Extraction of Uncertain Parameters of Single-Diode Photovoltaic Module using Hybrid Particle Swarm Optimization and Grey Wolf Optimization Algorithm

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Abstract. Precise photovoltaic (PV) module electrical modelling is essential because of the comprehensive system installation of PV power stations. The scientists have therefore suggested a photovoltaic single-diode model (SDM) for effective PV modelling. The SDM is a simple and non-linear model comprising five unknown parameters. This paper, therefore, presents a novel hybrid approach called particle swarm optimization (PSO) and grey wolf optimization (GWO), in order to extract unknown parameters from the SDM model. This paper also shows a new cost function based on the values of the datasheet instead of using extensive experiments. This paper, therefore, used standard test condition (STC) data to estimate two parameters by optimizing three remaining parameters by using PSOGWO algorithm. This proposed algorithm is applied to two commercial PV panels, namely KC200GT and SQ85, to find its parameters. Following this, the I-V curves of these PV modules were plotted under STC for five individual runs of the simulation. To prove the performance of the proposed PSOGWO algorithm, it is compared based on the statistical results with other algorithms, such as GWO and hybrid GWO-cuckoo search (GWOCS).

Keywords: GWO, Parameters, Photovoltaic, PSO, Single-diode model.

1 Introduction

The solar PV energy is the renewable energy most commonly used in residential, industrial, vehicle, large power stations because of its advantages, such as low maintenance, noiseless operation, and no CO_2 emission. However, the cost competitiveness in PV markets, unstable prices, and political aspects of fossil fuels have significantly enhanced investment in PV [1-2]. For PV investigations, such as maximum power tracking, thermodynamic impacts, partial shades of PV [3-5] and stand-alone or grid-tied photovoltaic systems, accurate PV modelling and simulation is thus essential [6]. Then, the researchers recommended the exact electrical modelling of the PV module by analysis of the internal structure of the PV cell. Ideally, the PV cells are modelled using the single-diode model (SDM), double-diode model (DDM), and three-diode model, however, due to simplicity, most of the researchers consider SDM alone for their further applications. Thus, an electrical equivalent of the PV cell/module includes a current source (I_p) in parallel with diode and shunt resistance (R_{sh}), and then connected with a series resistance (R_{se}). In this model, the diode is modelled by a non-linear exponential expression with three parameters, such as photocurrent (I_p), ideality factor (a), and reverse saturation current (I_{sd}). Then, for SDM, there are five unknown parameters, such as I_p, R_{sh}, R_{se}, a, and I_{sd} [7].

In literature, mostly the researchers preferred SDM or DDM for the estimation of electrical parameters of the PV cell/module. The researchers have tried using analytical methods, iterative methods, meta-heuristics methods, or its combination with analytical and iterative methods to estimate the unknown parameters of the photovoltaic modules. In some of the analytical techniques, the datasheet values at STC and nominal operating cell temperature (NOCT) are used. Nevertheless, the analytical methods use rough solutions due to the assumption of constant values for R_{se} and R_{sh}. Some methods, such as the Lambert function and bond graph model ignores the value of R_{se} or R_{sh}. Few iterative methods, such as least squares, Gauss-Seidel, and Newton-Raphson, are used for parameter estimation problems. Nevertheless, due to the drawbacks, such as ignoring few parameters, assumption off constant values, and incorrect initial value selection, iterative and analytical methods are not preferable. Nowadays, metaheuristics algorithms are utilized to estimate the parameters of both SDM and DDM by minimizing the error or objective function [8]. In most of the literature, the root-mean-square error (RMSE) is considered as the objective function, in which RMSE is defined as the root of the average of the current difference between the experimental data and the estimated data. To do this, many algorithms, such as PSO, GWO, whale optimization, artificial bee colony, Jaya optimization, teaching-learning optimization, firefly optimization, Rao algorithms, slime mould optimization, salp swarm optimization, etc. and many hybrid versions of above-said algorithms [9]. Nevertheless, to minimize the RMSE, the experimental data of the cell/module is required, which is not present in datasheet provided by the manufacturer. Thus, the researchers proposed an alternate objective function and then applied algorithms to estimate the parameters of the module. But, the selection of upper and lower bounds of optimized parameters is the main drawback of above-said methods. Recently, the most of the researchers used SDM for the parameter estimation problems of the PV module and therefore, the optimization methods, such as PSO, WOA, Rao, Coyote optimization are applied to extract the five uncertain parameters of the PV module [10]. Nevertheless, no optimization algorithm can find the global optimum solution for all engineering problems based on no free lunch theory. This motivates the researchers to apply new algorithms to find the optimal values of five parameters of the SDM of the PV module.

