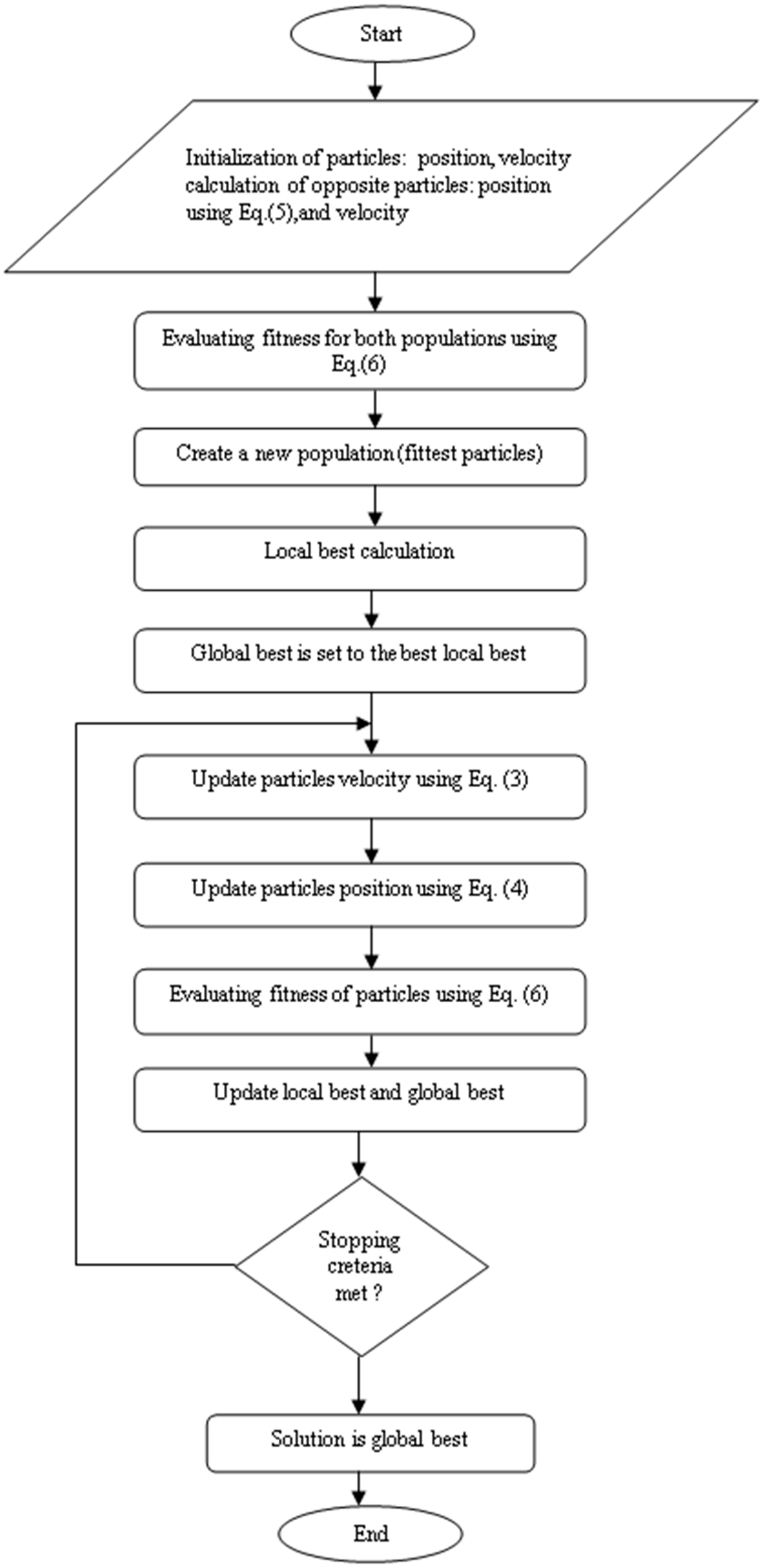


**Figure 6.** The flowchart of the IOBPSO algorithm.

**Algorithm 1** IOBPSO

```
Input: T, Ns, V_Data , I_Data
Output: global best
for each particle
        Initialize particle position
        Initialize particle velocity
        Calculate cost value of particles using Equation (6)
        Initialize opposite particle position using Equation(5)
        Initialize opposite particle velocity
        Calculate cost value of opposite particles using Equation (6)
    If opposite particle cost < particle cost
    Update particle
    end if
    Update particle best
    If particle best cost < global best cost
    Update global best
    end if
end for
for (t =1: Max number of iterations)
    for each particle
            Update velocity using Equation (3)
    Update position using Equation(4)
    Calculate cost value using Equation (6)
    If particle cost < particle best cost
        Update particle best
        If particle best cost < global best cost
            Update global best
        end if
    end if
    end for
end for
return global best
end procedure
```

## 4. Test Results and Discussion

The proposed algorithm IOB-PSO is used to identify the parameters of the single diode model. The algorithm is tested for two different PV modules. The obtained results are compared with other methods results to prove its effectiveness. It is developed in MATLAB R2016a and executed under Windows 10 64-bit OS, on a PC with Intel® Core™ i5-2450M CPU processor @ 2.50GHz, 4GB RAM.

