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Orthogonal Learning-Based Gray Wolf Optimizer for Identifying the Uncertain Parameters of Various Photovoltaic Models

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Abstract - Determining the optimal parameters for the photovoltaic system (PV) model is essential during the design, evolution, development, estimation, and PV systems analysis. Therefore, it is crucial for the proper advancement of the best parameters of the PV models based on modern computational techniques. Thus, this work suggests a new Orthogonal-Learning-Based Gray Wolf Optimizer (OLBGWO) through a local exploration for estimating the unknown variables of PV cell models. The exploitation and exploration capability of the basic Gray Wolf Optimizer (GWO) is improved by the orthogonal-learning-based (OLB) approach, and this arrangement promotes a highly reliable equilibrium between the exploitation and exploration levels of the algorithm. In OLBGWO, the OLB strategy is used to find the best solution for the poor populations and directs the population to review the potential search area during the iterative process. Also, an exponential decay function is employed to decrease the value of vector a in GWO. The developed algorithm is directly applied to the parameter identification problem of the PV system. The proposed OLBGWO algorithm estimates the unknown parameters of the single-diode model (SDM), double-diode model (DDM), and PV module model. The performance of the OLBGWO is compared with other competitive algorithms to prove its superiority. The simulation results prove that the OLBGWO algorithm can achieve high solution accuracy with high convergence speed.

Key Words – Convergence; Gray Wolf Optimizer (GWO); Photovoltaic parameters; Optimization; Orthogonal learning

1. Introduction

Renewable energy can become a growing technology because of fossil fuel usage that can contribute to catastrophe and atmospheric pollution and change energy usage configurations

from fossil fuel to green energy [1,2]. Society has demanded renewable energy to be used in water, wind, solar, and several other fields, where solar energy has tremendous potential due to its abundance of supplies and environment responsive. Because of the effective use of solar power in producing electric power, solar photovoltaic (PV) systems are much in demand, and developments are continuing to grow [3,4]. However, there are some detrimental aspects to the performance of the PV systems, such as direct exposure of the panel to the outside and inadequate productivity of PV panels [5,6]. Therefore, it is important to identify the practical efficiency of PV modules to plan effectively, optimize, estimate, control, and simulate PV systems. The actual model is used as per the current and voltage samples collected to accomplish this purpose [7]. The PV model can be constructed using the mathematical model, and the internal parameters can be defined [8,9]. The researchers have reported numerous PV models, such as the Single-Diode Model (SDM), Double-Diode Model (DDM), and Three-Diode Model (TDM), and out of which the SDM and DDM are preferred models for PV systems. Besides, the performance of PV models is based on uncertain internal parameters [10]. It is challenging to evaluate all the unknown parameters and keep them stable due to aging, deterioration, and unstable working states. It is critical to estimate, emulate, design, and optimize the PV systems without defining the above-said parameters. Therefore, attention is drawn to the performance of swarm-based optimization algorithms in estimating variables in PV systems [11,12].

To construct a computation model for photovoltaic systems, an appropriate objective function needs to be used. Fitness is the multimodal function due to noise in the collected current and voltage samples, and it is not easy to deal with that to find viable solutions [13,14]. The researchers spent countless days dealing with this issue and creating several different techniques. Previously, deterministic approaches were used by several researchers to mitigate such challenges. For example, the exact method, 5-point analytical method, Newton method [15], and curve-fitting method [16], are used to address the same problem. Several gradient computations are required for deterministic methods and perform well when performing a local search. The authors of [17] reported an analytical technique to identify the parameters of the PV cell. However, the authors have not discussed the various PV models. In comparison, it is quickly struck at the local optimum. This inactivity problem would prevent the algorithm from optimizing solutions' quality on further reiterations [18,19]. Such approaches, with the initial stage, are rigid. Thus, the choice of initial points has a significant influence on the speed of

convergence and the reliability of the solution of such methods. The researchers ought to have an objective function with convex and distinguishable features to use these methods; these restrictions can restrict the application of these techniques. Evolutionary approaches have discovered their effectiveness and outcomes relative to conventional methods without such strict limitations [20,21]. In recent years, specific optimizers and their enhancement variants have also been reported to define the PV system variables.

To identify the model parameters under various operating conditions, a penalty-based differential evolution was reported in [22]. An enhanced adaptive differential evolutionary (DE) algorithm with a rigid design focused on objective value was discussed to identify variables of solar panels [23]. To identify the model parameters, a chaotic particle-swarm-optimization (PSO) technique was suggested. The chaotic search [24] improves the global search and convergence ability. To define PV cell parameters, simulated annealing (SA) was used, and then the SDM, DDM, and PV module models have been utilized to check the efficiency of SA [25]. The authors of [26] merged SA with Levenberg-Marquardt to address problems with extracting parameters. To refine the variables of the three models described, the researchers of [27] used a Moth Flame Optimizer (MFO). To mimic the PV cell characteristics, the authors of [28] used a bacterial foraging algorithm. The authors of [29] implemented the artificial bee colony to extract the parameters of the PV cells. The artificial bee swarm optimization [30] and harmony search algorithm [31] have been introduced for parameter extraction of SDM and DDM. The authors of [32] constructed five different mutant bacterial foraging algorithms for SDM and DDM parameter estimation. For parameter identification of various models, the authors of [33] integrated the generalized opposition-learning and Nelder-Mead simplex method into the flower pollination algorithm. To estimate the variables of SDM and DDM, the authors of [34] developed mixed cooperative swarm optimization algorithms. The Salp Swarm Algorithm (SSA) was used by the authors of [35] to optimize the DDM parameters. For static and dynamic parameter identification of the PV models, the authors of [36] suggested a chaotic widespread learning PSO. The authors of [37] suggested a chaotic Jaya algorithm for finding the unknown variables of the SDM, DDM, and PV module model, including the commercial PV modules. The authors of [38] suggested hybrid Gray Wolf Optimizer (GWO) to extract the PV cell parameters; however, the basic version of GWO is positively stuck at local optima when it solves multimodal optimization problems. The authors of [39,40] proposed metaphorless and stochastic algorithms, such as the Rao algorithm

[39] and Slime Mould Algorithm (SMA) [40] for extracting the uncertain parameters of various PV models. However, commercial PV modules are not analyzed. The authors of [41] reported political optimizer algorithms for estimating the PV cell parameters of SDM. However, the authors fail to describe the DDM and other commercial PV module model. To get the optimal parameters of a TDM, the authors of [42] used the sunflower optimization algorithm.

Although the metaheuristics and their alternatives are better than the deterministic approaches on the solution quality and the convergence rate, they have inherent drawbacks: the first is that the efficiency requires to be further enhanced on both the quality of the solution and the speed of convergence; the latter is that they have been developed to solve the particular problems of optimization, the inadequate portability limits the other practical problems. To get the best variables of PV models, the authors of [43] reported a reinforced moth search technique to define the best triple-junction PV module parameters in which the disruptor operator would increase the basic moth-search algorithm diversity. The authors of [44] implemented the opposition-based-learning (OBL) and Nelder-Mead simplex techniques into the sine-cosine algorithm (SCA). The authors of [45] suggested the MFO with orthogonal Nelder-Mead concept for solar PV parameter identification optimization problem. The researchers of [46] merged the interior search algorithm with PSO to handle the parameter estimation of PV cell/module. Therefore, the authors of [38] suggest hybrid version GWO, i.e., by combining the features of PSO and GWO to identify the parameters of the PV cell. However, the convergence speed of the hybrid algorithm is relatively very high. The authors of [47] suggested Harris Hawks Optimizer (HHO) integrated by means of combining the OBL and chaotic local search for model parameter identification. The researchers of [23] reported an electromagnetism algorithm to obtain the unknown variables of the SDM of the PV panel.

The GWO algorithm for addressing parameter optimization frameworks and practical engineering issues was created by Mirjalili [48]. The GWO algorithm has been extended to several fields because it was developed and implemented to address different engineering practices. The GWO algorithm has been updated to be in line with the search space of diverse problems because of the difficulty of real-world optimization problems. The following are the possibilities to improve the GWO algorithm: Firstly, the update mechanism of the GWO is modified. Changes are made in the update stage because the GWO has some limitations to real-

world engineering problems. The changes are possible by introducing an update mechanism, new operators, encoding schemes, and structural change of the population and hierarchy [49]. Latter, improvements have been made to enhance GWO by introducing chaotic concepts or levy flight concepts. To empower the discovery GWO algorithm, further enhanced versions apply the principle of hybridization. The hybrid versions are possible by integrating PSO, DE, etc., with the GWO algorithm. Another possible modification is introducing the crowding distance and non-dominated sorting approaches to convert the GWO into multiobjective GWO to handle large-scale optimization problems [50]. As per the No-Free-Lunch theorem, one algorithm might not be suitable for all types of engineering problems [51]. Therefore, this paper proposes a new update mechanism called orthogonal-learning-based strategy to improve the solution accuracy and convergence speed by considering the above-all facts. GWO's first version deals with the deterioration of exploratory tendencies and the intensity of convergence. In this paper, an improved GWO to find variables of various PV models is incorporated with the OLB strategy. The key contributions of this study are given as follows:

- A new algorithm called the OLBGWO algorithm is proposed by integrating the concept of orthogonal-learning with the GWO algorithm.
- A better candidate solution for GWO is created using OLB, which directs the weaker populations to acceptable search areas to increase the exploitation and exploration abilities. Besides, OLB assists the weaker populations in leaping out of the local optimum and speeding up the exploitation and exploration abilities of the GWO.
- The OLB mechanism leads to the necessary balance between exploitation and exploration.
- In addition to OLB, the exploration phase of the GWO is also improved by employing the exponential decay function to decrease the value of vector a in GWO.
- The OLBGWO algorithm performance is demonstrated by the experimental results and comparisons with other competitive algorithms.

This research is arranged as follows: The description of the problem is provided in Section 2. The basic version of GWO and the proposed OLBGWO algorithm is discussed in detail in Section 3. To verify the performance of the OLBGWO algorithm, the experiment outcomes are

analyzed, and a discussion of the previous findings are given in Section 4. Finally, in Section 6, the findings and future directions are stated.

2. Problem Formulation

This section of the paper discusses the mathematical modeling of the solar cell and PV module based on SDM and DDM [34,39,52]. Later, the objective function formulation is also discussed to address the parameter identification problem of various models.

2.1. Solar Photovoltaic Cell Model

The SDM is typically adopted to study the behavior of the cell, i.e., characteristics of the PV cell. The electrical circuit structure of the single-diode model is illustrated in Fig. 1. The overall current of the photovoltaic cell is presented in Eq. 1.

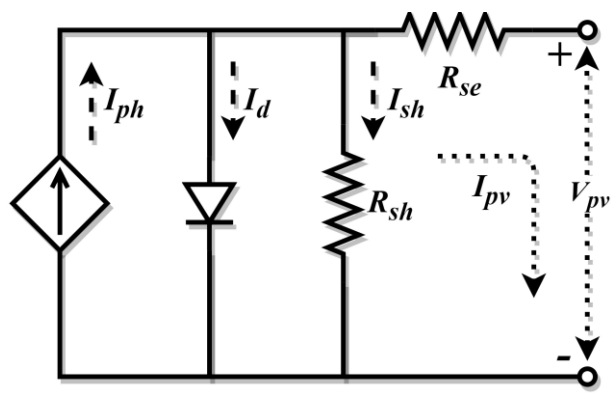


Figure 1. SDM of the solar cell

$$I_{pv} = I_{ph} - I_d - I_{sh} \tag{1}$$

where I_{pv} denotes the total current, I_{ph} represents the photocurrent, I_{sh} represents the current through the shunt resistor, and I_d denotes the diode current. Eq. 1 can be rewritten as per Shockley equation as follows.

$$I_{pv} = I_{ph} - I_{sd}\left(\frac{q\left(V_{pv} + I_{se}R_{se}\right)}{nkT} - 1\right) - \frac{V_{pv} + I_{se}R_{se}}{R_{sh}} \tag{2}$$

where I_{sd} represents the diode's reverse saturation current, V_{pv} denotes the total voltage, R_{se} and R_{sh} denote the ohmic resistances, n represents the diode ideality factor, k denotes Boltzmann

constant (1.380653×10^{23} J/K), T denotes the temperature in K, and q denotes the electron charge (1.60217646×10^{-19} C). It can be realized evidently from Eq. 2 that there are five uncertain variables, such as I_{ph}, I_{sd}, R_{se}, R_{sh}, and n for the SDM of the solar cell.

As per the discussion from [39], the SDM of the PV cell does not study the loss due to recombination current effects in the depletion region. Therefore, the precision of the SDM is enhanced by connecting another diode parallel with the existing first diode. The model is called DDM, and it considers the loss due to the recombination. The electrical circuit of such a model is illustrated in Fig. 2. The overall current of the PV cell is presented in Eq. 3.

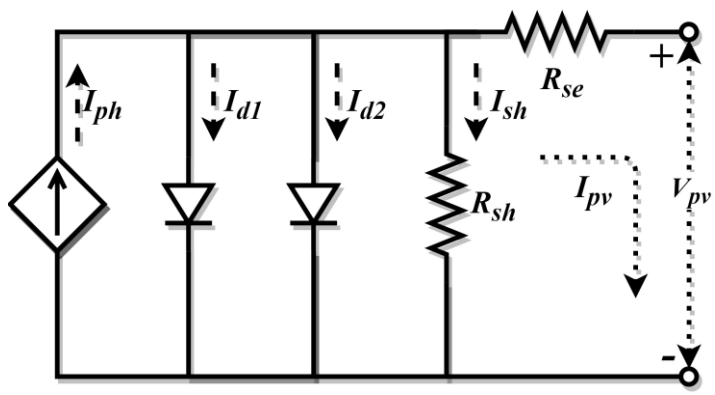


Figure 2. DDM of the solar cell

$$I_{pv} = I_{ph} - I_{sd1}\left(\frac{q\left(V_{pv} + I_{se}R_{se}\right)}{n_1 kT} - 1\right) - I_{sd2}\left(\frac{q\left(V_{pv} + I_{se}R_{se}\right)}{n_2 kT} - 1\right) - \frac{V_{pv} + I_{se}R_{se}}{R_{sh}} \tag{3}$$

where I_{sd1} and I_{sd2} denote the diode saturation current of diode-1 and diode-2, respectively, n_1 and n_2 denote the recombination and diffusion diode ideality factors, respectively. It can be noted evidently from Eq. 3 that there are seven uncertain variables, such as I_{ph}, I_{sd1}, I_{sd2}, R_{se}, R_{sh}, n_1, and n_2 for the DDM of the PV cell.

2.2. Solar Photovoltaic Module Model

The solar photovoltaic module has been made by connecting N_{sh} parallel-connected cells and N_{se} number of series-connected cells. The electrical circuit of the photovoltaic panel is illustrated in Fig. 3. The total current of the solar module is presented in Eq. 4.

$$I_{pv}/N_{sh} = I_{ph} - I_{sd}\left(\frac{q\left(V_{pv}/N_{se} + I_{se}R_{se}/N_{sh}\right)}{nkT} - 1\right) - \frac{V_{pv}/N_{se} + I_{se}R_{se}/N_{sh}}{R_{sh}} \tag{4}$$

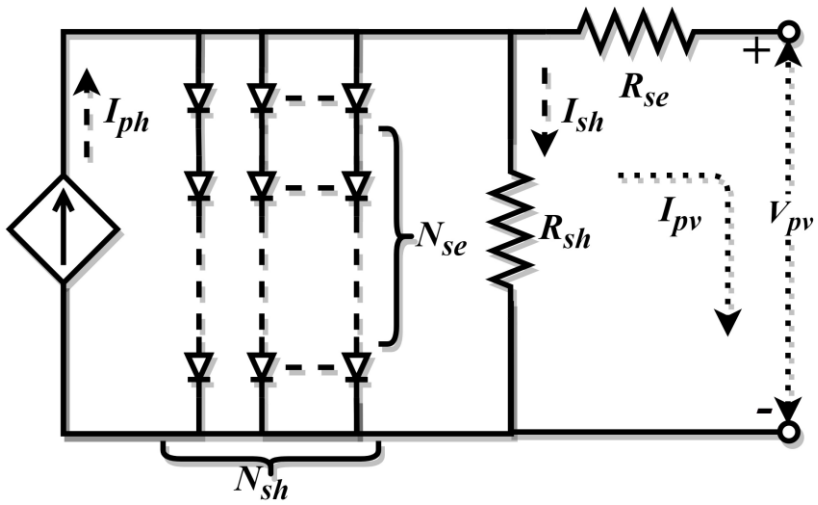


Figure 3. Electrical circuit of photovoltaic model

2.3. Objective Function Formulation

The photovoltaic model parameter estimation problem is typically converted into a computational optimization process by optimizing the difference between the estimated value and experimental value. A root-mean-square-error (RMSE) is normally viewed as the error function and is represented in Eq. 5.

$$\mathrm{RMSE}(X) = \sqrt{\frac{1}{M}\sum_{i=1}^{M} f\left(V_{pv}, I_{pv}, X\right)^2} \tag{5}$$

where X denotes the design variables, i.e., five variables for SDM and seven variables for DDM, and M denotes the number of experimental samples.

For SDM of the solar cell, the expression for $f\left(V_{pv}, I_{pv}, X\right)$ is written as follows:

$$\left.\begin{aligned} f\left(V_{pv}, I_{pv}, X\right) = I_{ph} - I_{pv} - I_{sd}\left(\frac{q\left(V_{pv} + I_{se}R_{se}\right)}{nkT} - 1\right) - \frac{V_{pv} + I_{se}R_{se}}{R_{sh}} \\ X = \left\{I_{ph}, I_{sd}, R_{se}, R_{sh}, n\right\} \end{aligned}\right\} \tag{6}$$

For DDM of the solar cell, the expression for $f(V_{pv}, I_{pv}, X)$ is written as follows:

$$\left.\begin{array}{c} f(V_{pv}, I_{pv}, X) = I_{ph} - I_{pv} - I_{sd1}\left(\frac{q(V_{pv} + I_{se}R_{se})}{n_1 kT} - 1\right) - I_{sd2}\left(\frac{q(V_{pv} + I_{se}R_{se})}{n_2 kT} - 1\right) - \frac{V_{pv} + I_{se}R_{se}}{R_{sh}} \\ X = \{I_{ph}, I_{sd1}, I_{sd2}, R_{se}, R_{sh}, n_1, n_2\} \end{array}\right\} \quad (7)$$

For the PV module model, the expression for $f(V_{pv}, I_{pv}, X)$ is written as follows:

$$\left.\begin{array}{c} f(V_{pv}, I_{pv}, X) = I_{ph} - I_{pv}/N_{sh} - I_{sd}\left(\frac{q(V_{pv}/N_{se} + I_{se}R_{se}/N_{sh})}{nkT} - 1\right) - \frac{V_{pv}/N_{se} + I_{se}R_{se}/N_{sh}}{R_{sh}} \\ X = \{I_{ph}, I_{sd}, R_{se}, R_{sh}, n\} \end{array}\right\} \quad (8)$$

3. Proposed Orthogonal-Learning-Based Gray Wolf Optimizer (OLBGWO) Algorithm

This section of the paper presents the original version of Gray Wolf Optimizer (GWO) and introduces the orthogonal-learning concept. Then, the integration of OLB and the GWO for solving the parameter estimation problem of various photovoltaic models is discussed.