Recently, the authors of [11] introduced a new hybrid algorithm called PSOGWO by combining the PSOs exploitation ability with GWO’s exploration ability. In which, the particles of the PSO algorithm is replaced by a particle enhanced with GWO. In

hybrid PSOGWO, the GWO algorithm helps the PSO to minimize the opportunity of dwindling to a local optimum. The inventors of this algorithm tested PSOGWO using classical engineering problems and benchmark functions, but PSOGWO has not been utilized for parameter estimation problems due to its freshness.
The paper is organized as follows. Section 2 covers the mathematical modelling of the SDM and the formulation of the objective function. Section 3 covers the basic concept of PSOGWO and its application to parameter estimation problem. Simulation results are discussed in Section 4, and section 5 concludes the paper.

2 Mathematical Modelling of SDM and Problem Formulation

2.1 Mathematical Modelling

The PV module comprises several PV cells in parallel (N_{sh}) or series (N_{se}) to produce high voltage and high current. The equivalent circuit of the PV module based SDM is discussed in this section of the paper. The SDM of the photovoltaic module is represented by the current source, I_p in parallel with diode and shunt resistance, R_{sh}, and series resistance, R_{se}, as illustrated in Fig. 1 [12].

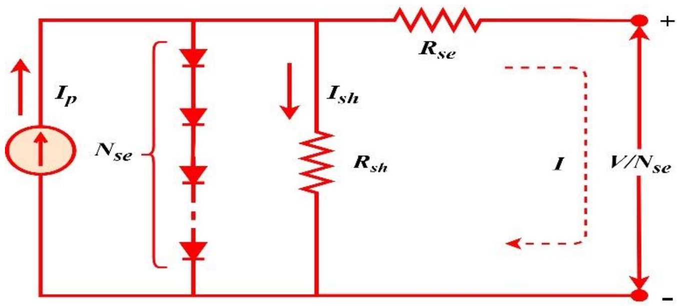


Fig. 1. Equivalent SDM circuit of the photovoltaic module

The photocurrent, I_p is changed with respect to the solar insolation. As per Shockley equation, the equation of the PV module current, I, is written as follows, in which q represents the electron charge and is equal to 1.60217×10^{-19} C, T denotes the absolute temperature of the module, the output voltage of the PV module is denoted as V, and k denotes the Boltzmann constant which is equal to 1.3806×10^{-23} J/K.

$$I = I_p - I_{sd}\left[exp\left(\frac{q(V + IR_{se})}{akTN_{se}}\right) - 1\right] - \frac{(V + IR_{se})}{R_{sh}} \tag{1}$$

The analysis is further made by considering the operating points, such as short-circuit, open-circuit, and maximum power point (MPP). By considering these points, Eq. 1 is modified as follows. The short-circuiting the PV module is the first condition and substitute the voltage $V=0$, and current $I=I_{sc}$ in Eq. 1 and the expression for the photocurrent is written as follows.

$$I_p = I_{sc} + I_{sd}\left[exp\left(\frac{qR_{se}I_{sc}}{akTN_{se}}\right) - 1\right] + \frac{R_{se}I_{sc}}{R_{sh}} \tag{2}$$

The open-circuiting the PV module is the second condition and substitute the voltage $V=V_{oc}$ and current $I=0$ in Eq. 1 and the expression for the photocurrent are written as follows.

$$I_p = I_{sd}\left[exp\left(\frac{qV_{oc}}{akTN_{se}}\right) - 1\right] + \frac{V_{oc}}{R_{sh}} \tag{3}$$

From Eq. 2 and Eq. 3, the equation for the diode reverse saturation current is written in Eq. 4, and by substituting Eq. 4 in Eq. 3, the expression for the photocurrent is written in Eq. 5.

