ACTA IMEKO
ISSN: 2221-870X
June 2024, Volume 13, Number 2, 1 - 10

Modelling photovoltaic modules with enhanced accuracy using particle swarm clustered optimization

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ABSTRACT
Accurately simulating and operating photovoltaic (PV) modules is vital for thoroughly analyzing their performance under different conditions. The main focus of this paper is to address the inherent nonlinearity in solar PV systems. To achieve this, the particle swarm clustered optimization (PSCO) is applied to extract parameters of solar modules, allowing for a more comprehensive understanding of their behavior. PSCO aims to enhance the accuracy and effectiveness of PV module analysis. For that, PSCO utilizes clusters within the particle population, enabling localized communication and information sharing. By doing so, it effectively facilitates efficient exploration and exploitation of diverse regions, fostering a comprehensive understanding of the behavior of PV modules under different conditions. Through this approach, PSCO maximizes the accuracy and effectiveness of parameter extraction, contributing to advancements in PV system analysis and performance evaluation. The effectiveness of PSCO is demonstrated in extracting parameters for the three-diode model (TDM) of the STP6-120/36 and Photowatt-PWP201 PV modules. PSCO surpasses state-of-the-art algorithms with significantly low root mean square error (RMSE) values of 0.0145 A and 0.0019 A, showcasing its superior accuracy. Additionally, PSCO achieves the lowest power errors of 0.16054 W and 0.01484 W for the respective modules, emphasizing its excellent performance.

Section: RESEARCH PAPER

Keywords: Particle Swarm Clustered Optimization (PSCO); PV parameter extraction; PV modelling; solar PV

Citation: El marghichi Mouncef, Abdelilah Hilali, Azeddine Loulijat, Abdelhak Essounaini, Abdelkhalek Chellakhi, Modelling photovoltaic modules with enhanced accuracy using particle swarm clustered optimization, Acta IMEKO, vol. 13 (2024) no. 2, pp. 1-10. DOI: 10.21014/actaimeko.v13i2.1699

Section Editor: Laura Fabbiano, Politecnico di Bari, Italy

Received October 23, 2023; **In final form** March 23, 2024; **Published** June 2024

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1. INTRODUCTION

Humanity's survival and progress rely on accessible and sustainable energy. Traditional energy sources are depleting, leading to ecological decline. To address this, a transition to renewable energy is crucial. These sources are environmentally friendly, abundant, and versatile, offering solutions to ecological concerns [1].

Significant progress has been made in harnessing renewable energy sources, such as solar and wind power, leading to increased energy production [2]. Photovoltaic (PV) technology has played a crucial role in various applications, including satellite power, water desalination, and heating/cooling systems [3], [4]. Accurate simulation and modeling of solar cells have been achieved through numerical simulation and adaptive control methods [5], [6].

Photovoltaic cells are constructed using a P-N junction semiconductor material that comprises several distinct regions: the quasi-neutral, space-charge, and defect regions. These regions introduce losses due to charge carrier recombination and diffusion, making it essential to consider them when developing a photovoltaic model. Various approaches are used in PV models to address these losses. The single-diode model (SDM) is a popular choice due to its simplicity and efficiency, allowing it to represent losses in the quasi-neutral region. For increased accuracy, the double-diode model (DDM) is employed, which incorporates losses in both the SDM and space-charge region. Moreover, the three-diode model (TDM) offers even higher precision by encompassing losses in the defect region in addition to those already considered in the DDM [7].

Accurate modeling is crucial for optimizing and deploying photovoltaic systems, demanding precise parameter estimation for PV cell models [8]. Yet, the nonlinear and nonconvex nature of PV models presents substantial challenges. To address these hurdles, three distinct techniques for parameter estimation have been developed by researchers: analytic, deterministic, and metaheuristic approaches [9]. These approaches are utilized to guarantee the precise estimation of PV model parameters and improve the overall efficiency of PV system optimization and implementation.

Analytic methods rely on specific data points and formulate simple equations for parameter estimation. While fast and convenient, they depend on accurate manufacturer data and may be affected by PV degradation over time [10], [11].

Deterministic methods utilize multiple measurements to accurately ascertain the unknown parameters and employ a loss function to measure the difference between predicted and actual data points. These approaches have the potential to converge to local optimal solutions since they depend on gradient information. Evolutionary-based algorithms, such as the Differential Evolution Algorithm (DEA) and Genetic Algorithm (GA), apply evolutionary principles to tackle the parameter estimation problem [12]-[14].

Extracting parameters from photovoltaic models is a multifaceted endeavor due to the intricate nature of these models, which involve nonlinearity and an abundance of parameters. In pursuit of precise parameter estimation, the field has witnessed a surge in the utilization of metaheuristic techniques, attracting considerable attention. To address the complexities of this task, various methodologies have been introduced in academic research.