3.1. Gray Wolf Optimizer (GWO) Algorithm

The Gray Wolf Optimizer (GWO) is a recently designed metaheuristic swarm-based algorithm simulating the wolves' swarm's hunting actions [48]. The best individual is named α wolves in the optimizer, the second-and third-best agents are identified respectively as β and δ, as well as the further agents, are named ω wolf. The wolf swarm's activity surrounding the prey is modeled as per Eq. 9.

$$X(l+1) = X_p(l) - A \cdot \left|C \cdot X_p(l) - X(l)\right| \quad (9)$$

where l symbolizes the current iteration, X symbolizes the vector position of the wolf, X_p symbolizes the position vector of the prey, A and C are vector coefficients and are written as follows.

$$A = 2 \cdot a \times r_1 - a \quad (10)$$

$$C = 2 \cdot a \times r_2 \quad (11)$$

$$a = 2 - \frac{2 \times l}{Max\_l} \tag{12}$$

where r_1 and r_2 are the random values between [0, 1] and Max_l denotes the maximum number of iterations. The other individual's positions are updated by the best three wolves, such as α, β, and δ, and it is mathematically modeled as follows.

$$X_a = X_\alpha - A_a \cdot |C_a \cdot X_\alpha - X| \tag{13}$$

$$X_b = X_\beta - A_b \cdot |C_b \cdot X_\beta - X| \tag{14}$$

$$X_c = X_\delta - A_c \cdot |C_c \cdot X_\delta - X| \tag{15}$$

$$X(l+1) = \frac{X_a(l) + X_b(l) + X_c(l)}{3} \tag{16}$$

where A_a, A_b, and A_c are similar to A for best three wolves, C_a, C_b, and C_c are similar to C for best three wolves, and $X(l+1)$ is the final updated position of the individual.

3.2. Modified Vector Parameter

Among all minimization approaches, reaching the global best is a popular and stimulating task [53]. Typically, the optimal route to converge near the least can be separated into two segments. In the initial stages, the populations are spread across the entire search area. In the later stages, the populations take advantage of the value attained to converge on the global best. In GWO, these two phases are balanced by adjusting the parameters a and A. The balance between exploitation and exploration is achieved by the parameters a and A. Therefore, half of the iteration is allocated to the exploration phase, and the remaining half of the iterations is allocated to the exploitation phase. The local minima problem can be minimized by having large exploration ability. Therefore, in this paper, instead of a linear decrease of the parameter a, the exponential decay function is utilized to decrease the vector value a. In basic grey wolf optimizer, the value of a linearly decreases from 2 to 0 as given in Eq. 12. In this paper, the value of a is decreased, as presented in Eq. 17.

$$a = 2\left(1 - \frac{l^2}{Max\_l^2}\right) \tag{17}$$

Based on Eq. 17, the number of iterations utilized for exploitation and exploration is 30% and 70%, respectively.

3.3. Orthogonal-Learning-Based (OLB) Approach

The agent α has a critical part in directing the other followers, and it plays a dynamic part in pushing the entire population in the direction of the global optimum. This paper adopts an OLB approach and builds leadership vectors to lead the agent in the direction of the best. In the OLB mechanism, the position of the individual is updated using an orthogonal-experimental design [54,55]. This paper considers two individuals in the group for the OLB strategy, such as the current evaluation of individual X_i and a random individual who is diverse from the current individual. Firstly, the vector solution is separated into j groups; every group is equivalent to a factor, to put on the orthogonal-experimental design strengths to GWO. Secondly, Q levels are created in the position of each dimension to take information in each dimension. Lastly, to produce M solutions, the orthogonal array is used. The procedure is as follows.

Vector Group **-** Each dimension correlates straight to a factor whenever the vector solution has a limited number of dimensions. When the solution vector's dimensionality is large, reducing the factors needs grouping. A random grouping approach is adopted in this study to better leverage the unique benefits of the population.

Construction Level – For every dimension, k=1, 2, …, dim, $X_{j,k,}$ and $X_{i,k}$ are utilized to build the Q levels. It is mathematically modeled as shown in Eq. 18.

$$\text{Level}_y = X_{i,k} + \frac{y-1}{Q-1}\left(X_{j,k} - X_{i,k}\right), k = 1,2,\dots,Q \tag{18}$$

Generate New Solution – By using the traditionally generated orthogonal array $L_M(Q^d)$ and dimensional level construction, new candidate solutions are generated ($Z = (z_1, z_2, \dots, z_M)$).

Generate the Best Prediction Solution – By analyzing the fitness, the optimal-level combination experiments are calculated, and it is considered the best prediction solution. Eq. 19 has been used to find the mean fitness for each factor.

$$\Delta_{i,j} = \left[\frac{Q}{M}\sum f_i\right] \tag{19}$$

where f denotes the orthogonal experiment fitness, and compare the fitness at diverse levels and dimensions. Lastly, the low average fitness is selected and is combined to get the best predictive solution. It is possible to generate M+1 candidate solutions as per earlier discussions. The smallest fitness is considered as the optimal solution. To avoid the misuse of the OLB approach from interrupting the existing population search space and intervening with the complete search procedure, a trigger constraint is applied to the OLB strategy. For the whole population, a precise experimental approach is to attach a trial matrix. Each cell corresponds to an individual who is utilized to track the stagnation of fitness. The OLBGWO algorithm calculates the objective function when the gray wolf optimizer executes the search agent update procedure and relates the present fitness to one of the earlier iterations. The value of the trial matrix referring to the population is added by 1 if the new fitness is not good. The lack of progress of the jth individual of the ith agent is presented in Eq. 20.

$$\mathrm{Trial}_j^i = \begin{cases} \mathrm{Trial}_j^i + 1, & if\ fit\left(X_{j,l}^i\right) \geq fit\left(X_{j,l-1}^i\right) \\ \mathrm{Trial}_j^i, & if\ fit\left(X_{j,l}^i\right) < fit\left(X_{j,l-1}^i\right) \end{cases} \tag{20}$$

Until executing an OLB procedure on every individual solution, the suggested methodology relates the stagnation limit with the number of stagnations. If the number of stagnations is higher than or equal to the maximum bound, then the operator must execute an OLB update operation, and the maximum bound is assigned to 0. It allows finding the optimal global solution as easy as possible, eliminates undue interference with the search phase, and reduces the difficulty of estimating the algorithm. The Pseudocode of the OLBGWO is given in the *Algorithm*. In addition, the flowchart of the suggested OLBGWO algorithm is illustrated in Fig. 4.

Algorithm: Pseudocode of OLBGWO algorithm

```
Initialize the maximum number of iterations Max_l, population size N, and
initialize the random population Xi, a, A, and C
For i=1:N
      Find the initial fitness value
End For
Find Xα, Xβ, and Xδ
While l ≤ Max_l
            For i=1:N
                Update the agent position using Eq. 13-15
                Update the population using OLB
                Select the best individual in OLB_Position as individual in Xi
            End For
            The vectors A, C, and a are updated using Eq. 10-11, and Eq. 17
            Compute the objective value of all population
            Update Xα, Xβ, and Xδ using Eq. 13-15
      l= l+1
End While
Return Xα
```

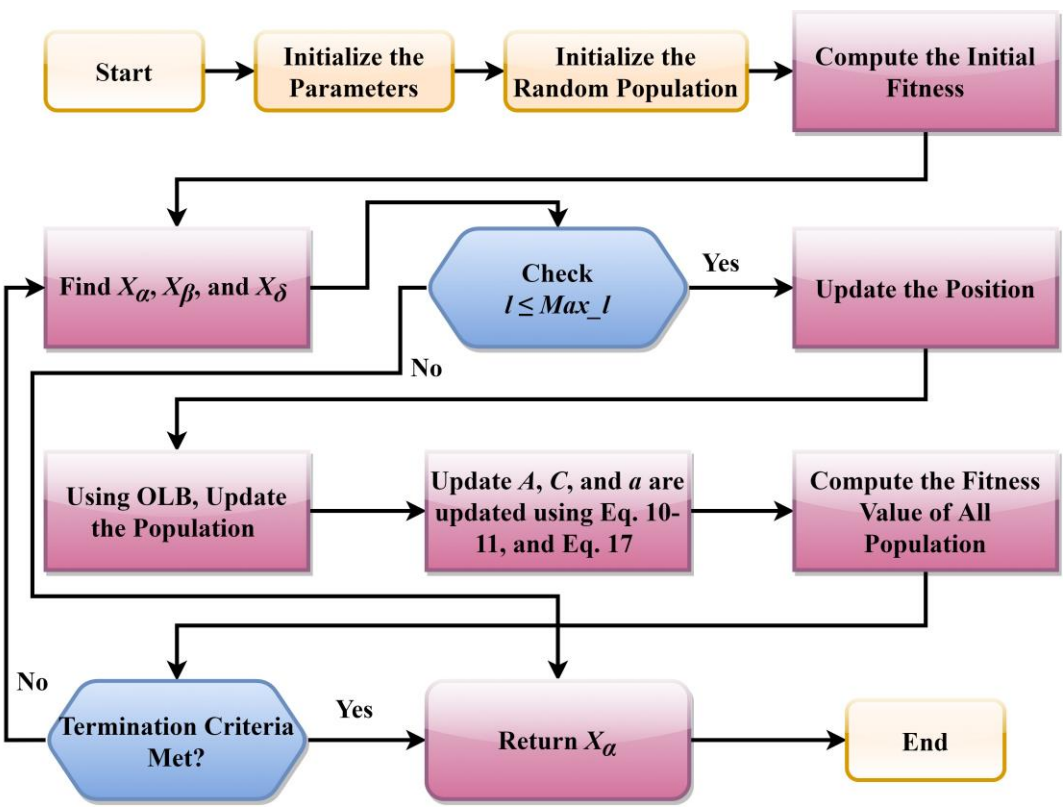


Figure 4. Flowchart of the proposed OLBGWO algorithm

4. Simulation Results and Discussions

In this section, the simulation results are presented to prove the efficiency of the suggested OLBGWO algorithm. For the same, the simulation is done by means of MATLAB R2015a software installed on a PC with a 3.2 GHz clock frequency and 8 GB RAM. The proposed OLBGWO algorithm is directly applied to the parameter identification of various photovoltaic models. The photovoltaic models, such as SDM and DDM of the RTC France Si solar cell (Case-1), SDM of the Photowatt-PWP201 PV module (Case-2), SDM of the ST40 PV module (Case-3), and SDM of the KC200GT PV module (Case-4) under various operating conditions are considered for verifying the performance of the OLBGWO. The efficiency of the OLBGWO is compared with the other state-of-the-art algorithms, such as PSO, GWO, HHO, SSA, MFO, SMA, and SCA, and the experimental results proved that the OLBGWO gives competitive results and performing better than other stated algorithms. The control parameters of all selected algorithms are listed in Table 1. To have a fair comparison and analysis, each algorithm is run 30 times. The performance comparison of the OLBGWO with other algorithms, in terms of Min, Max, Mean, RMSE, and Wilcoxon signed-rank test (WRT), is discussed in detail. In addition, the upper and lower limits of all design variables for various models are itemized in Table 2.

Table 1. Parameter settings of all selected algorithms

Algorithm	Parameters	Values
GWO	N Max_l	30 1000
HHO	N Max_l	30 1000
SSA	N Max_l	30 1000
SCA	N Max_l a	30 1000 2
SMA	N Max_l z	30 1000 0.03
MFO	N Max_l b	30 1000 1
PSO	N Max_l w c_1 and c_2	30 1000 0.5 2
OLBGWO	N Max_l a Orthogonal experiment design levels Orthogonal experiment design factors	30 1000 As per Eq. 17 3 4

Table 2. Upper and lower limits of all design variables

Parameters	RTC France Si Cell		Photowatt-PWM201	
	Upper	Lower	Upper	Lower
I_{ph} (A)	1	0	8	0
R_{sh} (Ω)	100	0	1500	0
R_{se} (Ω)	0.5	0	0.4	0
I_{sd} (μA)	1	0	50	0
I_{sd1}, I_{sd2} (μA)	1	0	-	-
n	2	1	50	1
n_1, n_2	2	1	-	-

4.1. Case-1: RTC France Si Solar Cell

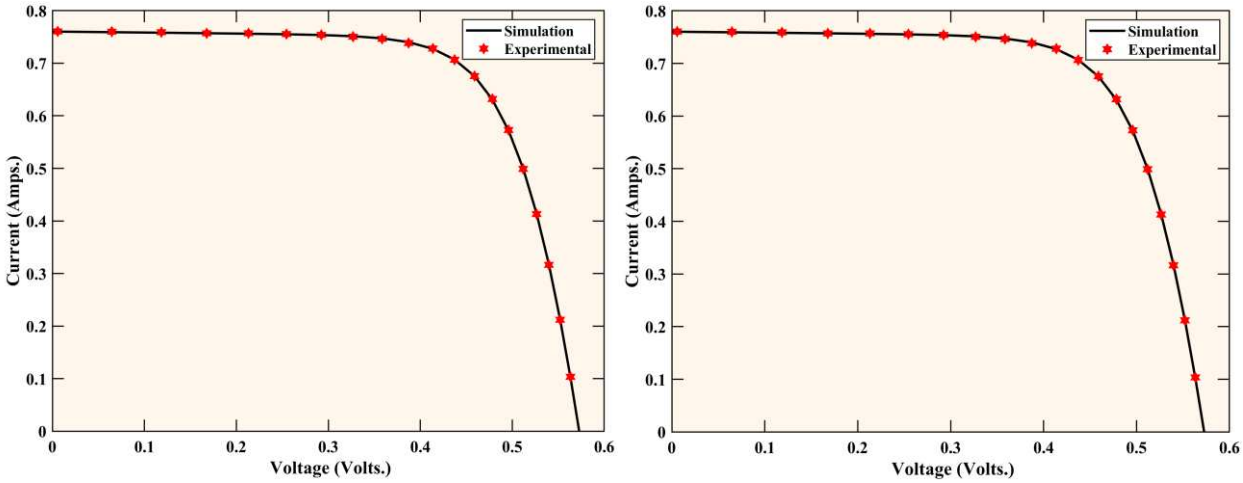
In this section, SDM and DDM of the RTC France Si solar cell are considered for experimentation. The RTC cell is a commercial cell with 57 mm diameter, and the experimental samples are collected at 1000 W/m^2 irradiation and 33 ºC cell temperature. The upper and lower limits for both models of RTC cell are listed in Table 2. The performance of the suggested OLBGWO algorithm is correlated with PSO, GWO, HHO, SCA, MFO, SSA, and SMA. The above-such algorithms are selected due to the availability of open-source codes, and these algorithms are attracted by the researchers for various applications. Fig. 5 displays the I-V characteristics of the simulation value estimated for both SDM and DDM and experimental value by the proposed OLBGWO algorithm. It can be illustrated that the estimated values obtained by the OLBGWO algorithm closely agree with the experiment samples in the entire voltage sample collection. The relative error (RE) and integral absolute error (IAE) values for the estimated current data and experimental data of both SDM and DDM are illustrated in Fig. 6 and Fig. 7, respectively. The values of RE and IAE are calculated using Eq. 21 and Eq. 22, respectively.

$$\mathrm{RE} = \frac{I - I_s}{I} \tag{21}$$

$$\mathrm{IAE} = |I - I_s| \tag{22}$$

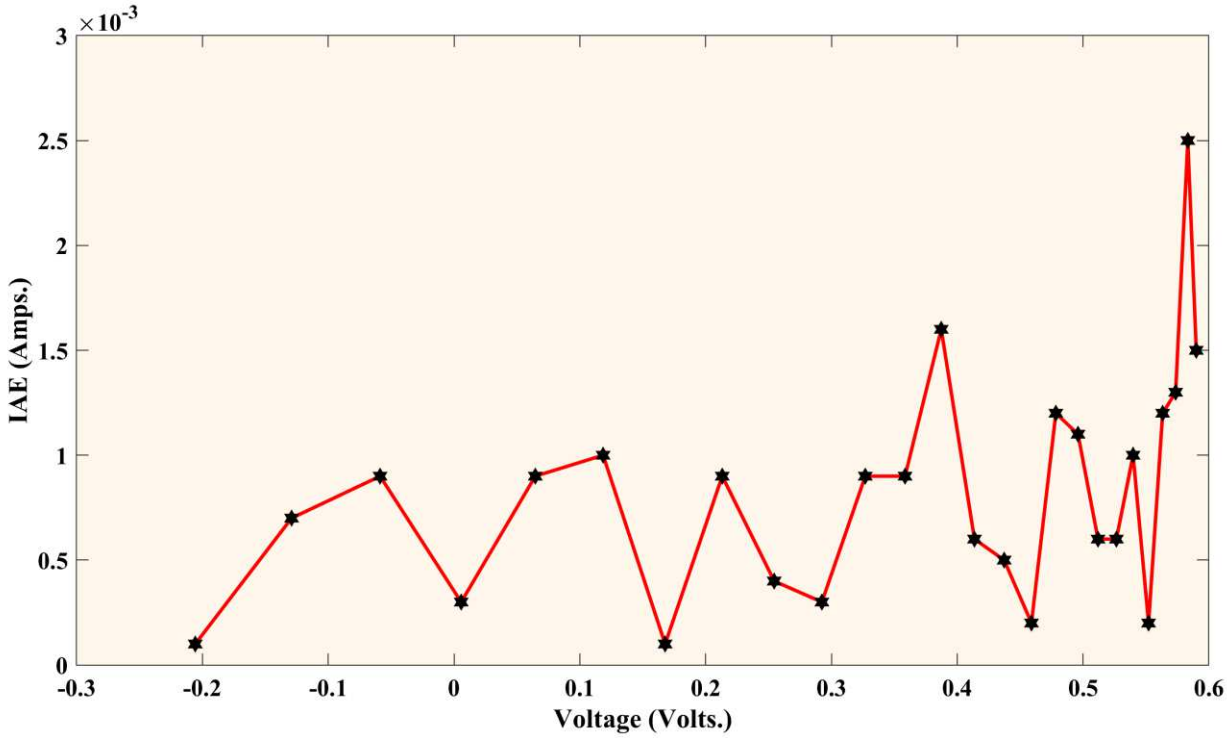
where I denote the experimental current sample and I_s denotes the simulated current value. The calculated IAE and RE values of SDM and DDM are listed in Table 3 and Table 4, respectively. From Table 3-4, it can be observed that the values of IAE are less than 2.50E-03 for SDM and 3.27E-03 for DDM, and RE values are within [-1.20E-03, 1.30E-02] for SDM and [2.03E-02, 1.26E-02] for DDM. From the obtained results, it can be decided that the proposed OLBGWO

algorithms can correctly replicate the real performance of the SDM and DDM of the PV cell. The sum of the IAE and RE values is 8.27E−04 and 4.77E−03 for SDM, 1.06E−03 and 4.45E−03 for DDM, respectively. It can be seen from Table 3 and Table 4 that the proposed OLBGWO can precisely identify the unknown parameters of the PV cell.