$$I_{sd} = \frac{I_{sc} + \frac{R_{se}I_{sc}}{R_{sh}} - \frac{V_{oc}}{R_{sh}}}{exp\left(\frac{qV_{oc}}{akTN_{se}}\right) - exp\left(\frac{qR_{se}I_{sc}}{akTN_{se}}\right)} \tag{4}$$

$$I_p = \frac{\left[I_{sc} + \frac{R_{se}I_{sc}}{R_{sh}} - \frac{V_{oc}}{R_{sh}}\right]\left[exp\left(\frac{qV_{oc}}{akTN_{se}}\right) - 1\right]}{exp\left(\frac{qV_{oc}}{akTN_{se}}\right) - exp\left(\frac{qR_{s}I_{sc}}{akTN_{se}}\right)} + \frac{V_{oc}}{R_{sh}} \tag{5}$$

The MPP of the PV module is the third condition and substitute the voltage $V=V_{mpp}$ and current $I=I_{mpp}$ in Eq. 1 and the current equation is as follows.

$$I_{mpp} = I_p - I_{sd}\left[exp\left(\frac{q\left(V_{mpp} + I_{mpp}R_{se}\right)}{akTN_{se}}\right) - 1\right] - \frac{\left(V_{mpp} + I_{mpp}R_{se}\right)}{R_{sh}} \tag{6}$$

2.2 Problem Formulation

In the problem formulation, the points at which open-circuit, short-circuit, and MPP is considered. The two parameters, such as (I_{sd} and I_p) is estimated analytically and three parameters, such as (R_s, R_p and a) optimized by using PSOGWO of the PV module. The formulation and solution of the objective function must guarantee that the target performance attained for the PV panel complies with the I-V relation. Thus, to minimize errors in the operating points, an advanced optimization algorithm is required. By considering all the facts, the objective function of the module is written as follows.

$$F_1 = I_{sc} + I_{sd}\left[exp\left(\frac{qR_{se}I_{sc}}{akTN_{se}}\right) - 1\right] + \frac{R_{se}I_{sc}}{R_{sh}} - I_p \tag{7}$$

$$F_2 = I_{sd}\left[exp\left(\frac{qV_{oc}}{akTN_{se}}\right) - 1\right] + \frac{V_{oc}}{R_{sh}} - I_p \tag{8}$$

$$F_3 = I_p - I_{mpp} - I_{sd}\left[exp\left(\frac{q\left(V_{mpp} + I_{mpp}R_{se}\right)}{akTN_{se}}\right) - 1\right] - \frac{\left(V_{mpp} + I_{mpp}R_{se}\right)}{R_{sh}} \tag{9}$$

The final objective function, F_T is written in Eq. 10.

$$F_T = {F_1}^2 + {F_2}^2 + {F_3}^2 \tag{10}$$

The value of Eq. 10 is reduced as small as possible by utilizing the values from the datasheet. The two parameters of the PV module are estimated by optimizing three variables by the solution vector as minimum as possible.

3 Hybrid PSOGWO and Its Application

A hybrid approach has been formulated by means of combining PSO and GWO algorithms that produce productive and fruitful results [11].

3.1 PSO Algorithm

As discussed in the literature, PSO is a practical algorithm for most of the engineering applications, and it is based on social actions of birds grouping during food search. The initial solution of PSO is randomly generated within the search space. The optimal position and location of each particle are kept in memory, and the particles are updated using the following equations.

$$\overline{X}_{q+1}^{i} = \overline{X}_{q}^{i} + \overline{V}_{q+1}^{i} \tag{11}$$

$$\overline{V}_{q+1}^{i} = w\overline{V}_{q}^{i} + c_1 r_1 \left(\overline{p}_{q}^{i} - \overline{X}_{q}^{i}\right) + c_2 r_2 \left(\overline{p}_{q}^{g} - \mathrm{X}_{q}^{i}\right) \tag{12}$$

Where the particles are represented as i, the iterations are denoted as q, and the random numbers are denoted by r_1 and r_2 between [0,1], w denotes the parameter weight, the position vector is denoted as X, the particle velocity is V, the coefficients are denoted as c_1 and c_2, $\overline{p}_{q}^{i}$ is current best of the particle and $\overline{p}_{q}^{g}$ is the best position exists in the swarm. The new velocity and position of the particles are not known with insignificant option. As an alternative, it is substituted in the search space by a random position to avoid local optimum solutions.