Among these methodologies is the Grey Wolf Optimizer combined with Cuckoo Search Algorithm, referred to as GWOCS, and documented in [15]. GWOCS is meticulously crafted to strike an equilibrium between the exploitation and exploration of search space, with a pronounced focus on enhancing the accuracy of parameter extraction. Another notable methodology, the Multiple Learning Backtracking Search Algorithm (MLBSA), put forth in [16], sets its sights on delivering dependable and precise parameter estimations for photovoltaic models.

In the study outlined in [17], researchers opted to employ the Gradient-Based Optimizer (GBO) to estimate parameters across three distinct PV models: SDM, DDM, and TDM. The findings from this investigation effectively underscore the prowess of GBO, as it adeptly achieves both accurate modeling and robust simulation of photovoltaic modules.

In a different vein, the Sunflower Optimization Algorithm (SFO), as introduced in [18], leverages the graceful movement of sunflowers toward sunlight as its guiding principle. Remarkably, the experiments conducted within this study yielded error rates consistently below 0.5%, serving as a testament to the effectiveness of SFO in achieving intricate and precise modeling and simulation, especially in the context of the three-diode PV model.

The modified JAYA algorithm, unveiled in [19], presents a noteworthy approach for the accurate modeling of current and voltage characteristics of solar cells. This adaptively modified algorithm exhibits superior robustness and precision in comparison to its counterparts, thus advancing the state-of-the-art in parameter estimation.

Diving deeper into the realm of research, the Whale Optimization Algorithm (WOA) has taken center stage, as evidenced by its application in parameter estimation for single, double, and three-diode PV models, detailed in [20]. The models underwent meticulous validation through rigorous simulations under diverse conditions and were judiciously benchmarked against other optimization methods and experimental data.

The realm of parameter extraction for photovoltaic models has also witnessed the emergence of novel hybrid strategies that amalgamate multiple techniques. These innovative hybrid approaches, expounded upon in references [21]-[25], are carefully designed to amalgamate the unique strengths of different optimization methods. The resultant synergy significantly bolsters the precision and resilience of parameter estimation, thereby contributing to the state-of-the-art in the field.

1.1. Paper objective

The NFL theorem [26] states that no single metaheuristic optimization technique can universally solve all optimization problems, emphasizing that the effectiveness of an optimizer on one set of problems does not guarantee similar performance on another. Widely accepted, this theorem serves as the foundation for adapting existing techniques for new problem domains.

Extensive explorations in the realms of solar cell parameter estimation and the application of metaheuristic techniques have unveiled a host of limitations and challenges that researchers grapple with. Some of the prominent challenges encompass issues linked to non-adaptive weight metrics, sluggish computational speed, the ever-looming threat of converging into local optima, and the pivotal need to minimize root mean square error (RMSE) values. It is these realizations and challenges that have ignited the spark of innovation among researchers, propelling them to seek ground-breaking solutions and devise highly efficient methodologies to overcome these inherent shortcomings.

This article introduces a search mechanism, the Particle Swarm Clustered Optimization (PSCO) algorithm, to effectively estimate PV cell parameters, specifically for the three-diode model (TDM). PSCO utilizes clusters within the particle population to facilitate localized communication and information sharing, enabling efficient exploration and exploitation. The dynamic nature of the algorithm allows it to adapt to the changing search space and determine optimal photovoltaic parameters.

The PSCO algorithm shows robust performance with high precision, convergence, and a balanced approach to exploration and exploitation. This study aligns with the NFL theorem and leverages the PSCO algorithm's success. The proposed solution quickly achieves optimal global values, demonstrating its efficacy and efficiency.

The algorithm's performance is validated on real solar modules, including STP6-120/36 and Photowatt-PWP201. It is compared against six robust strategies, confirming its robustness, speed, and effectiveness for parameter estimation in photovoltaic models.

In summary, this investigation yields a set of noteworthy contributions:

- Introduction of an innovative PSCO methodology tailored for parameter estimation in the TDM, resulting in a significant reduction in the loss function.
- A comprehensive comparative analysis that pits the PSCO algorithm against six modern and robust counterparts across four different PV modules, namely, STP6-120/36 and Photowatt-PWP201.
- Thorough verification of the algorithm's effectiveness through the meticulous evaluation of absolute power and current errors.
- The execution of simulations for I-V and P-V curves, utilizing the parameter values obtained through the PSCO algorithm, to provide a visual validation of its remarkable efficiency.

1.2. Paper structure

The paper is structured as follows: Section 2 presents the TDM PV model and its equations. Section 3 provides an overview of PSCO method. Section 4 describes the implementation setup for the Photowatt-PWP201 and STP6-120/36 solar panels. Section 5 presents the results and discussion. Finally, the paper concludes in the last section.

2. SOLAR PV MODELLING

This section explores the mathematical models of the three-diode model (TDM) for solar PV cells and modules.