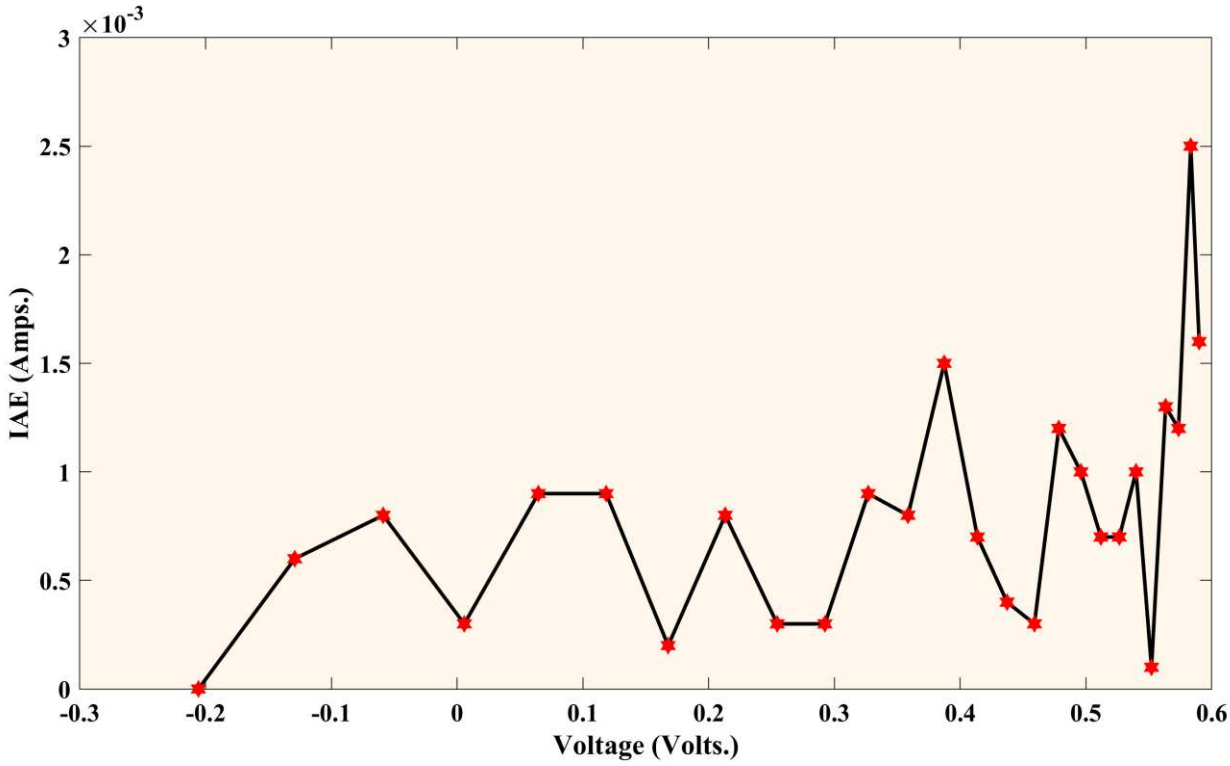


(a) **(b)**

Figure 5. I-V characteristics of the PV cell; (a) SDM, (b) DDM

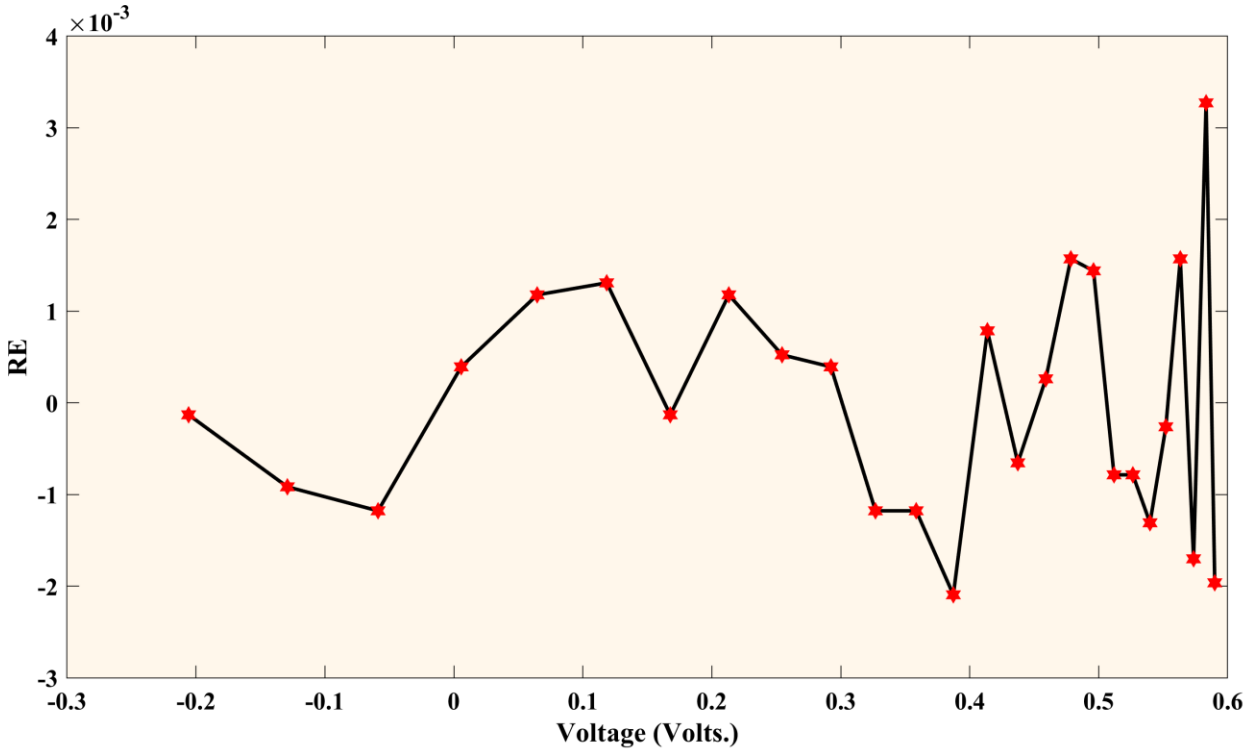


(a)

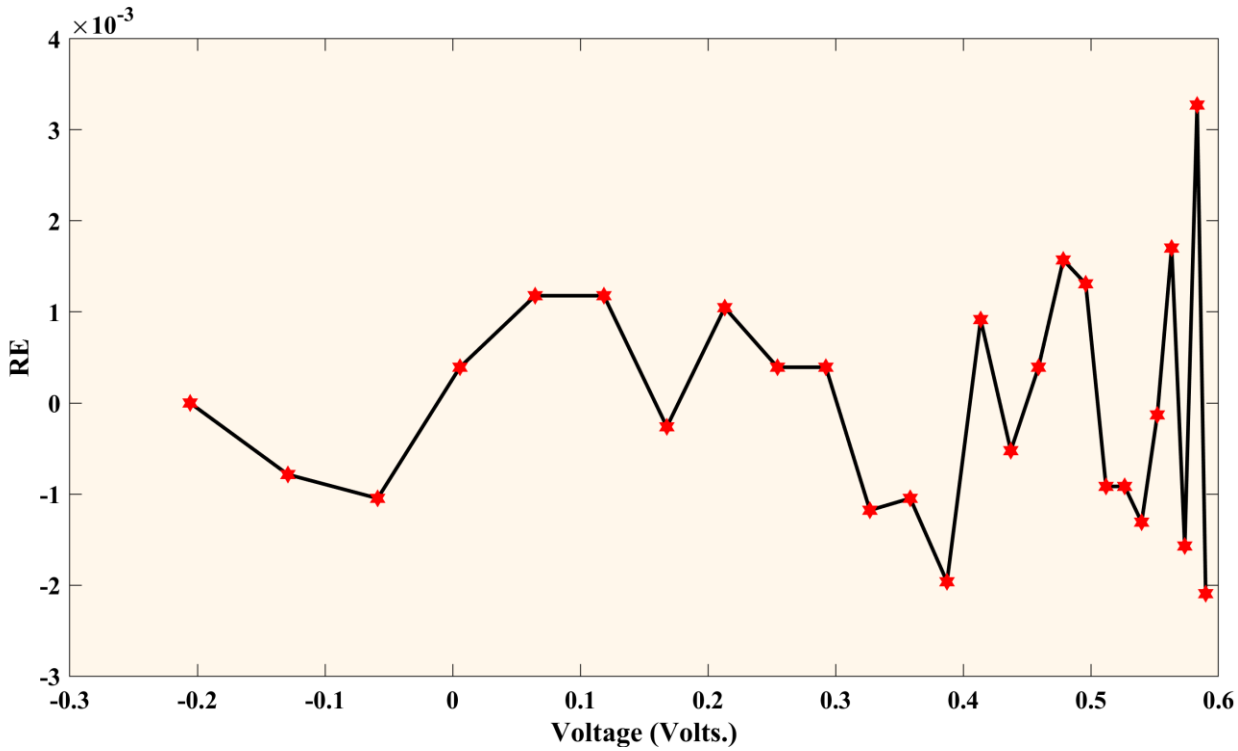


(b)

Figure 6. IAE values of the PV cell; (a) SDM, (b) DDM



(a)



(b)

Figure 7. RE values of the PV cell; (a) SDM, (b) DDM

Table 3. IAE and RE values of the SDM of the PV cell

V (V)	I (A)	I_s (A)	IAE (A)	RE
-0.2057	0.764	0.7641	1.00E-04	-1.31E-04
-0.1291	0.762	0.7627	7.00E-04	-9.19E-04
-0.0588	0.7605	0.7614	9.00E-04	-1.18E-03
0.0057	0.7605	0.7602	3.00E-04	3.94E-04
0.0646	0.76	0.7591	9.00E-04	1.18E-03
0.1185	0.759	0.7580	1.00E-03	1.32E-03
0.1678	0.757	0.7571	1.00E-04	-1.32E-04
0.2132	0.757	0.7561	9.00E-04	1.19E-03
0.2545	0.7555	0.7551	4.00E-04	5.29E-04
0.2924	0.754	0.7537	3.00E-04	3.98E-04
0.3269	0.7505	0.7514	9.00E-04	-1.20E-03
0.3585	0.7465	0.7474	9.00E-04	-1.21E-03
0.3873	0.7385	0.7401	1.60E-03	-2.17E-03
0.4137	0.728	0.7274	6.00E-04	8.24E-04
0.4373	0.7065	0.7070	5.00E-04	-7.08E-04

0.459	0.6755	0.6753	2.00E-04	2.96E-04
0.4784	0.632	0.6308	1.20E-03	1.90E-03
0.496	0.573	0.5719	1.10E-03	1.92E-03
0.5119	0.499	0.4996	6.00E-04	-1.20E-03
0.5265	0.413	0.4136	6.00E-04	-1.45E-03
0.5398	0.3165	0.3175	1.00E-03	-3.16E-03
0.5521	0.212	0.2122	2.00E-04	-9.43E-04
0.5633	0.1035	0.1023	1.20E-03	1.16E-02
0.5736	-0.01	-0.0087	1.30E-03	1.30E-02
0.5833	-0.123	-0.1255	2.50E-03	-2.03E-02
0.59	-0.21	-0.2085	1.50E-03	7.14E-03
Sum			8.27E-04	4.77E-03

Table 4. IAE and RE values of the DDM of the PV cell

V (V)	**I (A)**	**I_s (A)**	**IAE (A)**	**RE**
-0.2057	0.764	0.7640	0.00E+00	0.00E+00
-0.1291	0.762	0.7626	7.85E-04	-7.87E-04
-0.0588	0.7605	0.7613	1.05E-03	-1.05E-03
0.0057	0.7605	0.7602	3.93E-04	3.94E-04
0.0646	0.76	0.7591	1.18E-03	1.18E-03
0.1185	0.759	0.7581	1.18E-03	1.19E-03
0.1678	0.757	0.7572	2.62E-04	-2.64E-04
0.2132	0.757	0.7562	1.05E-03	1.06E-03
0.2545	0.7555	0.7552	3.93E-04	3.97E-04
0.2924	0.754	0.7537	3.93E-04	3.98E-04
0.3269	0.7505	0.7514	1.18E-03	-1.20E-03
0.3585	0.7465	0.7473	1.05E-03	-1.07E-03
0.3873	0.7385	0.7400	1.96E-03	-2.03E-03
0.4137	0.728	0.7273	9.16E-04	9.62E-04
0.4373	0.7065	0.7069	5.24E-04	-5.66E-04
0.459	0.6755	0.6752	3.93E-04	4.44E-04
0.4784	0.632	0.6308	1.57E-03	1.90E-03
0.496	0.573	0.5720	1.31E-03	1.75E-03
0.5119	0.499	0.4997	9.16E-04	-1.40E-03
0.5265	0.413	0.4137	9.16E-04	-1.69E-03
0.5398	0.3165	0.3175	1.31E-03	-3.16E-03
0.5521	0.212	0.2121	1.31E-04	-4.72E-04
0.5633	0.1035	0.1022	1.70E-03	1.26E-02
0.5736	-0.01	-0.0088	1.57E-03	1.20E-02
0.5833	-0.123	-0.1255	3.27E-03	-2.03E-02
0.59	-0.21	-0.2084	2.09E-03	7.62E-03
Sum			1.06E-03	4.45E-03

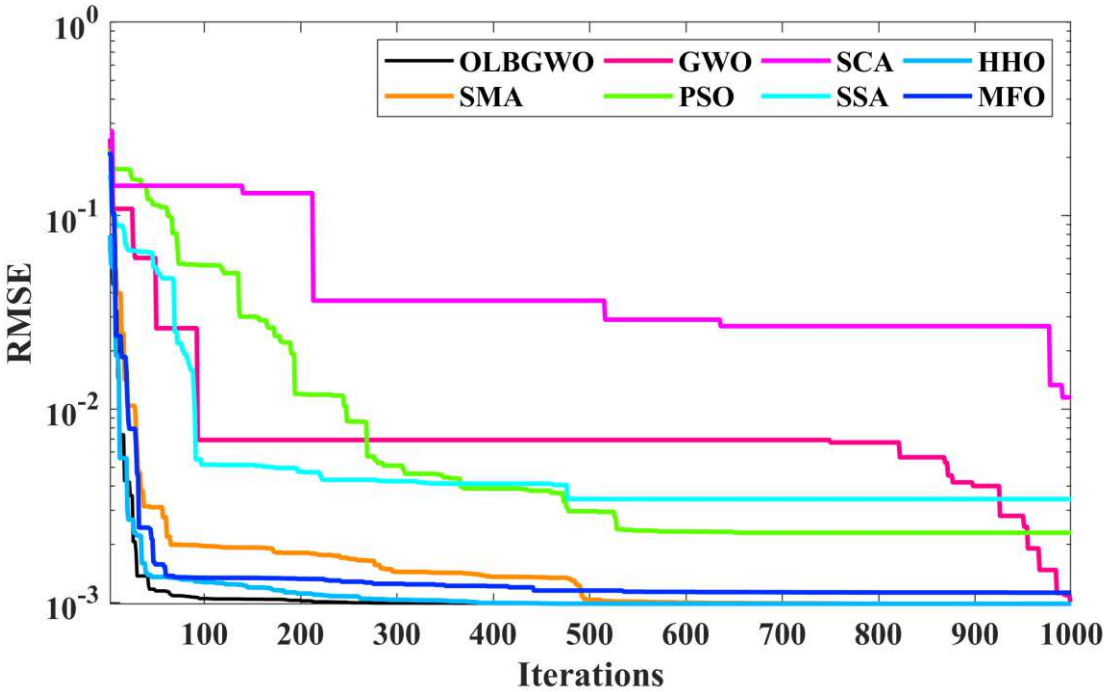
The obtained RMSE values by the suggested OLBGWO algorithm and other selected algorithms are listed in Table 5 and Table 6 after 30 individual runs of all algorithms. The statistical analysis of RMSE values of SDM and DDM, including Max, Min, Mean, standard deviation (SD), and runtime (RT) of all algorithms are listed in Table 5 and Table 6, respectively. From Table 5-6, it is observed that the OLBGWO displays better performance as per Min, Max, SD, and RT values. Therefore, it is concluded that the proposed OLBGWL algorithm can display more stable and reliable results compared to other competitive algorithms. The convergence of both SDM and DDM of the PV cell is illustrated in Fig. 8. From Fig. 8, it can be seen that the convergence speed of the proposed OLBGWO algorithm is faster than the other selected algorithms. Few algorithms, such as PSO, SSA, GWO, and SCA, are trapped into local optima too early. Therefore, as per the convergence speed and the solution accuracy, the suggested OLBGWO technique performs better than other competitors.

Table 5. Statistical values for the SDM of the PV cell

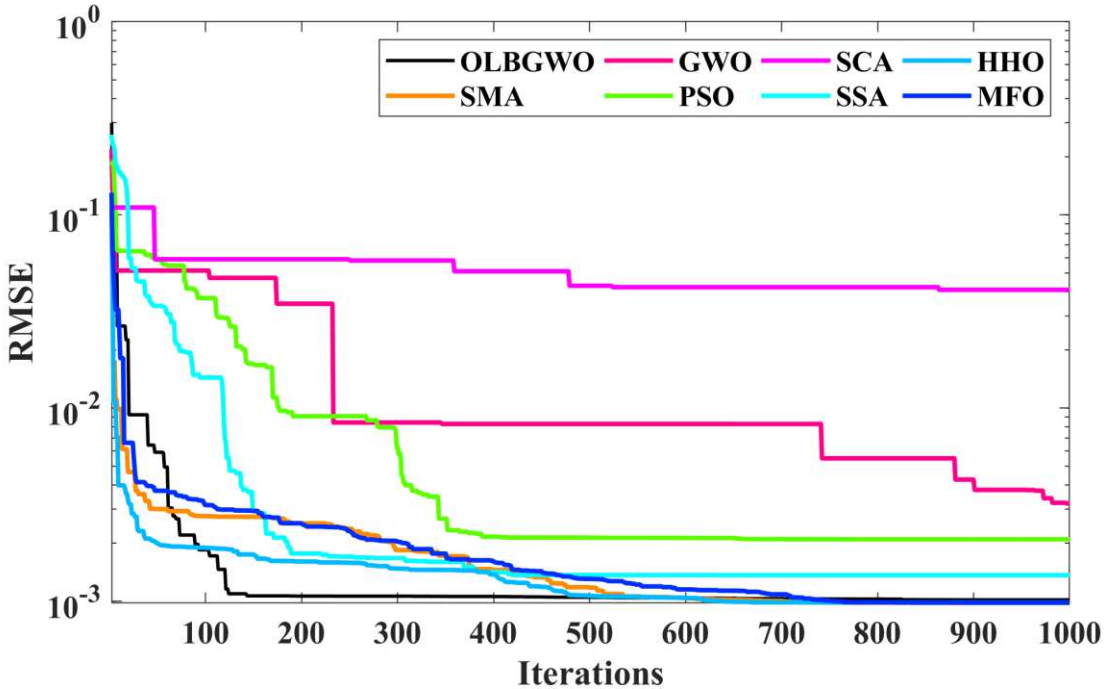
Algorithm	Min	Max	Mean	SD	RT	Remarks
OLBGWO	0.000986	0.000986	0.000986	1.4E-08	17.28646	
SMA	0.000986	0.001031	0.001001	2.62E-05	22.88021	+
GWO	0.001005	0.003252	0.00201	0.001142	17.25	+
PSO	0.002296	0.00658	0.004269	0.002161	43.25521	+
SCA	0.011492	0.042765	0.031969	0.017742	56.53125	+
SSA	0.003426	0.041475	0.019636	0.01964	45.59896	+
HHO	0.000989	0.000991	0.00099	1.16E-06	60.35938	+
MFO	0.001125	0.001707	0.001476	0.000309	17.86979	+

Table 6. Statistical values for the DDM of the PV cell

Algorithm	Min	Max	Mean	SD	RT	Remarks
OLBGWO	0.000983	0.000986	0.000985	1.78E-06	17.48438	
SMA	0.000984	0.000986	0.000985	9.01E-06	22.76563	+
GWO	0.00321	0.007358	0.005242	0.002075	17.33333	+
PSO	0.002093	0.013568	0.006233	0.00637	43.55208	+
SCA	0.040949	0.046102	0.04334	0.002596	57.04167	+
SSA	0.001365	0.004889	0.003331	0.001797	45.34375	+
HHO	0.000986	0.001006	0.000993	1.13E-05	60.94271	+
MFO	0.001018	0.001941	0.001447	0.000465	18.14063	+



(a)



(b)

Figure 8. Convergence curve of all algorithms; (a) SDM, (b) DDM

The best estimated variables and RMSE acquired from all algorithms, including OLBGWO for SDM and DDM, are listed in Table 7 and Table 8, respectively. From Table 7-8, it can be

observed that the proposed OLBGWO algorithm finds the best RMSE value, i.e., 9.8602E-04 for SDM and 9.8254E-04 for DDM, which are less than the other selected algorithms. Therefore, it can be concluded that the suggested OLBGWO algorithm is a robust tool to identify the unknown parameters of the PV cell.