Table 1 presents the search ranges used for the optimization of the model parameters. Table 2 presents the IOB-PSO parameters.

**Table 1.** ODM parameter search ranges.

| Parameters | Search Range |
|---|---|
| $I_{ph}$ | $[0.95 \times I_{sc}, 1.05 \times I_{sc}]$ |
| $I_s$ | [1 µA, 5 µA] |
| n | [1, 2] |
| $R_{sh}$ | $[\frac{V_{mpp}}{I_{sc} - I_{mpp}}, 1500\ \Omega]$ |
| $R_s$ | $[0, \frac{V_{mpp} - V_{oc}}{I_{mpp}}]$ |

**Table 2.** IOB-PSO parameters.

| Parameters | Value |
|---|---|
| Cognitive factor $c_1$ | 1.5 |
| Social factor $c_2$ | 2.0 |
| Inertia weight w | [0.2, 0.9] |
| Random values $r_1$, $r_2$ | [0, 1] |
| Number of particles | 30 |
| Maximum iteration | 1000 |

The IOB-PSO algorithm is used to estimate parameters for the various PV modules. The electrical specifications of the utilized modules are described in Table 3.

**Table 3.** Electrical specifications of the PV modules.

| Module | Type | $N_s$ | Temperature [°C] | Irradiance [w/m$^2$] |
|---|---|---|---|---|
| STM6-40/36 | Mono-crystalline | 36 | 51 | NA |
| Photowatt-PWP201 | Poly-crystalline | 36 | 45 | 1000 |

NA: not available.

The IOB-PSO is tested for the mono-crystalline STM6-40/36 module using I-V experimental data [13] measured at T = 51 °C; and for the Photowatt-PWP201 poly-crystalline module with I-V data measured under a temperature of T = 45 °C [13]. The obtained results are presented and compared with other previously published methods in Tables 4 and 5, respectively.

**Table 4.** STM6-40/36 extracted parameters achieved by various methods.

| Meth. | Parameters | | | | | Error |
|---|---|---|---|---|---|---|
| | $I_{ph}$[A] | $I_s$[μA] | n | $R_s$[Ω] | $R_{sh}$[Ω] | RMSE |
| ABC [14] | 1.50 | 1.664 | 1.487 | 4.99 | 15.21 | $1.838 \times 10^{-3}$ |
| CIABC [14] | 1.664 | 1.676 | 1.498 | 4.40 | 15.62 | $1.819 \times 10^{-3}$ |
| CSA [13] | 1.664 | 2.000 | 1.534 | 2.91 | 15.841 | $1.794 \times 10^{-3}$ |
| ImCSA [13] | 1.664 | 2.000 | 1.534 | 2.92 | 15.841 | $1.795 \times 10^{-3}$ |
| IOB-PSO * | 1.663 | 2.88 | 1.57 | 0.0015 | 598.74 | $1.772 \times 10^{-3}$ |

* Proposed method.

**Table 5.** Photowatt-PWP201 extracted parameters achieved by different methods.

| Meth. | Parameters | | | | | Error |
|---|---|---|---|---|---|---|
| | $I_{ph}$[A] | $I_s$[μA] | n | $R_s$[Ω] | $R_{sh}$[Ω] | RMSE |
| CPSO [13] | 1.0286 | 8.3010 | 1.451194 | 1.0755 | 1850.1 | $3.5 \times 10^{-3}$ |
| PS [13] | 1.0313 | 3.1756 | 1.341358 | 1.2053 | 714.2857 | $1.18 \times 10^{-2}$ |
| SA [13] | 1.0331 | 3.6642 | 1.356142 | 1.1989 | 833.3333 | $2.7 \times 10^{-3}$ |
| CARO [15] | 1.03185 | 3.28401 | 1.35453 | 1.20556 | 841.3213 | $2.427 \times 10^{-3}$ |
| IOB-PSO * | 1.030 | 3.495668 | 1.35 | 1.200877 | 986.306335 | $2.4251 \times 10^{-3}$ |

* Proposed method.