2.1. Three-Diode Model (TDM)

The photovoltaic generator consists of a current source (I_{ph}), three diodes, a resistor (R_{sh}), and a series resistor (R_s), as shown in Figure 1. By applying the principle of current division, the current from the source is divided among the diodes and parallel resistor, yielding the generated current of the photovoltaic unit, expressed as follows [27]:

$$I_{\text{out}} = I_{\text{ph}} - \sum_{k=1}^{3} I_{\text{ok}} - \frac{I_{\text{out}}\, R_{\text{s}} + V}{R_{\text{sh}}}, \tag{1}$$

In this context, n represents the quantity of parallel diodes, specifically "$n = 3$." The output voltage is denoted as "V," while the current in diode "k" is represented by "I_{ok}" and can be defined as follows [27]:

$$I_{\text{ok}} = I_{\text{stk}} \left(e^{\frac{q\,(I_{\text{out}}\, R_{\text{s}} + V)}{n_k\, K\, T}} - 1 \right), \tag{2}$$

The symbol I_{stk} represents the saturation current, and q denotes the elementary charge of an electron ($1.602 \cdot 10^{-19}$ C).

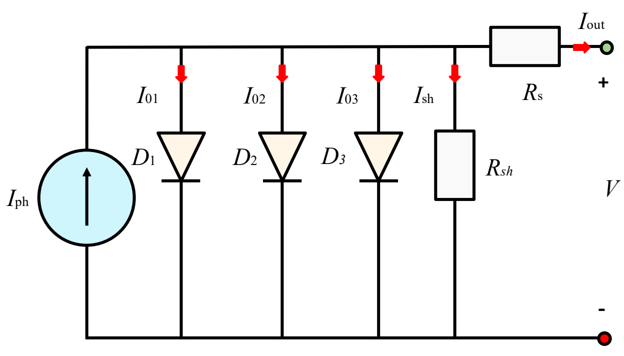

Figure 1. TDM equivalent circuit.

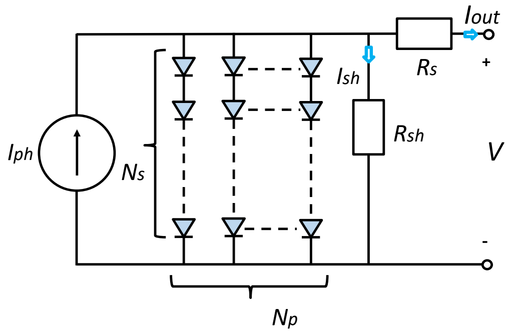

Figure 2. PV module.

Additionally, K refers to the Boltzmann constant, n_k represents the ideality factor of the diode, and T signifies the temperature in Kelvin. By combining equations (1) and (2), we arrive at the following expression [27]:

$$I_{\text{out}} = I_{\text{Ph}} - \sum_{k=1}^{3} I_{\text{stk}} \left(e^{\frac{q\,(I_{\text{out}}\, R_{\text{s}} + V)}{n_k\, K\, T}} - 1 \right) - \frac{I_{\text{out}} R_{\text{s}} + V}{R_{\text{sh}}}, \tag{3}$$

2.2. PV Module Model

The current I_{out} of a TDM-based PV module (Figure 2) with $N_s \times N_p$ solar cells arranged in series and/or parallel is expressed as [27]:

$$I_{\text{out}} = I_{\text{Ph}} - \sum_{k=1}^{3} I_{\text{stk}} \left(e^{\frac{q\left(\frac{I_{\text{out}}\, R_{\text{s}}}{N_{\text{p}}} + \frac{V}{N_{\text{s}}}\right)}{n_j\, K\, T}} - 1 \right) - \frac{\frac{I_{\text{out}}\, R_{\text{s}}}{N_{\text{p}}} + \frac{V}{N_{\text{s}}}}{R_{\text{sh}}}, \tag{4}$$

where I_{out} and V represent the current and voltage output of the PV module, respectively.

2.3. Cost function

The main objective of this study is to minimize the difference between the simulated and measured current of the solar cell. This is achieved by using the root mean square error (RMSE) as the loss function to identify the optimal values for the photovoltaic model parameters [28]. The cost function is defined based on the discrepancy between the estimated and measured current, quantified as follows:

$$F_{\text{Ob}} = \sqrt{\frac{1}{G} \sum_{h=1}^{G} |I_{\text{es}}(h) - I_{\text{mes}}(h)|^2}\ , \tag{5}$$

In the equation above, I_{es} represents the estimated current, I_{mes} represents the measured current, and G denotes the total number of data points.