Table 7. Optimal parameters found by selected algorithms for the SDM of the PV cell

Algorithm	I_p (A)	a	R_{sh} (Ω)	R_{se} (Ω)	I_{sd} (μA)	*RMSE*	*sig*
OLBGWO	0.760775446	1.481184371	53.71884978	0.036377049	3.23023E-07	0.000986022	
SMA	0.76077549	1.481182374	53.7190549	0.036377158	3.23017E-07	0.000986029	+
GWO	0.760594421	1.488054233	55.38693081	0.036041973	3.45601E-07	0.001005009	+
PSO	0.760651309	1.589218609	88.03038933	0.031629759	8.76874E-07	0.002296352	+
SCA	0.746825193	1.508266992	65.48976491	0.034759925	4.15848E-07	0.011492196	+
SSA	0.762156665	1.57813106	85.30097679	0.03408091	7.98838E-07	0.00342559	+
HHO	0.760775453	1.481186339	53.71962251	0.036376993	3.2303E-07	0.00098904	+
MFO	0.760273931	1.504819789	69.52501857	0.035540698	4.07479E-07	0.001124854	+

Table 8. Optimal parameters found by selected algorithms for the DDM of the PV cell

Algorithm	I_p (A)	a_1	a_2	R_{sh} (Ω)	R_{se} (Ω)	I_{sd1} (μA)	I_{sd2} (μA)	*RSME*	*sig*
OLBGWO	0.760781114	1.451328017	1.961750012	55.30775593	0.036722397	2.25939E-07	6.43151E-07	0.000982556	
SMA	0.760782154	1.989505615	1.450552025	55.40035877	0.036740871	7.31103E-07	2.24481E-07	0.000982885	+
GWO	0.765070224	1.999417133	1.491312557	29.33874544	0.034524345	6.7826E-07	3.36824E-07	0.003209823	+
PSO	0.759029723	1.496727776	1.525233743	85.08801224	0.034902051	3.19686E-07	7.51767E-08	0.002093125	+
SCA	0.743316562	1.621502389	1	11.55798222	0.014902051	0.000001	9.51767E-08	0.04094904	+
SSA	0.759613138	1.658890834	1.498387292	92.4022982	0.035572451	1.0924E-07	3.56849E-07	0.001364675	+
HHO	0.760777324	1.999999993	1.481062192	53.67960509	0.036380366	1.07041E-09	3.22607E-07	0.000986014	+
MFO	0.760885949	1.468213907	1.586601681	49.69347079	0.036876689	2.83604E-07	4.28614E-07	0.001017502	+

4.2. Case-2: Photowatt PWP-201 PV Module

In this section, the SDM of the Photowatt PWP-201 PV model is deliberated for experimentation. The Photowatt PWP-201 is a commercial PV module with 36 polycrystalline PV cells in series, and the experimental samples are collected at 1000 W/m^2 irradiation and 45 ^{o}C cell temperature. The upper and lower limits for both models are listed in Table 2. The

performance of the proposed OLBGWO algorithm is compared with PSO, GWO, HHO, SCA, MFO, SSA, and SMA. Fig. 9 displays the I-V characteristics of the simulation value estimated for the SDM and experimental value by the proposed OLBGWO algorithm. It can be illustrated that the estimated values obtained by the OLBGWO algorithm closely agree with the experiment samples in the entire voltage sample collection. The RE and IAE values for the estimated current value and experimental values of SDM is illustrated in Fig. 10 and Fig. 11, respectively. The calculated IAE and RE values of SDM are listed in Table 9. From Table 9, it can be seen that the values of IAE are less than 4.80E-03, and the values of RE are within the range of [-1.65E-03, 4.65E-03]. From these results, it can be decided that the suggested OLBGWO algorithms can correctly replicate the real performance of the SDM of the PV module. The sum of the IAE and RE values is 1.97E−03 and 1.44E−03, respectively. It can be observed from Table 9 that the suggested OLBGWO can precisely estimate the unknown parameters of the PV cell.

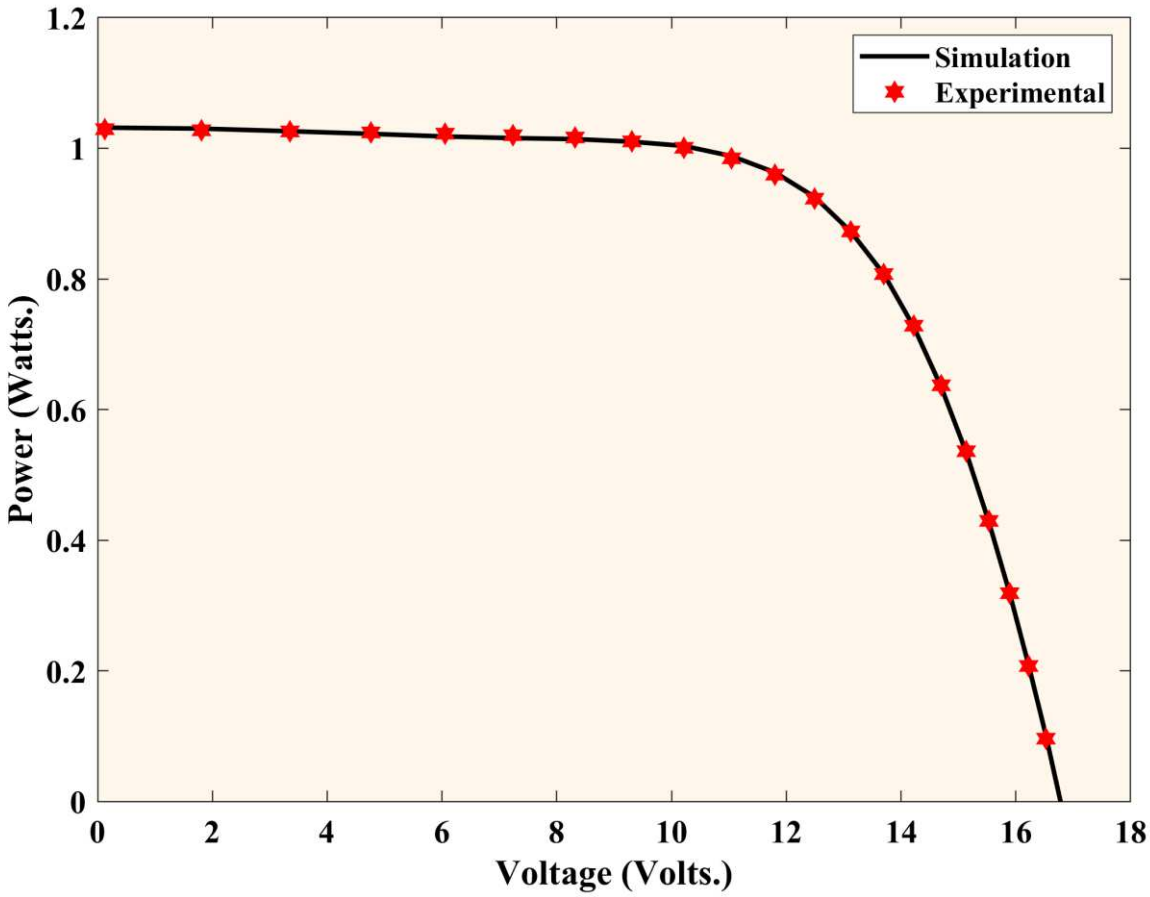


Figure 9. I-V characteristics of the PV module model

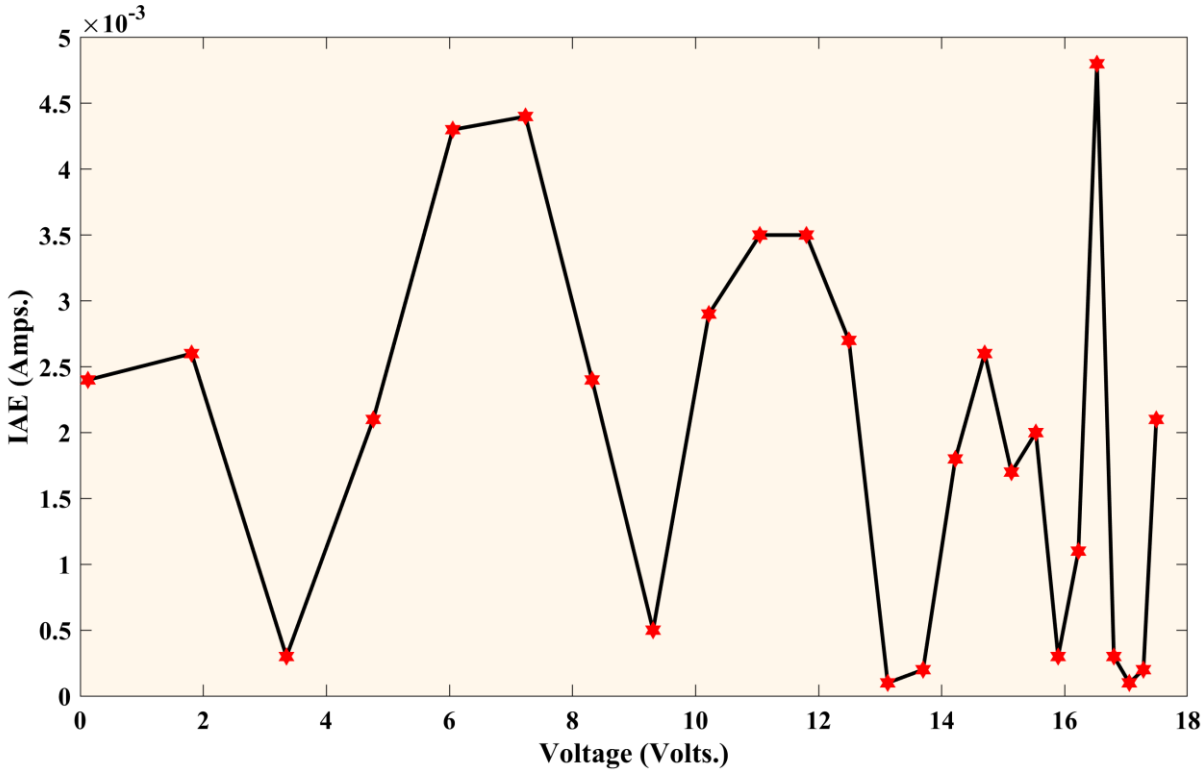


Figure 10. IAE values of the PV module model

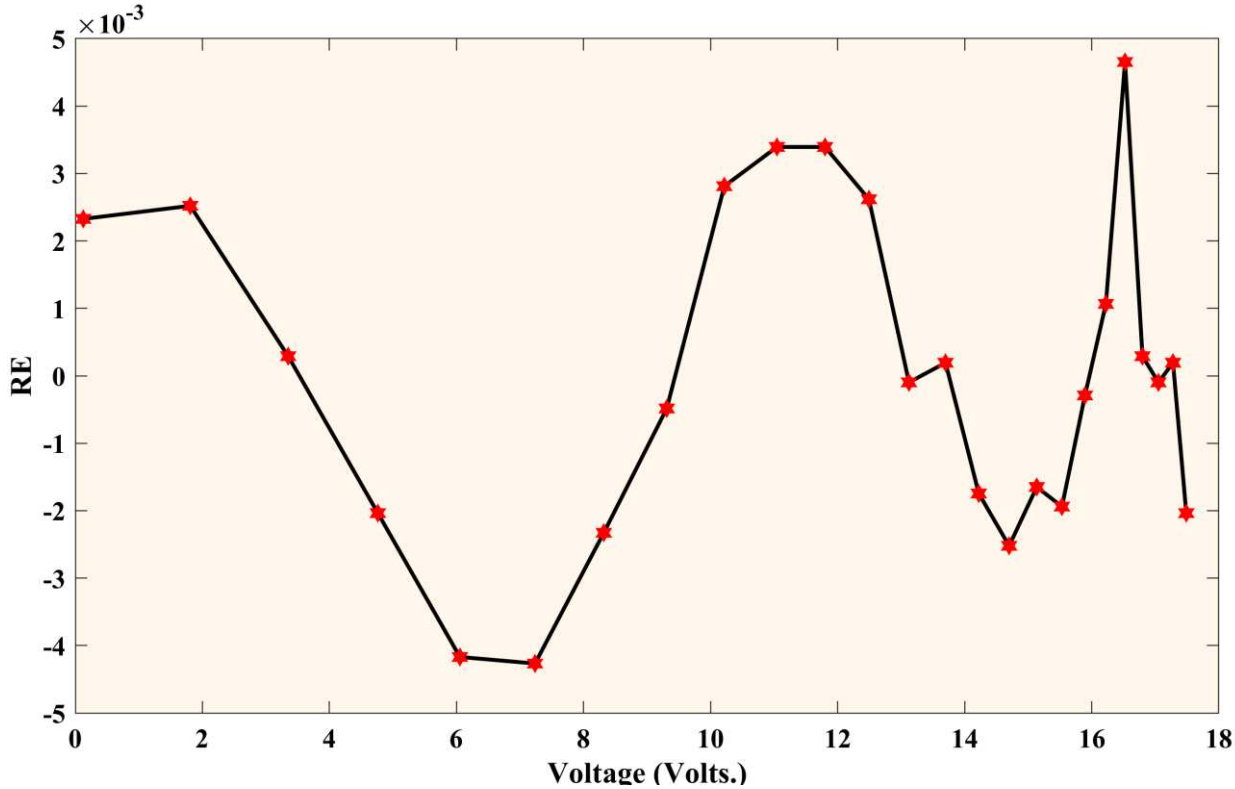


Figure 11. RE values of the PV module model

Table 9. IAE and RE values of the PV module model

V (V)	I (A)	I_s (A)	IAE (A)	RE
0.1248	1.0315	1.0291	2.40E-03	2.33E-03
1.8093	1.0300	1.0274	2.60E-03	2.52E-03
3.3511	1.0260	1.0257	3.00E-04	2.91E-04
4.7622	1.0220	1.0241	2.10E-03	2.04E-03
6.0538	1.0180	1.0223	4.30E-03	4.17E-03
7.2364	1.0155	1.0199	4.40E-03	4.27E-03
8.3189	1.0140	1.0164	2.40E-03	2.33E-03
9.3097	1.0100	1.0105	5.00E-04	4.85E-04
10.2163	1.0035	1.0006	2.90E-03	2.81E-03
11.0449	0.9880	0.9845	3.50E-03	3.39E-03
11.8018	0.9630	0.9595	3.50E-03	3.39E-03
12.4929	0.9255	0.9228	2.70E-03	2.62E-03
13.1231	0.8725	0.8726	1.00E-04	-9.69E-05
13.6983	0.8075	0.8073	2.00E-04	1.94E-04
14.2221	0.7265	0.7283	1.80E-03	1.75E-03
14.6995	0.6345	0.6371	2.60E-03	2.52E-03
15.1346	0.5345	0.5362	1.70E-03	-1.65E-03
15.5311	0.4275	0.4295	2.00E-03	-1.94E-03
15.8929	0.3185	0.3188	3.00E-04	-2.91E-04
16.2229	0.2085	0.2074	1.10E-03	1.07E-03
16.5241	0.1010	0.0962	4.80E-03	4.65E-03
16.7987	-0.0080	-0.0083	3.00E-04	2.91E-04
17.0499	-0.1110	-0.1109	1.00E-04	-9.69E-05
17.2793	-0.2090	-0.2092	2.00E-04	1.94E-04
17.4885	-0.3030	-0.3009	2.10E-03	-2.04E-03
0.1248	1.0315	1.0291	2.40E-03	2.33E-03
Sum			1.97E-03	1.44E-03

The obtained RMSE values by the proposed OLBGWO algorithm and other selected algorithms are listed in Table 10 after 30 individual runs of all algorithms. The statistical analysis of RMSE values of the PV module model, including Min, Max, Mean, Median, SD, and RT of all algorithms are listed in Table 10. Table 10 shows that the OLBGWO displays better performance as per Min, Max, SD, and RT values. Therefore, it is concluded that the proposed OLBGWL algorithm can display more stable and reliable results compared to other competitive algorithms. The convergence of the PV module model is illustrated in Fig. 12. From Fig. 12, it can be noticed that the convergence rate of the suggested OLBGWO algorithm is faster than the other selected algorithms. Few algorithms, such as PSO, SCA, and GWO, are trapped into local

optima too early. Therefore, as per the convergence rate and the solution accuracy, the suggested OLBGWO algorithm performs better than other competitors.

Table 10. Statistical values for the PV module model

Algorithm	Min	Max	Mean	SD	RT	Remarks
OLBGWO	0.0024	0.0024	0.0024	2.4284e-09	14.6667	
SMA	0.0025	0.0028	0.0027	5.4900e-06	20.0208	+
GWO	0.0027	0.0090	0.0055	0.0032	14.5156	+
PSO	0.0717	0.2799	0.2086	0.1187	37.6927	+
SCA	0.0133	0.2743	0.1210	0.1363	48.6563	+
SSA	0.0026	0.0771	0.0294	0.0414	40.5677	+
HHO	0.0026	0.0029	0.0026	5.8604e-06	52.1510	+
MFO	0.0025	0.2743	0.0935	0.1566	15.3177	+

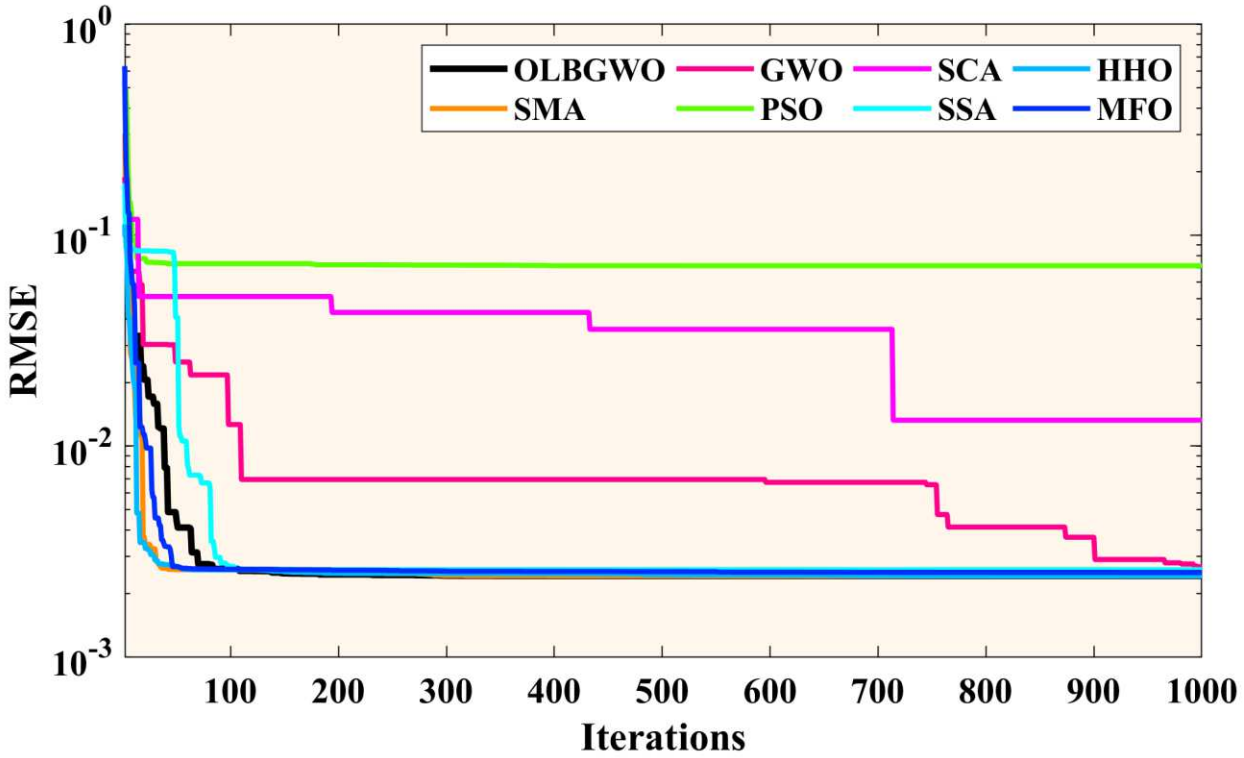


Figure 12. Convergence curve of all algorithms for the PV module model

The optimal identified variables and RMSE obtained from all algorithms, including OLBGWO for the photovoltaic panel model, are listed in Table 11. Table 11 shows that the proposed OLBGWO algorithm obtains the best RMSE, i.e., 1.256E-03, which are less than the other selected algorithms. Therefore, it can be concluded that the suggested OLBGWO technique is a robust tool to identify the unknown parameters of the PV module.