3.2 GWO Algorithm

With the inspiration of grey wolf leadership, the grey wolf algorithm is developed, and it has been used for a few engineering problems. There are four wolves in the hierarchy, and alpha wolves denote the best solution, beta wolves and delta wolves denote second and third optimal results, and omega wolves denote the candidate with best result. The hunting mechanism of the wolf is as follows. (i) Tracing and reaching the prey, (ii) Chasing, encircling and troublesome the prey to stop its move, (iii) Finally, attacking. The mathematical model of the prey encircling is given in Eq. 13.

$$D = \left|C \times X_{\mathrm{p}}(q) - X(q)\right| \tag{13}$$

$$X(q+1) = X_{\mathrm{p}}(q) - A \times D \tag{14}$$

Where the iteration is denoted as q, the prey position is represented by X_{p}, the wolf location is denoted by X, and the coefficient is denoted by C and A. The value of these coefficients is calculated using Eq. 15 and Eq. 16, respectively. In which, a is linearly reducing from 2 to 0, as q decreases.

$$C = 2 \times r_2 \tag{15}$$

$$A = a \times (2 \times r_1 - 1) \tag{16}$$

The alpha wolf leads the Grey wolves to find the prey location, and beta wolf and delta wolf also helps to find the location sometimes. The other wolves in the population follow the position of these three wolves to find the best solutions and the same is modelled as follows.

$$\begin{aligned} D_\alpha &= |C_1 \times X_\alpha - X(q)| \\ D_\beta &= |C_2 \times X_\beta - X(q)| \\ D_\delta &= |C_3 \times X_\delta - X(q)| \end{aligned} \tag{17}$$

The best three wolves' values are represented by X_α, X_β, and X_δ in each iteration.

$$\begin{aligned} X_1 &= |X_\alpha - a_1 D_\alpha| \\ X_2 &= |X_\beta - a_2 D_\beta| \\ X_3 &= |X_\delta - a_3 D_\delta| \end{aligned} \tag{18}$$

$$X_{\mathrm{p}}(q+1) \quad = \frac{X_1 + X_2 + X_3}{3} \tag{19}$$

Where $X_{\mathrm{p}}(q+1)$ denotes the new position of the prey. The value of *A* decides the trap of local optima, i.e. if the value of *A* is larger than or equal to 1, the hunt is abandoned elseif *A* value is less than 1, wolves attack the prey forcibly. The search process completed when the maximum number of iterations is reached.

3.3 Application of a Hybrid PSOGWO Algorithm

Without altering the overall operation of the GWO and PSO algorithms, a new hybrid PSOGWO algorithm has been established for parameter estimation problems. In all real-world problems, the PSO algorithm can be efficient. Nevertheless, some best solution is needed to avoid the local optimum trap. The GWO helps the PSO to decrease the possibility of evading the local optimum trap. As discussed earlier, the PSO algorithm guides such particles at random positions that are small to prevent local minima. In order to prevent the risk of local minimum trap, the exploration capabilities of the GWO are used to direct certain particles into positions that are partially enhanced rather than random positions. The run time is, however, long because, besides the PSO, the GWO algorithm is also employed. The achievement of better results can tolerate additional time, as long as the result is achieved in a viable time.

The pseudocode of the PSOGWO is given in Algorithm. The comprehensive details are available in [11] for better understanding. The required control parameters to apply the proposed PSOGWO algorithm for the extraction of solar photovoltaic parameter problem are listed in Table 1.