3. PSCO ALGORITHM

3.1. PSO

Particle swarm optimization (PSO) is a stochastic optimization algorithm. It belongs to the category of swarm algorithms, which are inspired by the collective behaviour of birds or fishes. Unlike evolutionary algorithms that use crossover and mutation operators, PSO utilizes a different computation process to find solutions. PSO, each particle in the search space is characterized by velocity and position vectors. Initially, the particles are randomly distributed, with their position vectors initialized randomly and velocity vectors set to zero. each iteration, the position and velocity vectors of the particles are updated using the following equations:

$$v_i^{t+1} = v_i^t w + r_1 \cdot C_1 \cdot \left(P_i^{\text{best}} - x_i^t\right) + r_2 \cdot C_2 \cdot \left(G_i^{\text{best}} - x_i^t\right), \tag{6}$$

$$x_i^{t+1} = v_i^{t+1} + x_i^t, \tag{7}$$

where r_1 and r_2 are random numbers between 0 and 1, w is the inertial weight, P_i^{best}represents the best position achieved by particle i, G_i^{best} is the best position of all particles, and C_1 and C_2 are the personal and global learning coefficients, respectively.

3.2. PSCO

The Particle Swarm Clustered Optimization (PSCO) technique, introduced in [29], addresses the limitations of PSO, such as getting trapped in local solutions and failing to reach the global solution. PSCO divides particles into clusters and follows the PSO procedure until a specified iteration, I_m, where each cluster aims to find a solution. subsequent iterations, particles gain knowledge from other particles, moving towards the cluster leader and the best particle of the entire population. This strategy ensures that clusters at I_m are near different local solutions, and moving particles from local solutions to the best particle helps overcome trapping. The particle velocity vectors are updated using the following equations [29]:

$$v_i^{t+1} = w v_{i,j}^t + r_1 \cdot C_1 \cdot \left(P_{i,j}^{\text{best}} - x_{i,j}^t\right) + r_2 \cdot C_2 \cdot \left(G_j^{\text{best}} - x_{i,j}^t\right), \quad t \le I_m \tag{8}$$

$$v_i^{t+1} = w v_{i,j}^t + r_1 \cdot C_1 \cdot \left(P_{i,j}^{\text{best}} - x_{i,j}^t\right) + r_2 \cdot C_2 \cdot \left(G^{\text{best}} - x_{i,j}^t\right), \quad t > I_m, \tag{9}$$

where $P_{i,j}^{\text{best}}$ represents the best-observed position of the ith particle in the jth cluster, G_j^{best} denotes the position of the leader of the jth cluster, and G^{best} represents the best particle position [29]. The position of particles is updated using the following equation:

$$x_{i,j}^{t+1} = v_{i,j}^{t+1} + x_{i,j}^t\,. \tag{10}$$

The learning coefficients for individual and global learning, denoted as C_1 and C_2, respectively, exhibit distinct values and undergo updates during an iterative process using the following equation [29]:

$$C_1 = 1.95 - 2\left(\frac{It}{MaxIt}\right)^{\frac{1}{3}}, C_2 = 0.05 - 2\left(\frac{It}{MaxIt}\right)^{\frac{1}{3}}. \tag{11}$$

The flowchart of the Particle Swarm Clustered Optimization (Figure 3) algorithm begins with the initialization step, where a population of particles is randomly assigned positions and velocities within the search space. The algorithm then proceeds to evaluate the fitness of each particle by calculating an objective function or fitness measure. Next, the personal best position P_i^{best} for each particle is updated based on the fitness evaluation, and the global best position G^{best} is determined among all the particles.

In the velocity and position update step, the algorithm adjusts the velocity and position of each particle using its current position, velocity, P_i^{best}, and G^{best}. This allows the particles to move towards better solutions. Additionally, a cluster formation