Table 11. Optimal parameters obtained by all algorithms for the PV module model

Algorithm	I_p (A)	a	R_{sh} (Ω)	R_{se} (Ω)	I_{sd} (μA)	*RMSE*	*sig*
OLBGWO	1.0305	48.6428	981.9818	1.2013	3.4823e-06	0.0024	
SMA	1.0305	48.6855	988.9833	1.2013	3.497e-06	0.0025	+
GWO	1.0305	50	1.1875e+03	1.1613	4.9087e-06	0.0027	+
PSO	0.9792	50	2000	0.3858	4.5303e-06	0.0717	+
SCA	1.0216	50	989.3061	1.1157	4.7498e-06	0.0133	+
SSA	1.0278	49.8818	1.8271e+03	1.1700	4.7807e-06	0.0026	+
HHO	1.0305	48.6978	987.4788	1.2014	3.5796e-06	0.0026	+
MFO	1.0289	49.5598	1.3652e+03	1.1754	4.4060e-06	0.0025	+

4.3. Case-3: Commercial ST40 PV Module

The OLBGWO is also examined for optimizing the problems of parameter identification of the commercial ST40 PV module. The experimental values of the ST40 commercial module under different temperature and irradiance conditions are collected to confirm the efficiency of the proposed OLBGWO algorithm. The ST40 PV module is a thin-film PV module, and it is made up of copper selenide. The short-circuit current of any PV module during different operating conditions can be computed by Eq. 23.

$$I_{sc}(G,T) = I_{sc(STC)} \times \frac{G}{G_{STC}} + \alpha(T - T_{STC}) \tag{23}$$

where G_{STC} and T_{STC} denote the irradiation and temperature at standard testing conditions (STC), G and T represent the actual irradiation and temperature, α denotes the temperature coefficient, and $I_{sc(STC)}$ represents the short-circuit current under STC.

The proposed OLBGWO algorithm is directly applied to this commercial PV module to validate the performance. The experimental samples are collected for two different conditions, such as constant temperature, i.e., at 25 ºC and variable irradiations, i.e., at 200 W/m^2, 400 W/m^2, 600 W/m^2, 800 W/m^2, and 1000 W/m^2, and constant irradiation, i.e., at 1000 W/m^2 and variable temperature, i.e., at 25 ºC, 40 ºC, 50 ºC, and 70 ºC. The parameters optimized by the proposed

OLBGWO algorithm are listed in Table 12 and Table 13, respectively, for both test cases. Table 12-13 display that the OLBGWO algorithm precisely estimates the parameters of the PV module. To visualize the identical curve between the experimental value and simulated value, I-V characteristics for both test cases are illustrated in Fig. 13 and Fig. 14, respectively.

Table 12. Optimized parameters at 25 ℃ temperature – ST40 PV module

Irradiation	I_p (A)	a	R_{sh} (Ω)	R_{se} (Ω)	I_{sd} (A)	RMSE
1000 W/m^2	2.6763	1.7628	355.9927	1.1040	1.6950e-06	9.5666e-04
800 W/m^2	2.1337	1.7682	393.2737	1.0931	1.7422e-06	0.0017
600 W/m^2	1.6049	1.7426	346.6038	1.1155	1.4121e-06	6.7540e-04
400 W/m^2	1.0662	1.8109	385.5736	1.0405	2.3474e-06	8.1112e-04
200 W/m^2	0.5328	1.7952	348.3370	0.9816	2.0292e-06	5.3039e-04

Table 13. Optimized parameters at 1000 W/m^2 irradiation – ST40 PV module

Temperature	I_p (A)	a	R_{sh} (Ω)	R_{se} (Ω)	I_{sd} (A)	RMSE
25 °C	2.6757	1.7605	362.4503	1.1070	1.6628e-06	8.1983e-04
40 °C	2.6796	1.7288	383.2375	1.1263	5.9453e-06	0.0014
50 °C	2.6921	1.7141	292.1694	1.1517	1.8227e-05	0.0018
70 °C	2.6923	1.7273	367.7540	1.1259	8.7521e-05	7.7772e-04

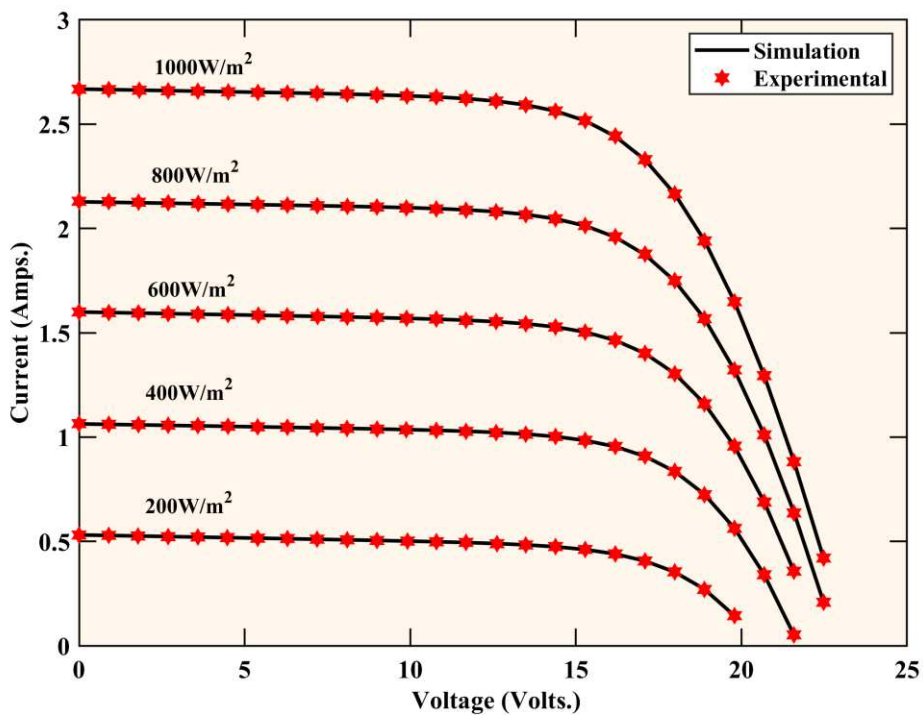


Figure 13. I-V characteristics of ST40 at 25 °C and different irradiation

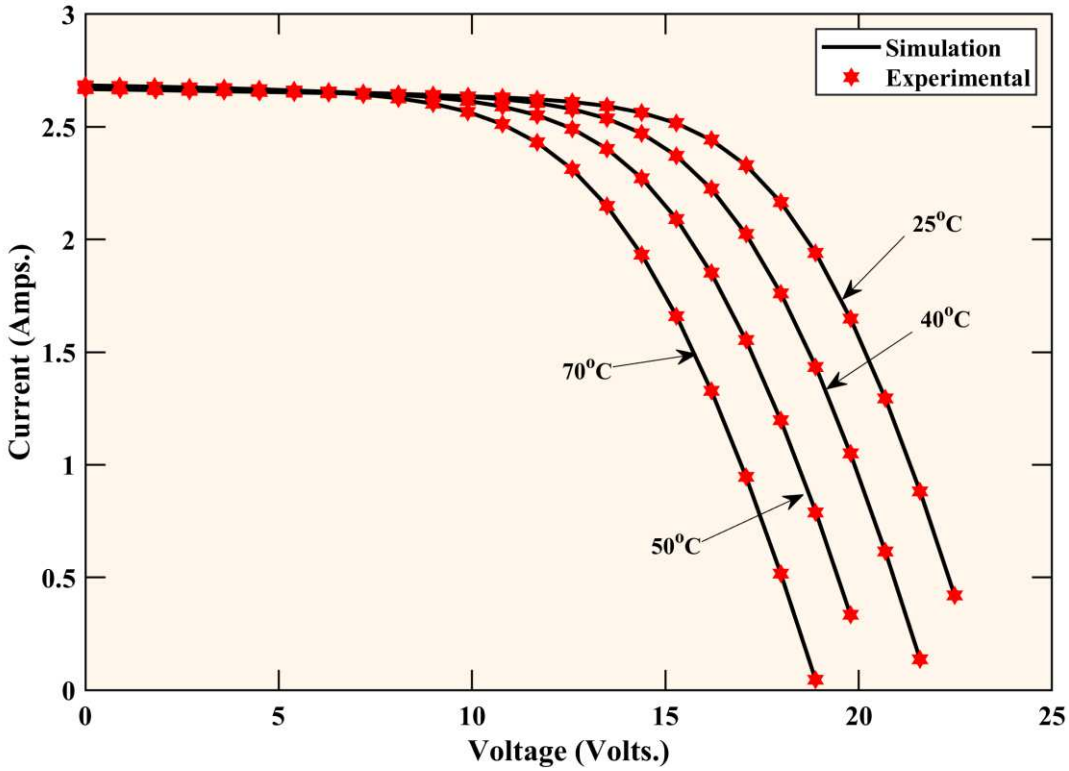


Figure 14. I-V characteristics of ST40 at 1000 W/m^2 and different temperature

From the obtained results, it is noticed that the I-V curves plotted using the estimated variables are steady with the experimental value data at different irradiation and the temperature ranges, and the proposed OLBGWO can attain a low RMSE value. From these discussions, it is clear that the efficiency of the suggested OLBGWO algorithm is reliable and stable in handling the dynamic change in operating conditions. From the above-all discussion, it is concluded that the proposed OLBGWO is a robust tool for identifying the parameters of the commercial PV module.

4.4. Case-4: Commercial KC200GT PV Module

To further confirm the efficiency, the OLBGWO algorithm is also examined while optimizing the parameters of the commercial KC200GT PV module. The experimental values of the KC200GT commercial module under different irradiance and temperature conditions are collected to confirm the efficiency of the OLBGWO algorithm. The KC200GT PV module is a multi-crystalline commercial PV module. The proposed OLBGWO algorithm is directly applied to this commercial PV module to validate the performance. The experimental samples are

collected for two different conditions, such as constant temperature, i.e., at 25 ºC and variable irradiations, i.e., at 200 W/m^2, 400 W/m^2, 600 W/m^2, 800 W/m^2, and 1000 W/m^2, and constant irradiation, i.e., at 1000 W/m^2 and variable temperature, i.e., at 25 ºC, 50 ºC, and 75 ºC. The parameters optimized by the proposed OLBGWO algorithm are listed in Table 14 and Table 15, respectively, for both test cases. Table 14 and Table 15 show that the OLBGWO algorithm precisely estimates the variables of the PV module. To visualize the identical curve between the experimental value and simulated value, I-V characteristics for both test cases are illustrated in Fig. 15 and Fig. 16, respectively.

Table 14. Optimized parameters at 25 ℃ temperature – KC200GT PV module

Irradiation	I_p *(A)*	*a*	R_{sh} *(Ω)*	R_{se} *(Ω)*	I_{sd} *(A)*	*RMSE*
1000 W/m^2	8.2097	1.2477	4.8684e+03	0.2863	4.7620e-08	0.0248
800 W/m^2	6.5646	1.1691	3.8246e+03	0.3016	1.3066e-08	0.0169
600 W/m^2	4.9317	1.2459	5.0000e+03	0.2703	4.2656e-08	0.0151
400 W/m^2	3.2776	1.1927	4.9867e+03	0.2431	1.8396e-08	0.0080
200 W/m^2	1.6452	1.1318	774.3192	0.1111	6.5410e-09	0.0034

Table 15. Optimized parameters at 1000 W/m^2 irradiation – ST40 PV module

Temperature	I_p *(A)*	*a*	R_{sh} *(Ω)*	R_{se} *(Ω)*	I_{sd} *(A)*	*RMSE*
25 ºC	8.2052	1.1695	3.4094e+03	0.3132	1.3195e-08	0.0136
50 ºC	8.2880	1.1515	4.9186e+03	0.3260	2.1583e-07	0.0063
75 ºC	8.3717	1.1141	1.4679e+03	0.3394	1.9443e-06	0.0052

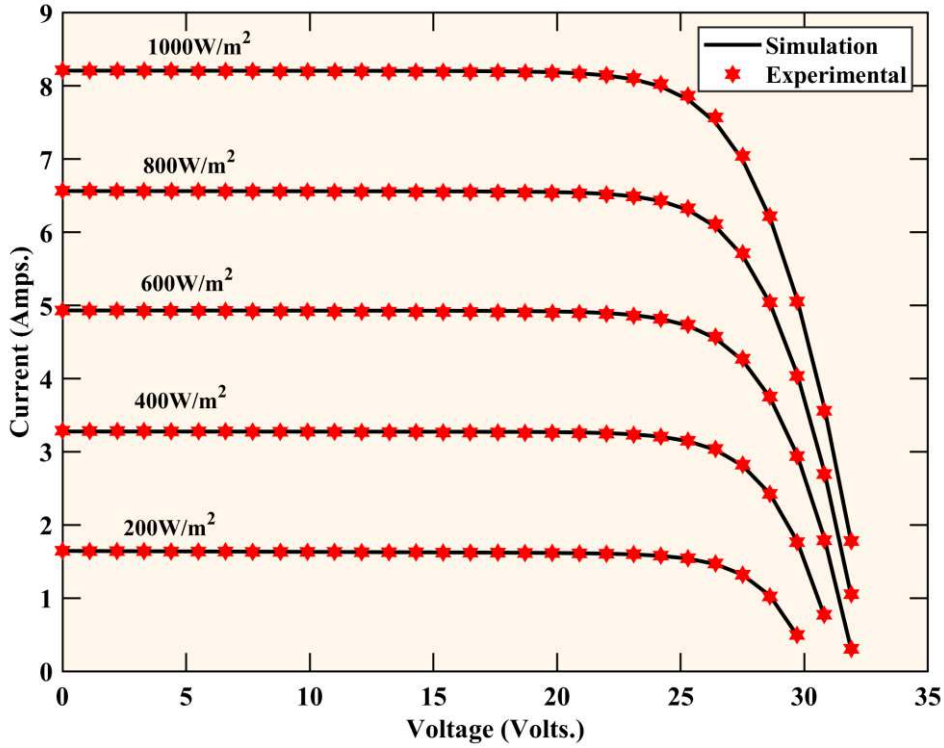


Figure 15. I-V characteristics of KC200GT at 25 ºC and different irradiation

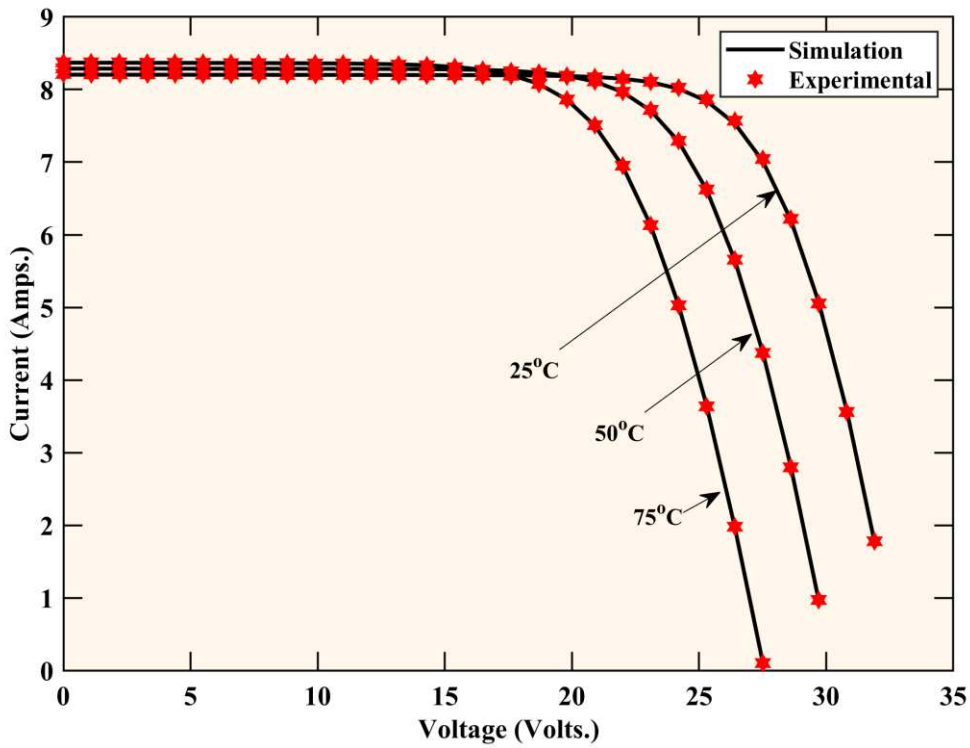


Figure 16. I-V curves of KC200GT at 1000 W/m^2 and different temperature

From the obtained results, it is noticed that the I-V curves plotted using the estimated parameters are steady with the experimental value data at different irradiation and the temperature ranges, and the proposed OLBGWO can attain a low RMSE value. From these discussions, it is clear that the efficiency of the suggested OLBGWO algorithm is reliable and stable in handling the dynamic change in operating conditions.

4.5. Statistical Test

In order to prove the superiority of the OLBGWO algorithm in terms of the overall ranking, the Wilcoxon signed-rank test (WRT) was carried out. A detailed comparison is made among different algorithms, such as OLBGWO, GWO, HHO, SSA, SMA, SCA, PSO, and MFO. The WRT has been carried out at a significant level of 0.05 to examine the performance for two test cases (Case-1 and Case-2). The WRT is a nonparametric test, and this test is used to find the statistical difference between the two techniques. The results for two different cases, such as Cae-1 and Case-2, are listed in Table 16 and Table 17, respectively. Finally, it is concluded that the OLBGWO algorithm performs better than other selected algorithms.