Using the identified parameters, the PV characteristics of the two modules were constructed and then compared with the experimental curves in Figures 7 and 8.

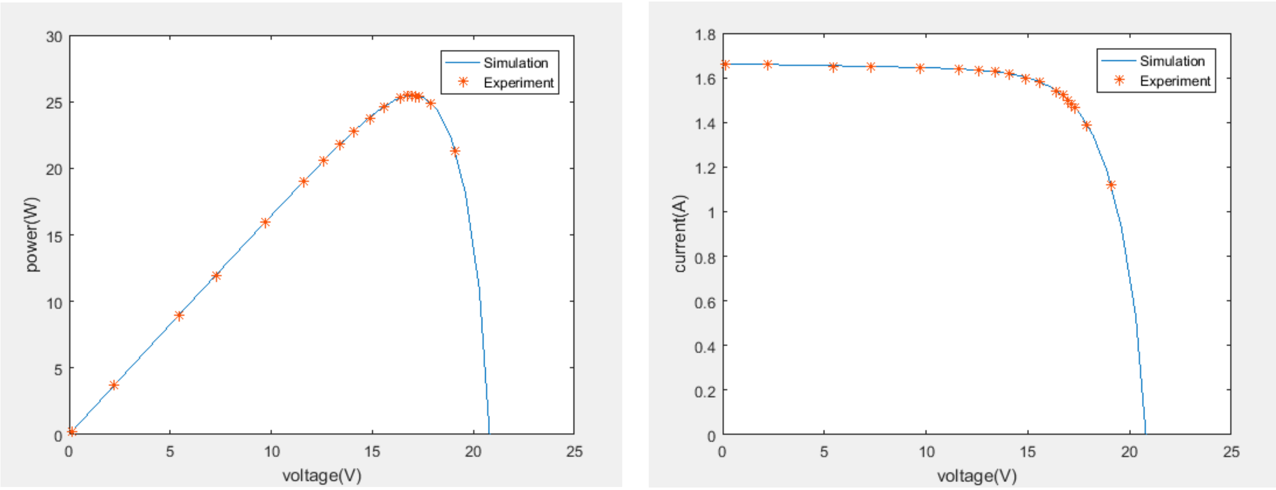


**Figure 7.** I-V and P-V experimental data and simulated data for the STM6−40/36 module.

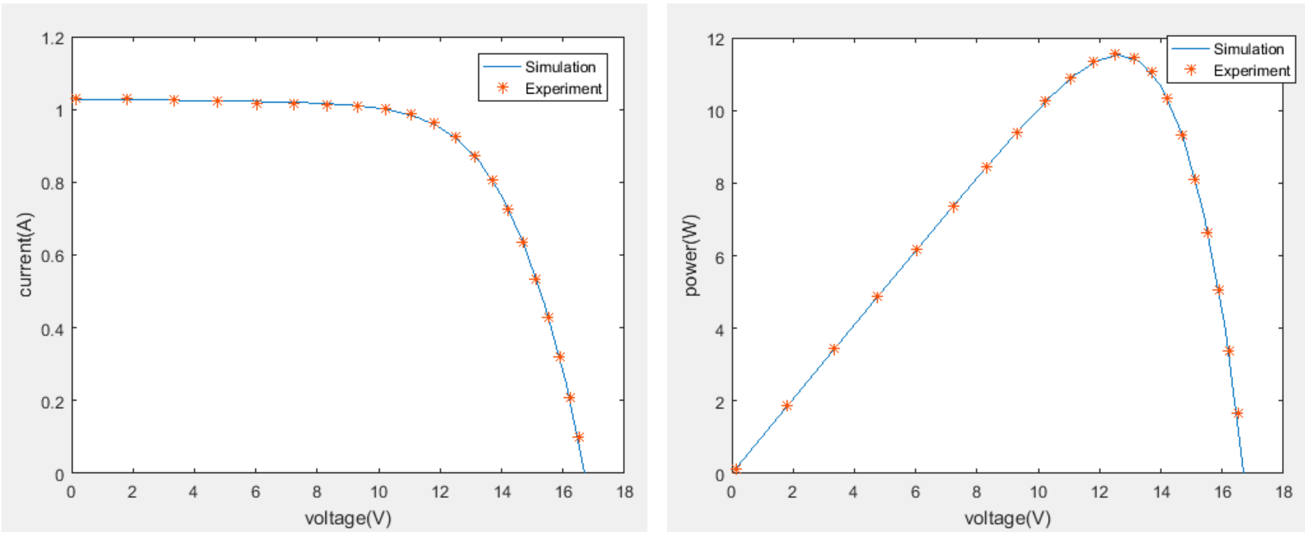


**Figure 8.** I-V and P-V experimental data and simulated data for the Photowatt-PWP201 module.

It can be noted that the RMSE error of the proposed IOB-PSO is the smallest and hence, the obtained results using the proposed algorithm are the best. Therefore, the efficiency of this method for identifying the model parameters is proven. Figures 7 and 8 show the comparison between I-V and P-V experimental and simulated data of the STM6-40/36 and the Photowatt-PWP201 modules. The simulated curves highly match the measured ones, which proves the reliability of the IOB-PSO algorithm.

Figure 9 presents the convergence curve of the IOB-PSO method for these modules; it can be noticed that the convergence is very fast. The algorithm reached the optimal solution within 207 iterations in an execution time of 19.0017 s for the monocrystalline module STM6-40/36, while for the Photowatt-PWP201 module, it needed 613 iterations (27.585 s). This proves that the proposed IOB-PSO method has a very fast convergence speed.

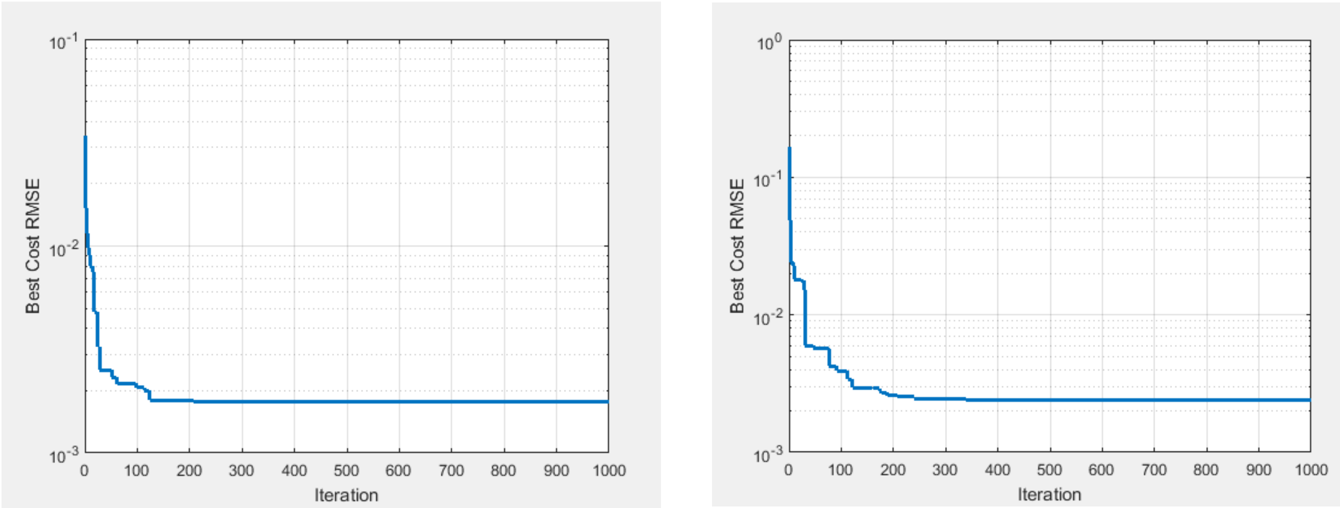


**Figure 9.** Convergence curve of the IOB-PSO for the (**a**) STM6−40/36 module (**b**) Photowatt-PWP201 module.

## 5. Conclusions

In this work, an efficient method for obtaining the I-V and P-V characteristics of a PV module based on the one diode model has been proposed, due to the non-availability of all needed parameters in the datasheet. The optimization algorithm was chosen for the identification of the ODM model parameters. The proposed method is an improved opposition-based particle swarm optimization; this algorithm was tested using the experimental I-V data that were acquired at different working conditions for various PV modules. The obtained results were compared with other methods outcomes provided in the references; this algorithm has showed a satisfying estimation of the five parameters extracted with minimum errors. Furthermore, the PV characteristics were plotted using the extracted parameters and compared with the experimental data. The simulated curves are found to be well-suited with the corresponding measured data, thus, the performance of the IOB-PSO algorithm proved to be good. Adding to the fact that this proposed algorithm has provided optimal results with an acceptable accuracy, the time taken for the IOB-PSO execution is less than 30 s.

This approach is found to be useful for designers since it is simple, fast, and provided accurate results.

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**Conflicts of Interest:** The authors declare no conflict of interest.

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