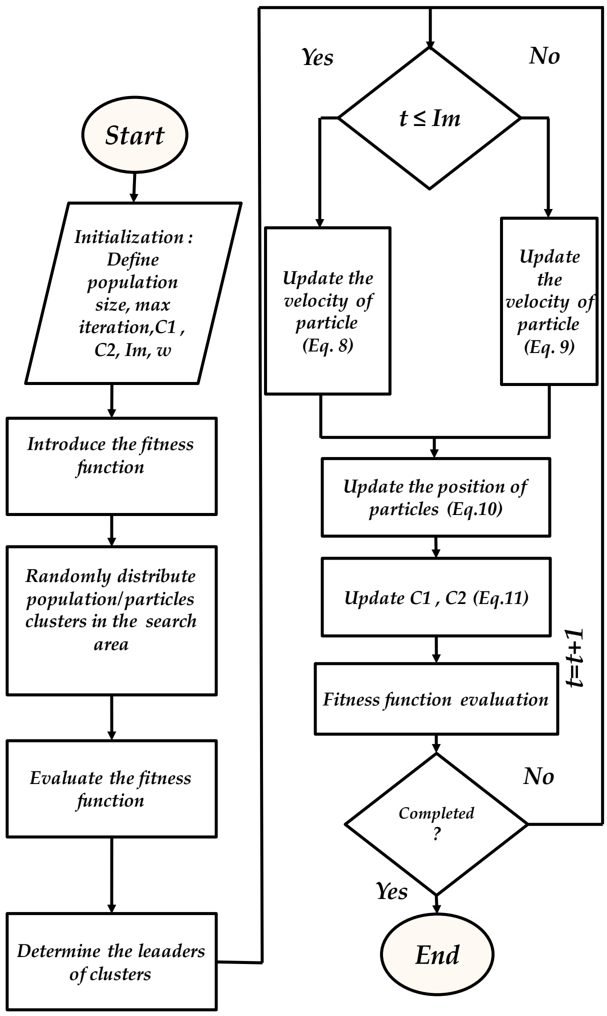

Figure 3. PSCO algorithm.

step is performed to group similar particles together, promoting exploration within each cluster.

To further refine the solutions, a local search is conducted within each cluster, enabling the algorithm to exploit the local neighborhood effectively. The algorithm continues to iterate through the fitness evaluation, position updates, cluster formation, and local search steps until a convergence criterion is met. The convergence criteria typically involve reaching the maximum number of iterations or achieving the desired solution accuracy.

3.3. The proposed PSCO for PV parameter estimation

The Particle Swarm Clustered Optimization (PSCO) algorithm is utilized for parameter extraction in the solar PV model. It begins by dividing particles into clusters and employing the Particle Swarm Optimization (PSO) procedure to find solutions up to a specified iteration. subsequent iterations, particles incorporate knowledge from both the cluster leader and the best particle in the population, enabling convergence to various local solutions while avoiding local optima traps. Figure 4 depicts the proposed algorithm for parameter extraction, which involves initializing the solar PV model, reading current and voltage measurements, and utilizing PSCO to minimize the cost function, Equation (5), and determine the best TDM model solution.

The objective is to estimate the nine parameters (I_{st3}, I_{st2}, I_{st1}, I_P, R_{sh}, R_s, n_1, n_2, and n_3) for the TDM PV modules STP6-120/36 and PWP201. Table 3 presents the lower and upper boundaries for these parameters. The performance analysis of the PSCO algorithm and the compared algorithms is carried out by examining the P-V and I-V characteristics of the modules, as shown in Figure 5 and Figure 6, respectively. The convergence curves of the loss function are depicted in Figure 7 and Figure 8, while the absolute current error is shown in Figure 9 and Figure 10. The parameters obtained using the PSCO algorithm are listed in Table 4.

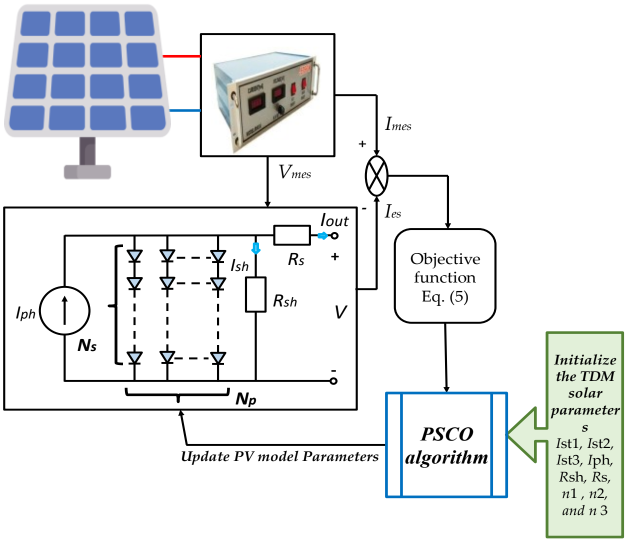

Figure 4. Proposed framework to estimate the TDM parameter WITH PSCO.

4. IMPLEMENTATION SETUP

The proposed PSCO algorithm (Figure 4) is employed to estimate the parameters of solar PV models, specifically the TDM model, using STP6-120/36 and PWP201 PV modules [30]. The algorithm's performance is evaluated by comparing it with EO (Equilibrium optimizer) [31], GWO (grey wolf optimizer) [32], RUN (Runge-Kutta optimizer) [33], SMA (slime mould algorithm) [34], WOA (whale optimization algorithm) [35], and GBO (gradient-based optimizer) [36]. The STP6-120/36 module is identified as monocrystalline, whereas the PWP201 module is classified as polycrystalline, both composed of 36 cells in series, as indicated in Table 1. To establish the solar PV model parameters, the PSCO algorithm settings are outlined in Table 2 and Table 3.