Table 16. Case-1: Statistical WRT results

OLBGWO Vs	*R+*	*R-*	*p-value*
SDM			
SMA	10	11	1
GWO	15	6	0.1
PSO	15	6	0.1
SCA	15	6	0.1
SSA	15	6	0.1
HHO	13	8	0.4
MFO	15	6	0.1
DDM			
SMA	10	11	1
GWO	15	6	0.1
PSO	15	6	0.1
SCA	15	6	0.1
SSA	15	6	0.1
HHO	15	6	0.1
	15	6	0.1

Table 17. Case-2: Statistical WRT results

OLBGWO Vs	*R+*	*R-*	*p-value*
SDM			
SMA	3	3	1
GWO	6	0	0.2500
PSO	6	0	0.2500
SCA	6	0	0.2500
SSA	6	0	0.2500
HHO	3	3	1
MFO	6	0	0.2500
DDM			
SMA	5	1	0.5000
GWO	6	0	0.2500
PSO	6	0	0.2500
SCA	6	0	0.2500
SSA	6	0	0.2500
HHO	6	0	0.2500
MFO	6	0	0.2500

4.6. Further Discussions

In this study, in order to minimize the early convergence of the GWO algorithm and improve its exploitation and exploration abilities, a productive scheme called OLB is integrated with the basic GWO. This new, updated GWO-based approach is used for PV cell and module parameter estimation. This can be inferred that the OLBGWO algorithm can reliably and effectively calculate the uncertain variables for the PV model based on the experimental outcomes of common SDM, DDM, and PV models and two commercial modules derived from the manufacturer's datasheets. The proposed OLBGWO algorithm behaves highly competitive in contrast to other techniques; this finding can be due to the fact that the perception of equilibrium between the primary GWO's exploitation and exploration ability is held in a more acceptable state. Several variables contribute towards a more efficient result in identifying parameters of PV models at different temperature and irradiation settings.

As discussed earlier, for estimation methods of SDM, DDM, and PV models, respectively, the developed OLBGWO algorithm has been used. From the I-V characteristics, it can be concluded that the results reported by OLBGWO agree with all experimental data. The proposed OLBGWO algorithm has better exploitation and exploration abilities than other competitors, including RMSE, convergence speed, and the extraction of best parameters. All the above-said features are

improved by the OLB strategy and modified vector parameter. The modified vector parameter *a* improves GWO's local search ability. It guarantees OLBGWO's performance in seeking the best solution with superior potential in the convergence phase. The OLB approach directs the weaker agent to better search space for getting a better convergence curve.

In addition, two practical datasets taken from the datasheets provided by the manufacturers, including KC200GT and ST40, were considered to evaluate the efficiency of the OLBGWO algorithm for handling the complex non-linear problems at various temperatures and irradiation. In the lower temperature, the parameters obtained by the OLBGWO are still compatible with the real information of KC200GT and ST40, and the proposed OLBGWO can still find the less RSME values. These findings can be related to OLBGWO's steadiness. Through the OLB and modified vector parameter process, the efficiency of the basic version of GWO in parameter estimation of the photovoltaic model is improved. The proposed OLBGWO algorithm can thus be considered the most promising approach for estimating the parameters.

5. Conclusions

An enhanced GWO algorithm called OLBGWO is proposed in this paper to extract the unknown parameters of various PV models reliably and efficiently. The modified vector parameter and OLB approaches are combined with the basic version of GWO in the OLBGWO to improve its search efficiency. The modified vector parameter can stimulate the ability to exploit and increase the solution accuracy, and the OLB increases the ability to explore and enable the weaker population to escape optimally from the local target. The findings suggest that the proposed OLBGWO algorithm shows a superior performance relative to the other state-of-the-art algorithms based on the convergence speed and solution accuracy.

Although the OLBGWO algorithm demonstrates reasonable success in solving the parameter estimation problem, the control parameter for the OLB method is fixed. Therefore, the suggested OLBGWO algorithm is not a universal parameter-free algorithm. Therefore, future research works are planned as follows: firstly, an adaptive parameter may be introduced in the OLBGWO algorithm to solve real-world problems without any additional parameters. Real-time optimization problems, such as unit commitment, controller tuning, feature selection, economic

load dispatch, image segmentation, multiobjective problems, etc., may be handled by developing the constrained and binary alternatives of the OLGWO algorithm.