Algorithm. PSOGWO Algorithm

```
Initialize population size (np) and maximum iterations (q_max)
P: Possibility rate
Particles Initialization
For i=1 to q_max do
For l=1 to np do
  Execute PSO algorithm
  Update the particle position and the velocity
    If rand(0,1) < P then          % to evade local optima
        Set A, C, a
      For j = 1 to 10 do
      For m = 1 to 10 do
          Run GWO Algorithm
          Update the positions of α, β, δ
          Update A, C, a
      End for
      End for
      Current position, X_p(q + 1) = (X_1+X_2+X_3)/3
    End if
End for
End for
```

Table 1. Control parameters of the PSOGWO

User Parameters	SDM
Dimension, *dim*	3
Number of particles, *np*	30
Maximum iteration, q_{max}	1000
Constant parameters, c_1 and c_2	0.5
Weight, *W*	Update by GWO
Optimized variables, $[Y_{lb}, Y_{ub}]$	R_{sh} = [50, 200] Ω, R_{se} = [0.001. 1] Ω, *a* = [1, 2]

The decision variable range is wider, which leads to better fitness for the optimization of the SDM of the PV module. The execution of PSOGWO algorithm is carried out by MATLAB 9.4 using Core i3-4110 laptop.

4 Simulation Results and Discussions

The proposed PSOGWO algorithm is applied to various commercial PV modules, such as KC200GT and SQ85, and the simulation results are presented in this section.

The simulation of the proposed algorithm is carried out for five individual runs to check the performance of the algorithm. The datasheet information of the PV modules is listed in Table 2.

Table 2. Specification of the PV modules

Parameters	KC200GT	SQ85
Maximum power output, P_{mpp}, in Watt.	200	85
Short-circuit current, I_{sc} in Amps.	8.21	5.45
Open-circuit voltage, V_{oc} in Volts.	32.9	22.2
Current at MPP, I_{mpp} in Amps.	7.61	4.95
Voltage at MPP, V_{mpp} in Volts.	26.3	17.2
Number of cells in series, N_s	54	36

The five individual I-V curves of the KC200GT PV module are shown in Fig. 2. Each curve is different, and the variations of curves are due to R_{sh}, R_{se} and n. The estimated parameters and the optimized of the KC200GT module are listed in Table 3.

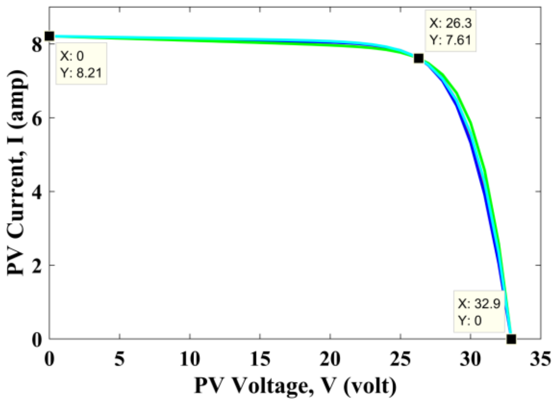


Fig. 2. I-V curves of the KC200CT module

All the five I-V curves are passed through 8.21 A; 26.3 V, 7.61 A; 32.9 V, as shown in Fig. 2. The scatter plot of all the algorithms is displayed in Fig. 3(a) and it explains the distribution of the search parameters in the search space. The PSOGWO tries to find the optimal values by targeting zero error during the optimization process. It is also conferred that single I-V curve is applicable for the module; however, with limited information, such as V_{oc}, I_{sc}, V_{mpp} and I_{mpp}, it is impossible to generate the same. Therefore, multiple I-V curves are displayed during each run of the algorithm; however, each run produces optimal parameter solution.

Table 3. Unknown parameters of the KC200CT module

Run no.	a	R_{sh} (Ω)	R_{se} (Ω)	I_p (A)	I_{sd} (A)	F_T
1	1.2774	135.2433	0.1739	8.2206	6.91E-08	1.19E-14
2	1.4202	137.6824	0.0984	8.2159	4.47E-07	1.58E-12
3	1.2325	127.3428	0.1920	8.2224	3.51E-08	7.84E-14

4	1.3411	84.6364	0.0613	8.2159	1.64E-07	2.11E-13
5	1.4957	173.1386	0.0807	8.2138	1.05E-06	1.52E-14

If experimental data is available, it is straightforward to get single I-V curve. However, the I-V relation is extracted only when the target error reaches zero. In this paper, the error value more than 1E-12 is considered as zero error. All the extracted parameters are considered for further analysis since the researchers looking at the parameters only on the MPPs. The best and worst I-V curve during five runs of simulation is displayed in Fig. 3(b) and it is observed that both best and worst curves almost match with the I-V curve provided by the manufacturer under STC. From Fig. 3(a), it is also noted that, in PSOGWO and GWOCS, broad search has occurred on throughout the search space. However, the GWO fails to search the solution in search space, and it is trapped by local optima.