5. RESULTS AND DISCUSSION

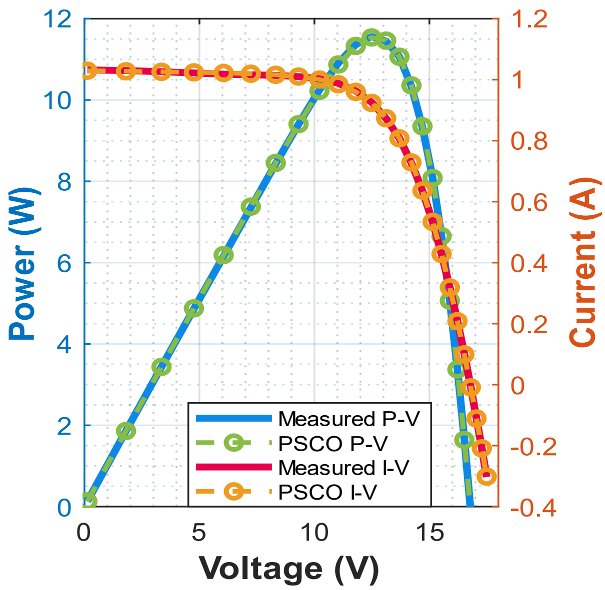

Figure 5. I-V and P-V curves (Photowatt-PWP201 module).

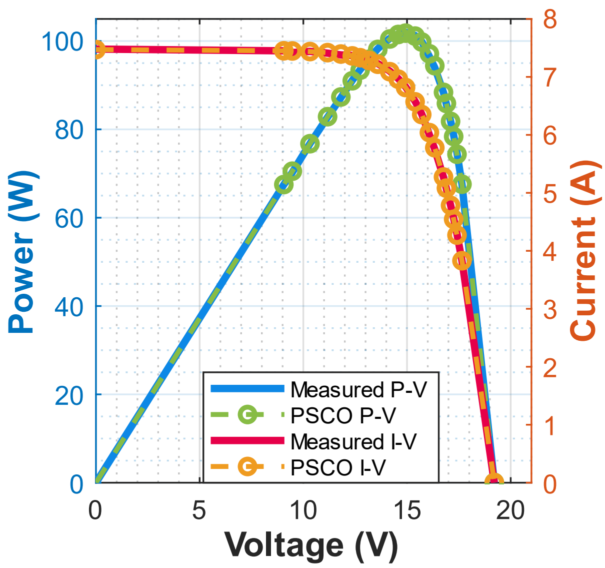

Figure 6. I-V and P-V curves (STP6-120/36 module).

Table 1. PV model.

PV type	Temp (◦C)	(Ns × Np) Cells
STP6-120/36	55	36 × 1
Photowatt-PWP201	45	36 × 1

Table 2. PSCO parameters.

PV type	Population number (N)	Number of iterations (T_{max})	number of decision variables (dim)
STP6-120/36	50	1500	9
Photowatt-PWP201	50	1500	9

Table 3. Limits of the TDM model.

Parameter	STP6-120/36		Photowatt-PWP201	
	Ub	Lb	Ub	Lb
I_{st1}, I_{st2}, I_{st3} (μA)	50	0	50	0
I_{ph} (A)	8	0	2	0
R_s (Ω)	0.36	0	2	0
R_{sh} (Ω)	1500	0	2000	0
n_1, n_2, n_3	50	1	50	1

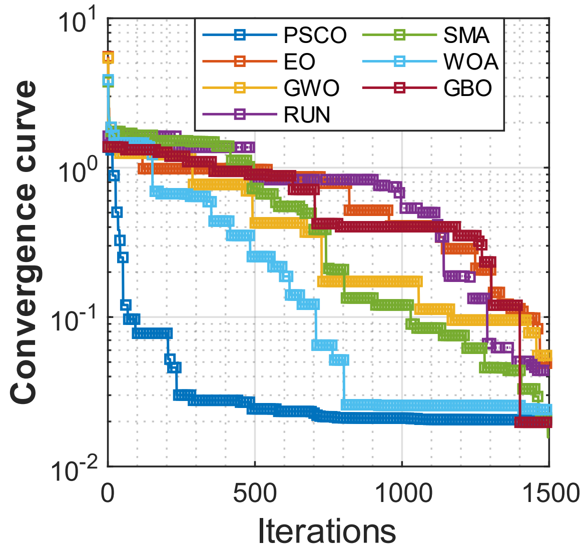

Figure 7. Fitness function (Photowatt-PWP201 module).

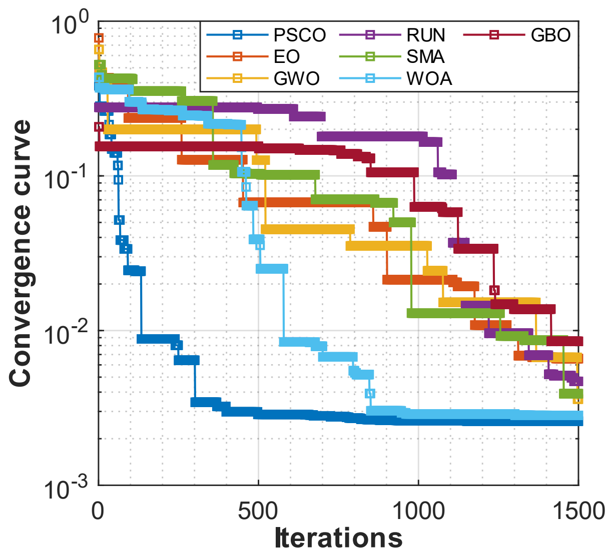

Figure 8. Fitness function (STP6-120/36 module).