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Figures

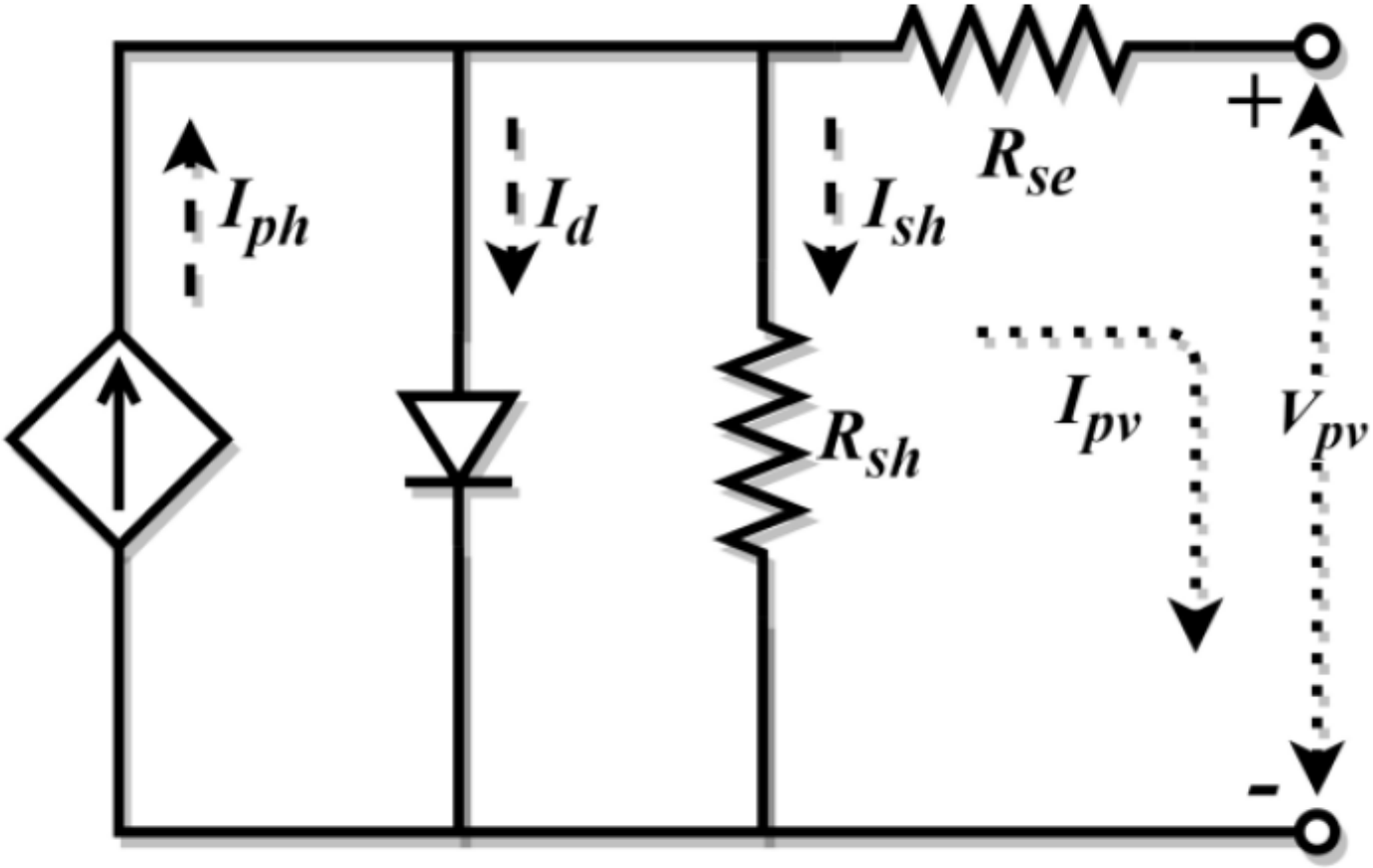

Figure 1

SDM of the solar cell

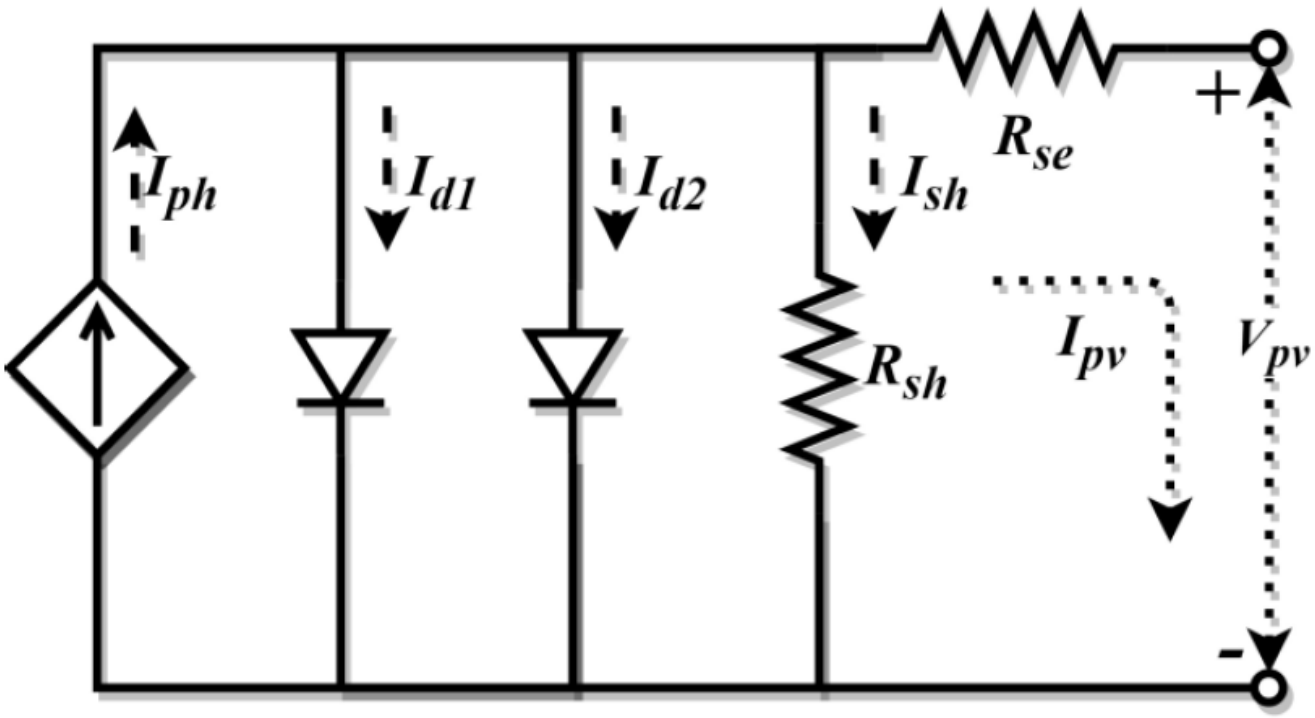

Figure 2

DDM of the solar cell

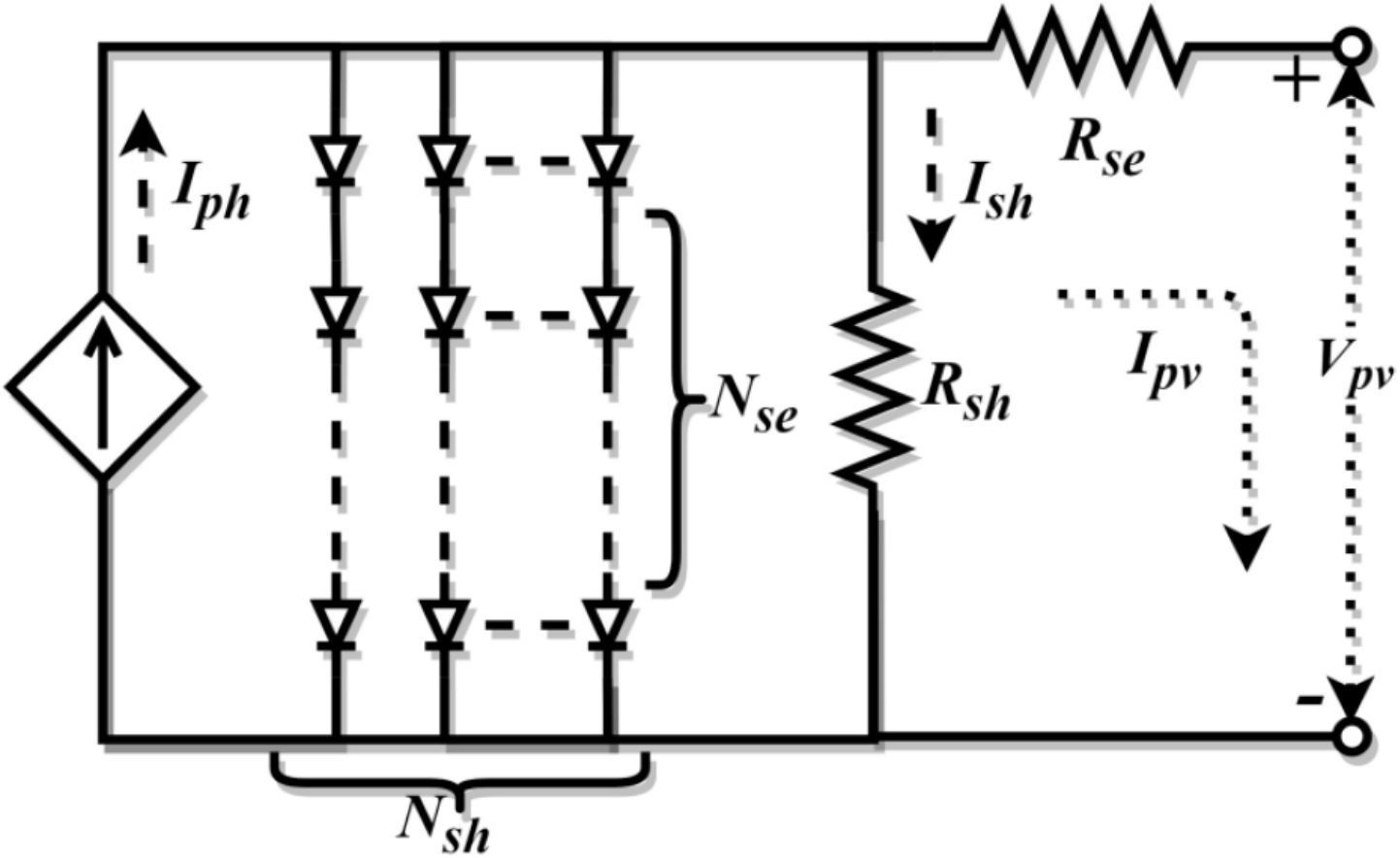

Figure 3

Electrical circuit of photovoltaic model

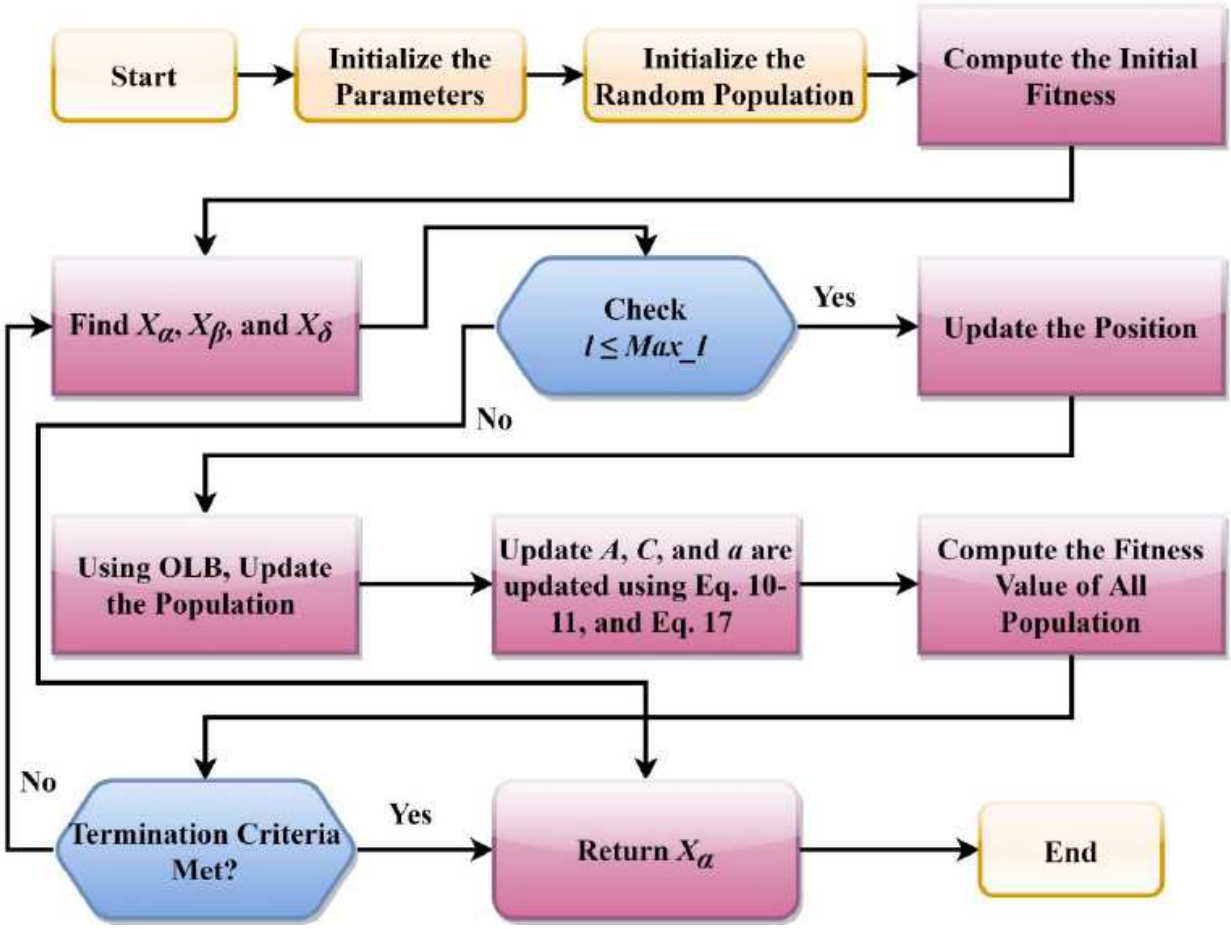

Figure 4

Flowchart of the proposed OLBGWO algorithm

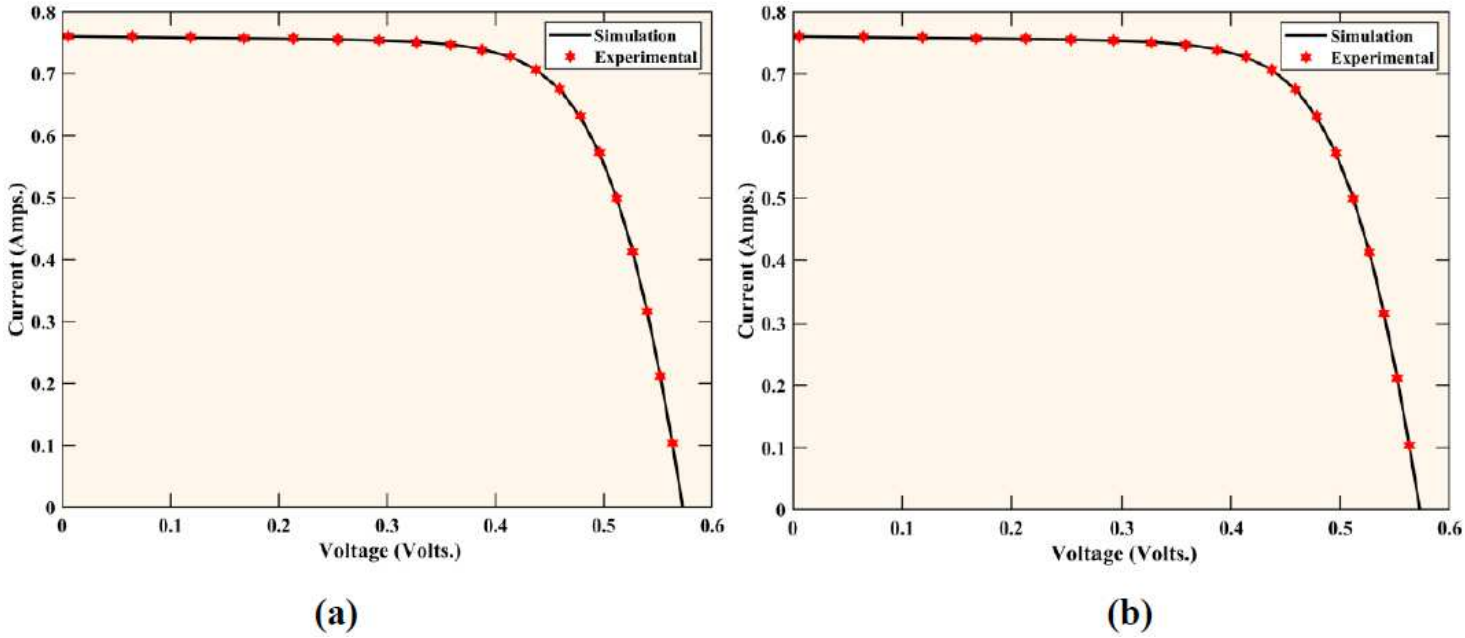

Figure 5

I-V characteristics of the PV cell; (a) SDM, (b) DDM

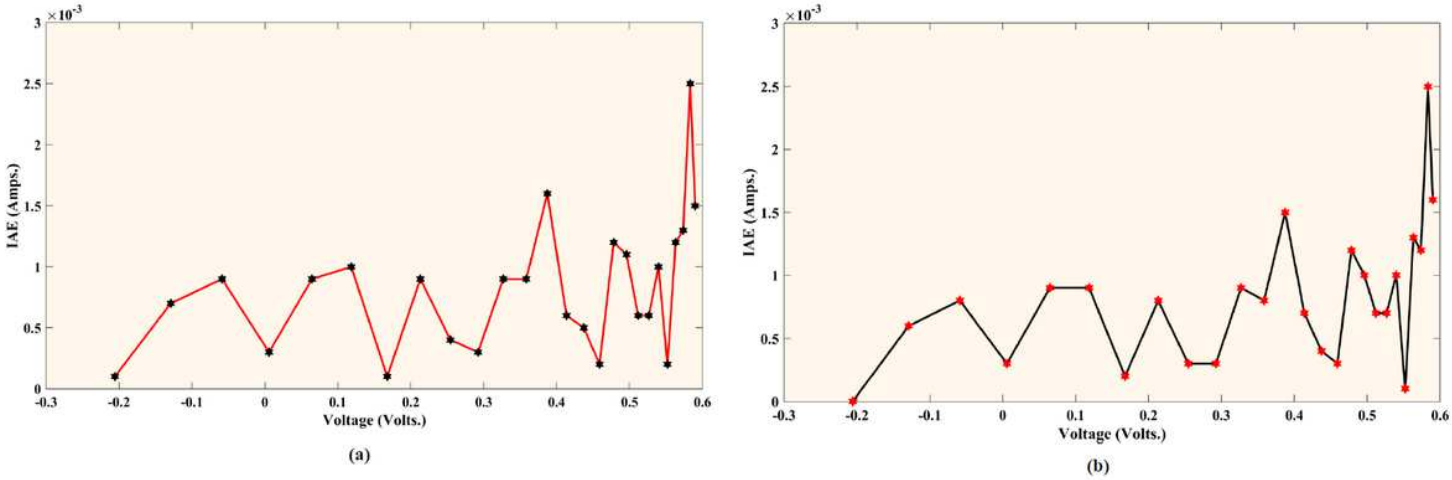

Figure 6

IAE values of the PV cell; (a) SDM, (b) DDM

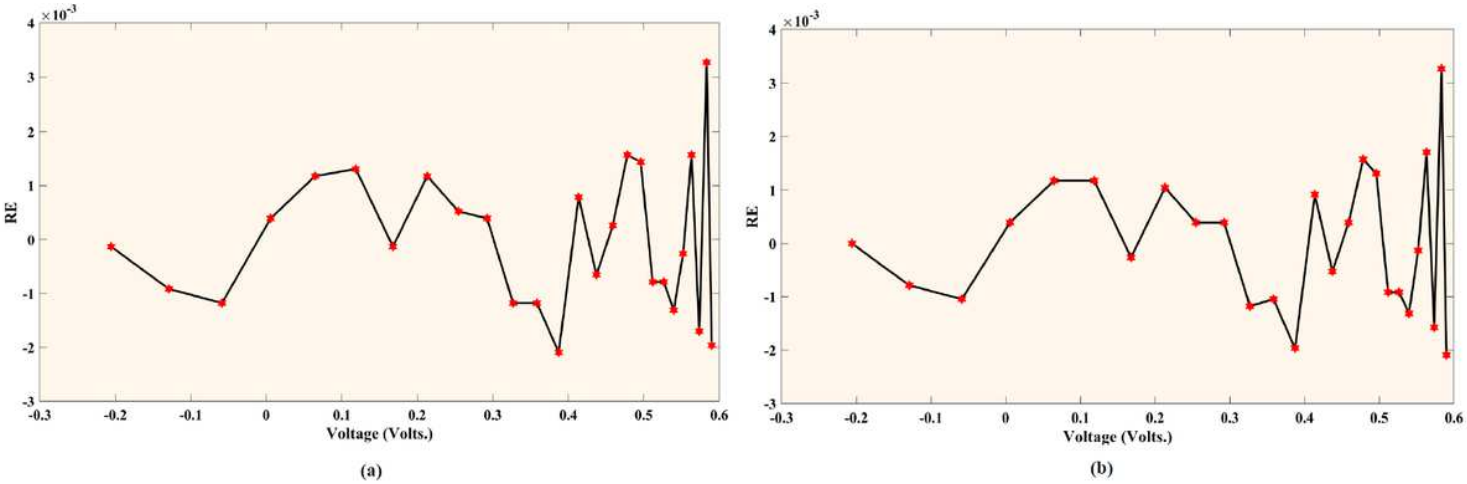

Figure 7

RE values of the PV cell; (a) SDM, (b) DDM

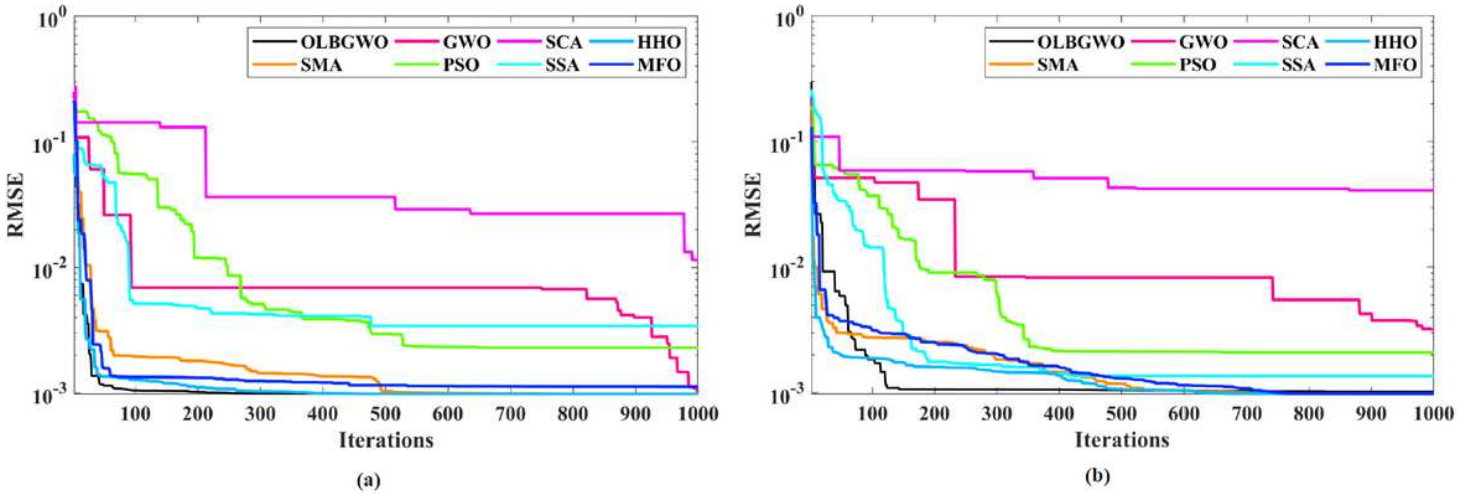

Figure 8

Convergence curve of all algorithms; (a) SDM, (b) DDM

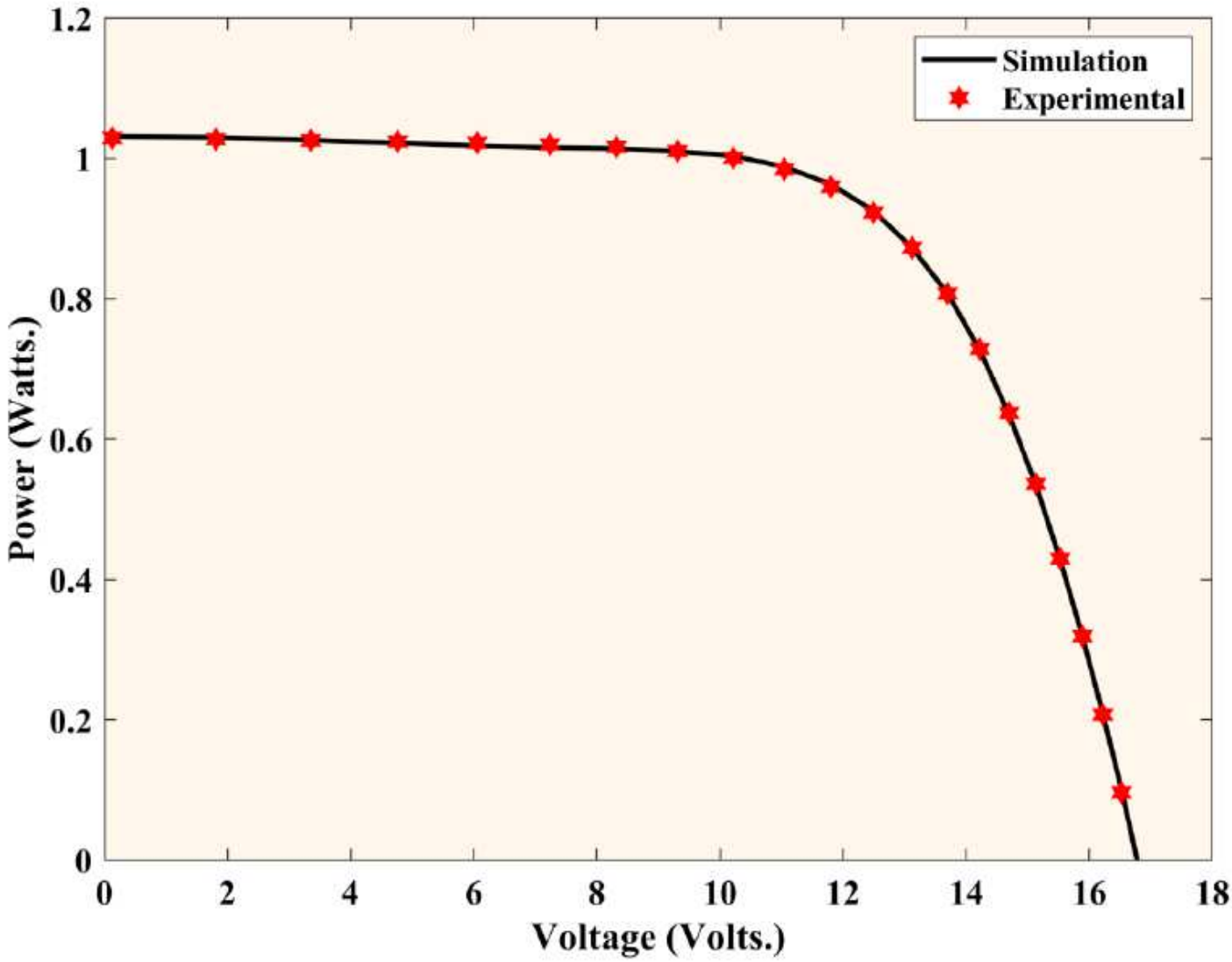