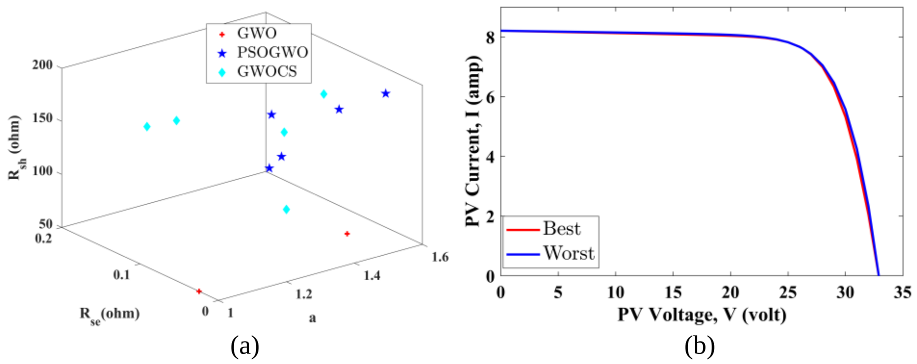


Fig. 3. KC200CT module; (a) Scattered plot; (b) Best and worst I-V curves

The simulation is also extended to SQ85 PV module and I-V curves during five individual runs are plotted in Fig. 4, in which, all the plots are passed through 5.45 A; 17.2 V, 4.95 A; 22.2 V.

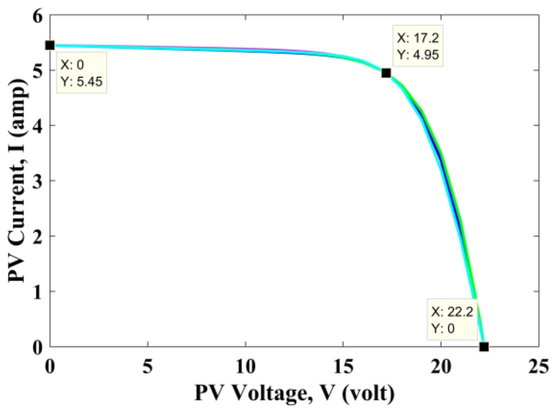
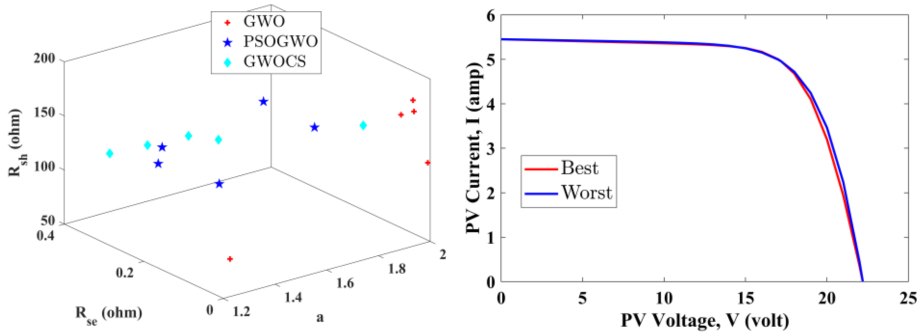


Fig. 4. I-V curves of the SQ85 module

The estimated/calculated parameters and the optimized of the KC200GT module are listed in Table 4. As similar to the previous case study, the optimal parameters are obtained by achieving zero error using PSOGWO algorithm during all the runs of the simulation. The scatter plot of all the algorithms is displayed in Fig. 5(a) and it explains the distribution of the search parameters in the search space. From Fig. 5(a), it is also noted that, in PSOGWO and GWOCS, broad search has occurred on throughout the search space. However, the GWO fails to search the solution in search space, and it is trapped by local optima. The best and worst I-V curve during five runs of simulation is displayed in Fig. 5(b).