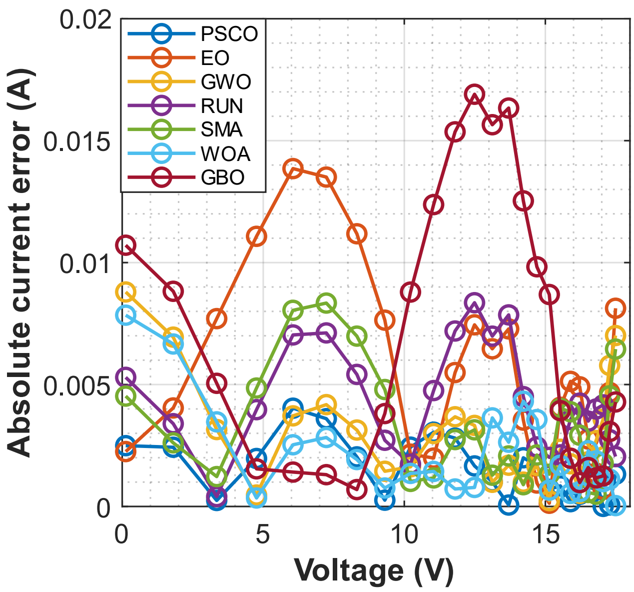

Figure 9. Absolute current error (Photowatt-PWP201 module).

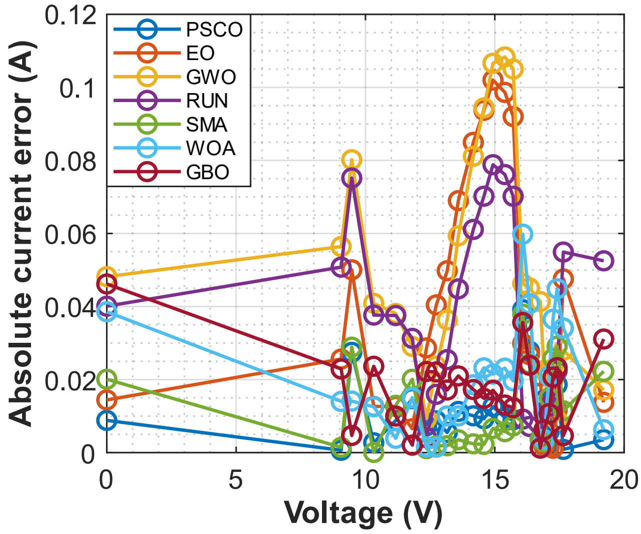

Figure 10. Absolute current error (STP6-120/36 module).

To evaluate the precision of the methods, we assess their predictive performance using three metrics: mean square error (MSE), root mean square error (RMSE), and normalized RMSE (NRMSE), denoted as [37]-[40]:

$$MSE = \frac{1}{L}\sum_{x=1}^{L} (I_{\mathrm{es}}(x) - I_{\mathrm{tr}}(x))^2 \,, \tag{12}$$

$$NRMSE = \frac{RMSE}{I_{\mathrm{es,max}} - I_{\mathrm{es,min}}} \,, \tag{13}$$

$$RMSE = \sqrt{\frac{1}{L}\sum_{x=1}^{L} (I_{\mathrm{es}}(x) - I_{\mathrm{mes}}(x))^2}, \tag{14}$$

where L represents the total number of data points, where I_{es} and I_{mes} represent the recorded and predicted output current values, respectively.

As can be observed from Table 5. PSCO stands out as the superior algorithm in both the STP6 and PWP201 models, as evidenced by the provided numerical results. In the STP6 model, PSCO achieved an RMSE value of 0.0145 A, significantly lower than the values obtained by competing algorithms such as EO (0.0511 A), GWO (0.0575 A), RUN (0.0453 A), SMA (0.0163 A), WOA (0.0250 A), and GBO (0.0206 A). This trend continues when considering the NRMSE values, where PSCO attains a value of 0.0019, outperforming all other methods that exhibit higher NRMSE values. Similarly, PSCO excels in terms of MSE, with the lowest value of $2.0915 \cdot 10^{-4}$, further highlighting its accuracy and precision in predicting the STP6 model.

For the PWP201 model, PSCO continues to demonstrate its exceptional performance. It achieves the lowest RMSE value of

Table 4. Parameters extracted for the TDM model.