Figure 9

I-V characteristics of the PV module model

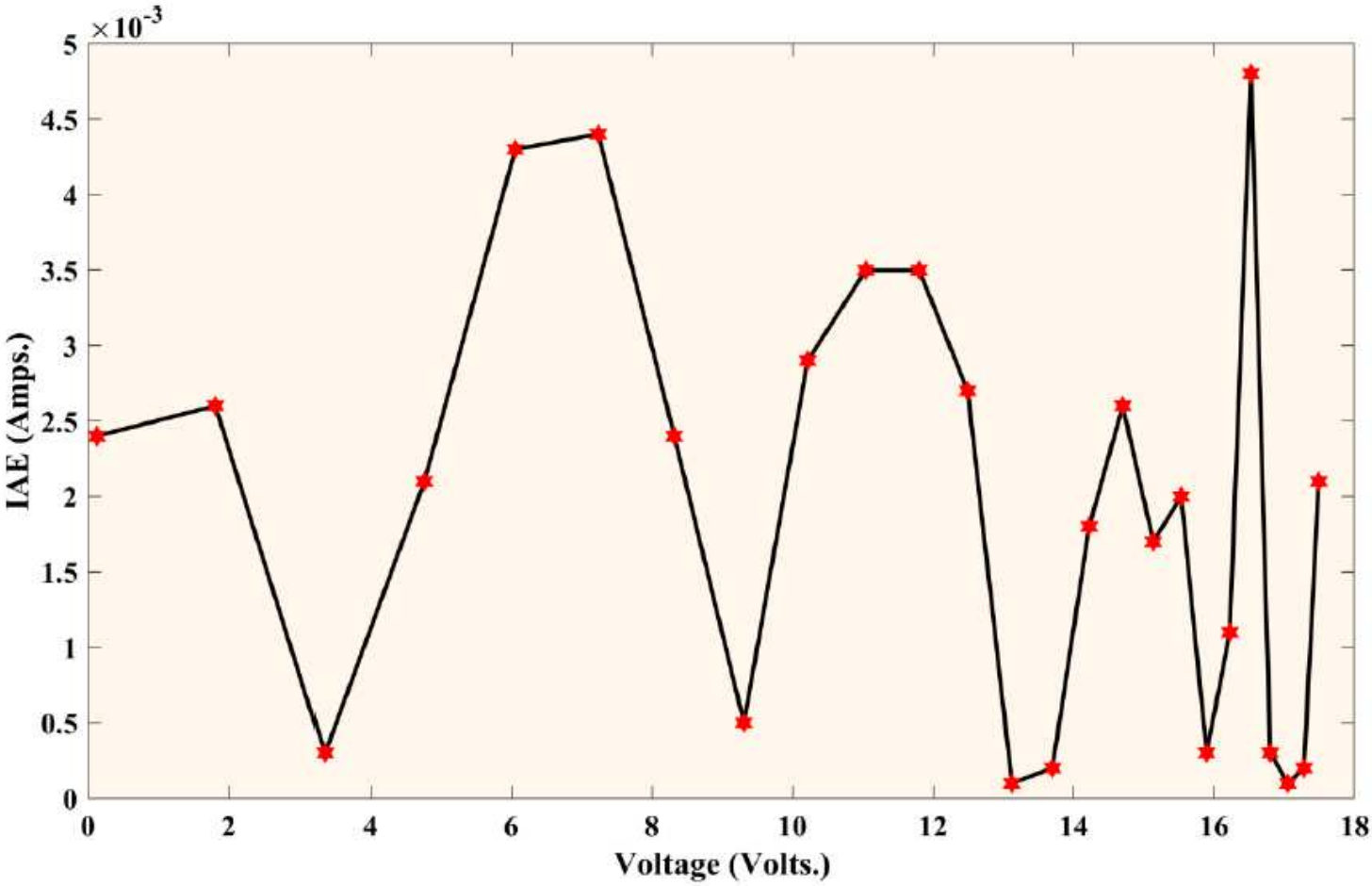

Figure 10

IAE values of the PV module model

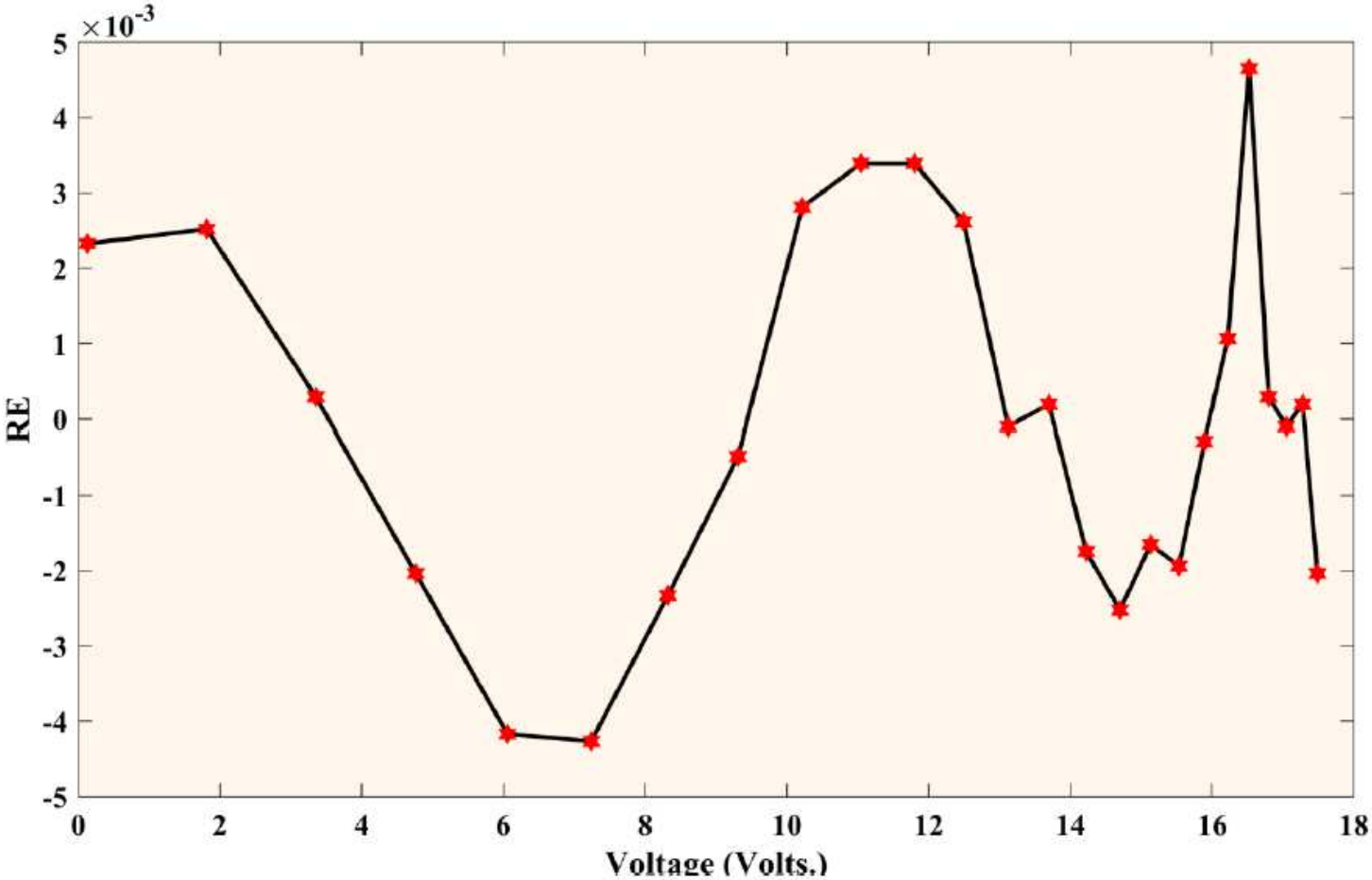

Figure 11

RE values of the PV module model

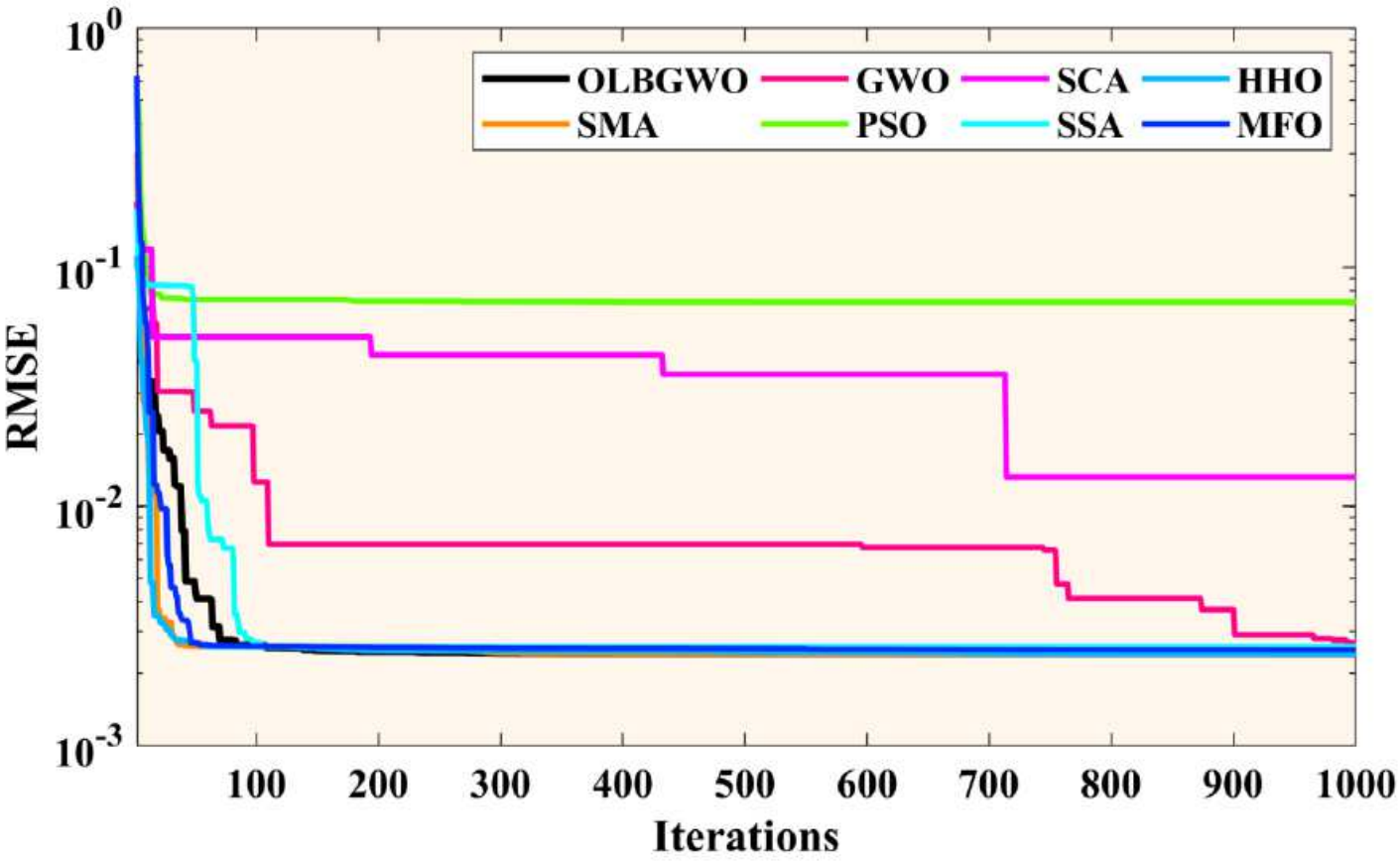

Figure 12

Convergence curve of all algorithms for the PV module model

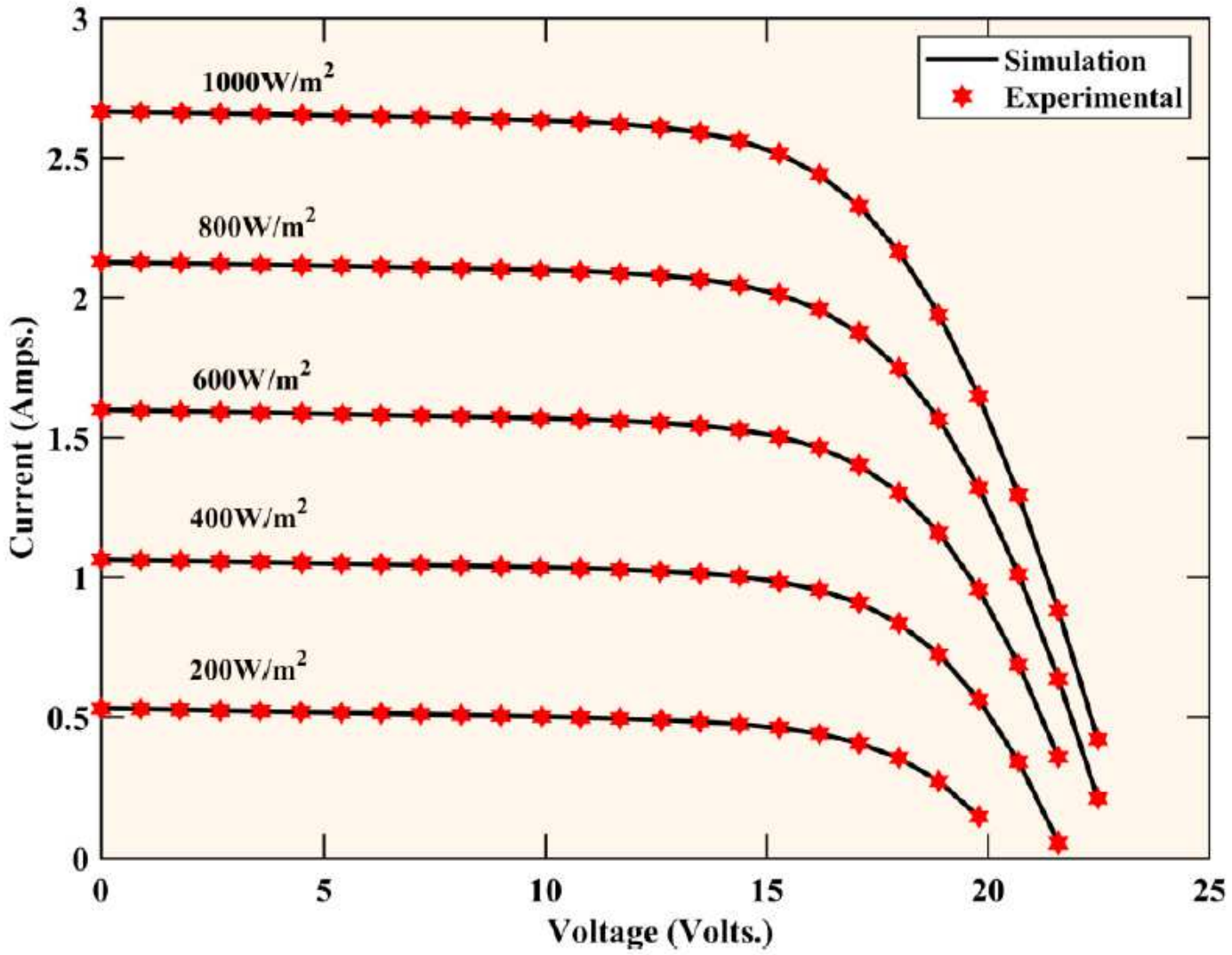

Figure 13

I-V characteristics of ST40 at 25°C and different irradiation

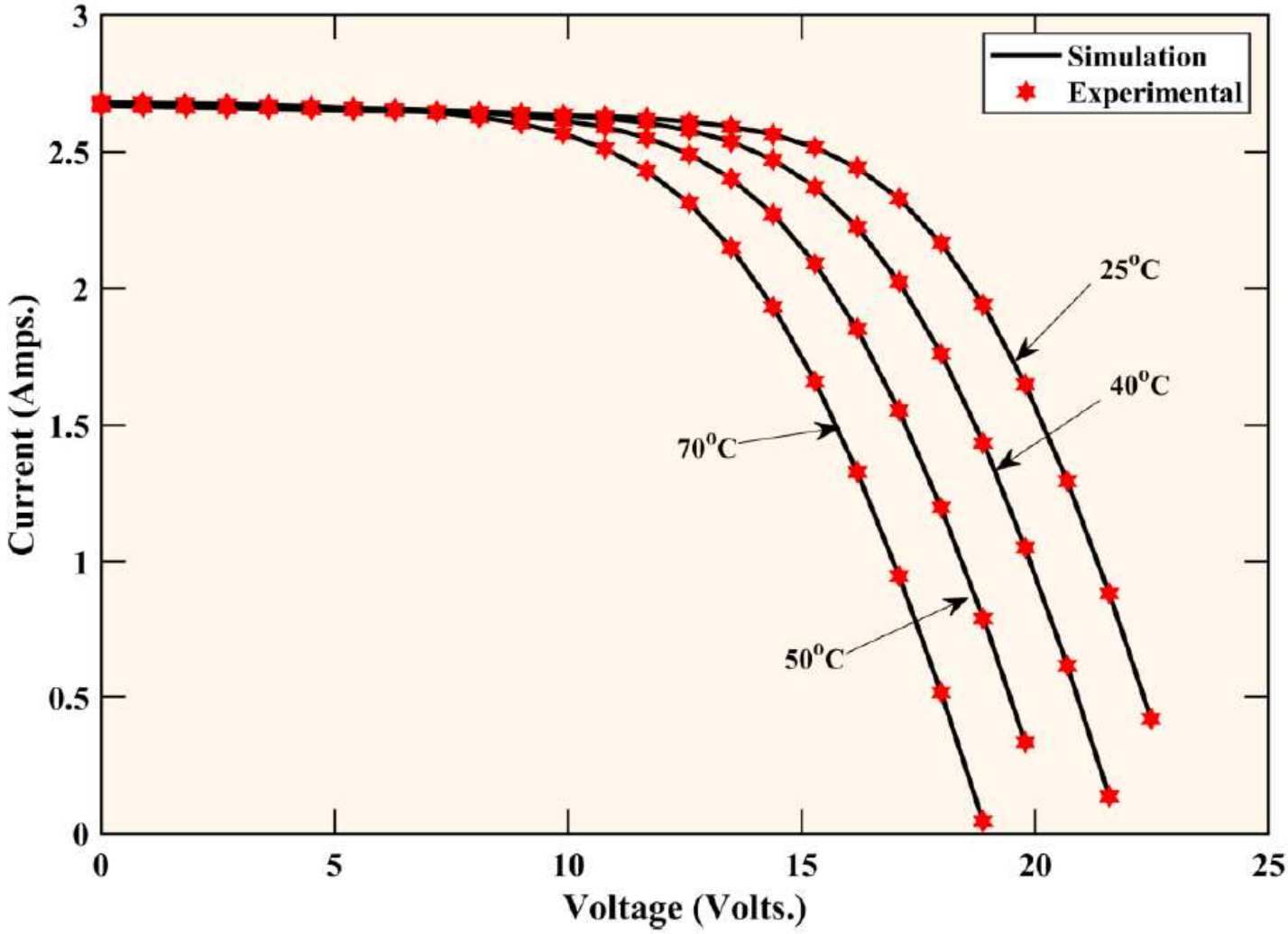

Figure 14

I-V characteristics of ST40 at 1000 W/m2 and different temperature

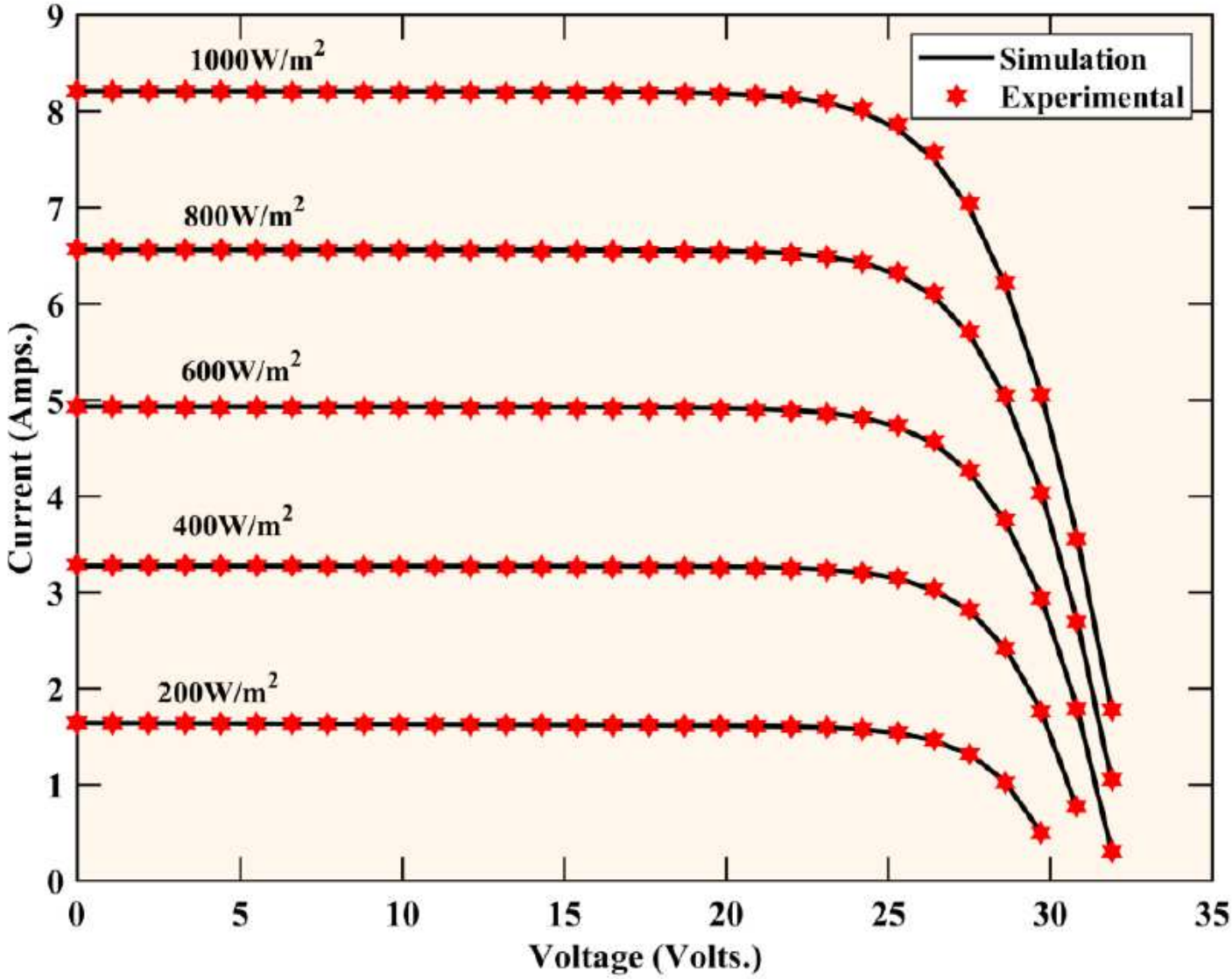

Figure 15

I-V characteristics of KC200GT at 25°C and different irradiation

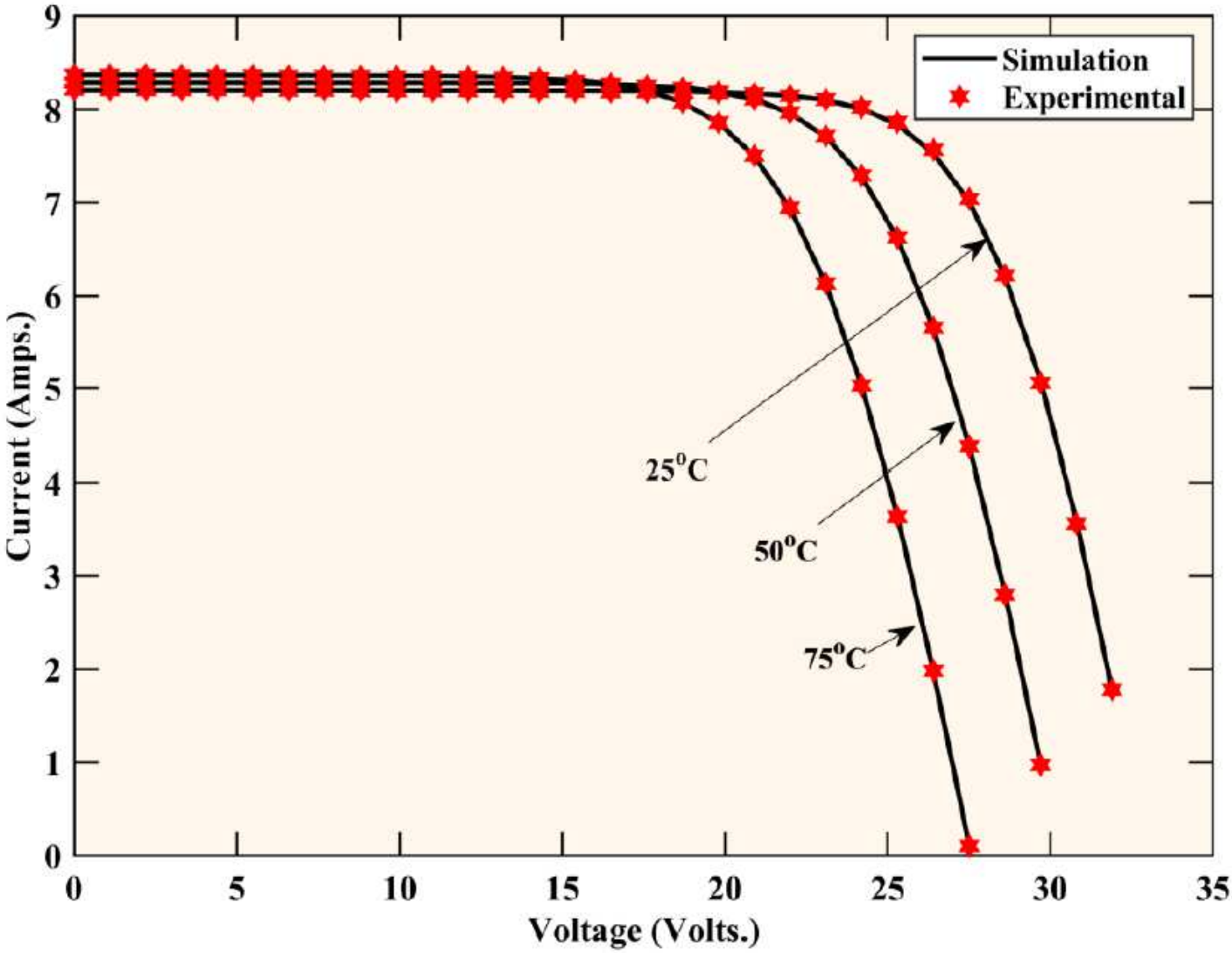

Figure 16

I-V curves of KC200GT at 1000 W/m2 and different temperature