Table 4. Unknown parameters of the SQ85 module

Run no.	a	R_{sh} (Ω)	R_{se} (Ω)	I_p (A)	I_{sd} (A)	F_T
1	1.5211	97.0422	0.2193	5.4623	7.34E-07	1.393E-14
2	1.6660	166.4632	0.2022	5.4566	2.95E-06	9.780E-15
3	1.4216	123.9053	0.2983	5.4631	2.46E-07	6.670E-12
4	1.7695	146.3195	0.1411	5.4552	6.82E-06	1.829E-15
5	1.4032	110.3144	0.2960	5.4646	1.96E-07	1.360E-13

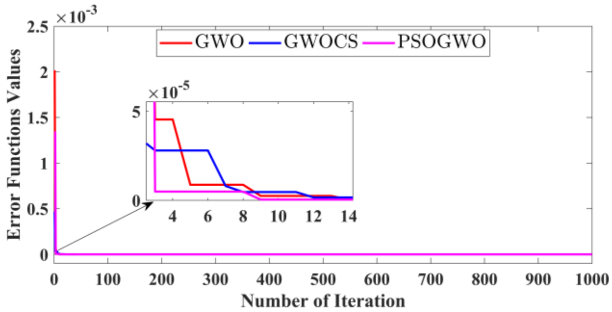


(a) (b)

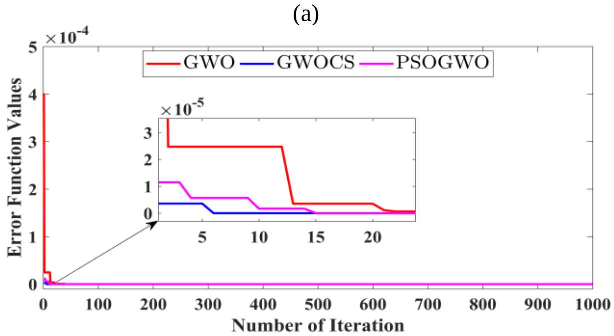
Fig. 5. SQ85 module; (a) Scattered plot; (b) Best and worst I-V curves

4.1 Comparison study

The effectiveness of the proposed hybrid PSOGWO for the parameter estimation problem is compared with GWO and GWOCS. The cost function is the same for all the algorithms which minimize the error to zero. The number search agents and a maximum number of iterations are equal to 30 and 1000, respectively, for all algorithms. The convergence curve of all algorithms is presented in Fig. 6, and it is observed that the PSOGWO algorithm attained quicker convergence than other algorithms. The summary of the statistical results is presented in Table 5 for various algorithms. The PSOGWO and GWOCS algorithms can able to produce less error during all runs.



(a)



(b)

Fig. 6. Convergence curves, (a) KC200CT, (b) SQ85

Table 5. Statistical results of GWO, PSOGWO, and GWOCS algorithms

Module	Algorithms	F_T Max	Min	Median	Standard Deviation	Run Time (S)
KC200CT	PSOGWO	7.65E-15	0.0020	2.17E-13	6.66E-07	5.50
	GWOCS	9.04E-12	0.0005	9.32E-10	1.49E-05	6.25
	GWO	1.52E-11	0.0013	2.54E-10	5.98E-04	4.55
SQ85	PSOGWO	2.49E-15	0.0004	8.49E-12	1.29E-07	5.42
	GWOCS	1.45E-13	3.57E-06	1.03E-09	2.52E-05	6.58
	GWO	1.36E-11	1.15E-05	1.52E-08	7.74E-04	4.54

However, GWO fails and trapped to an optimum local value. But, the GWO is observed to be quickest, followed by the PSOGWO and GWOCS. Due to the hybridization, the computation time is high for PSOGWO and GWOCS algorithms. The error values are observed to be less than 1E-12, and it can be considered as zero error for engineering problems.

5 Conclusion

A new hybrid PSOGWO algorithm is applied to the photovoltaic module parameter estimation problem, and the same is studied in this paper. Two parameters are analytically estimated, and the other three unknown parameters are optimized by PSOGWO algorithm. The proposed PSOGWO algorithm finds the optimal solution by achieving zero-error values during all runs of the simulation. Since the proposed method utilizes the information from the datasheet, there is no possibility of getting single I-V curve; however, each curve is optimal, and it can be useful for the researchers for their further applications. The experimental results and statistical results summary are presented for two commercial PV modules. The experiments are carried out for STC; however, it can be extended to other environmental conditions.

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