PV type	I_{st1} (µA)	I_{st2} (µA)	I_{st3} (µA)	I_{ph} (A)	R_s (Ω)	R_{sh} (Ω)	n_1	n_2	n_3
STP6-120/36	2.014	40.90	10.954	7.473	0.00467	18.28	1.33	34.08	26.29
Photowatt-PWP201	26.98	2.85	27.31	1.031	0.0341	24.50	13.75	1.38	24.51

Table 5. Predictive performance indicators.

PV type	Methods	RMSE (A)	NRMSE	MSE
STP6-120/36	PSCO	0.0145	0.0019	$2.0915 \cdot 10^{-4}$
	EO	0.0511	0.0068	0.0026
	GWO	0.0575	0.0077	0.0033
	RUN	0.0453	0.0061	0.0020
	SMA	0.0163	0.0022	$2.6620 \cdot 10^{-4}$
	WOA	0.0250	0.0033	$6.2478 \cdot 10^{-4}$
Photowatt-PWP201	PSCO	0.0019	0.0014	$3.6290 \cdot 10^{-6}$
	EO	0.0067	0.0050	$4.5143 \cdot 10^{-5}$
	GWO	0.0037	0.0028	$1.3509 \cdot 10^{-5}$
	RUN	0.0048	0.0036	$2.2909 \cdot 10^{-5}$
	SMA	0.0040	0.0030	$1.5879 \cdot 10^{-5}$
	WOA	0.0029	0.0022	$8.3284 \cdot 10^{-6}$

0.0019 A, surpassing the RMSE values of EO, GWO, RUN, SMA, WOA, and GBO. Moreover, PSCO also obtains the lowest NRMSE value of 0.0014, indicating its capability to provide more accurate predictions compared to alternative algorithms. In terms of MSE, PSCO again outperforms all other algorithms with the lowest value of $3.6290 \cdot 10^{-6}$, while the MSE values for the other methods, namely EO, GWO, RUN, SMA, WOA, and GBO, are significantly higher.

Table 6 summarizes the max, mean, min, and power errors, Equation (14), for three different algorithms.

$$P_{\text{error}} = \frac{1}{L} \sum_{x=1}^{L} |P_{\text{meas}}(x) - P_{\text{es}}(x)| \,, \tag{15}$$

where P_{es} represents the estimated power, P_{meas} denotes the measured power, and L indicates the total number of data points.

By analyzing the numerical results from Table 6, we can compare the performance of the PSCO algorithm against other algorithms for the STP6 and PWP201 models. In the STP6 model, PSCO exhibits a minimum error of 0.00064 A and a maximum error of 0.03913 A. Comparatively, other algorithms like EO, GWO, RUN, SMA, WOA, and GBO have higher minimum and maximum errors. Furthermore, the mean error for PSCO in the STP6 model is 0.01135 A, which is lower than the mean errors of the other algorithms. Additionally, PSCO achieves a power error of 0.16054 W, which is the lowest among all the methods considered. These results indicate that PSCO performs well in minimizing errors and accurately predicting the STP6 model.

Table 6. Min, Max, Mean and Power error.

PV type	Methods	Min error (A)	Max error (A)	Mean error (A)	Power error (W)
STP6-120/36	PSCO	0.00064	0.03913	0.01135	0.16054
	EO	0.00118	0.05005	0.03901	0.55123
	GWO	0.00889	0.08019	0.04869	0.66071
	RUN	0.00377	0.07518	0.03793	0.51192
	SMA	0.00005	0.03790	0.01202	0.17104
	WOA	0.00129	0.05980	0.01981	0.27944
Photowatt-PWP201	PSCO	0.000004	0.00403	0.00152	0.01484
	EO	0.00013	0.01385	0.00554	0.05650
	GWO	0.000238	0.00417	0.00298	0.03056
	RUN	0.000404	0.00711	0.004302	0.04872
	SMA	0.000501	0.00834	0.00327	0.03437
	WOA	0.000035	0.00431	0.00218	0.01967

Shifting our focus to the PWP201 model, PSCO maintains its impressive performance. It achieves the smallest minimum error of 0.000004 A and the maximum error of 0.00403 A, outperforming the competing algorithms. The mean error for PSCO in the PWP201 model is 0.00152 A, which is also lower compared to the mean errors of the other algorithms. Additionally, PSCO achieves a power error of 0.01484 W, which is considerably lower than the power errors of EO, GWO, RUN, SMA, WOA, and GBO. These results highlight the accuracy and reliability of the PSCO algorithm in predicting the PWP201 model with minimal errors.

In summary, the numerical results consistently show that the PSCO algorithm outperforms other algorithms in both the STP6 and PWP201 models. It achieves smaller minimum and maximum errors, lower mean errors, and reduced power errors. These results demonstrate the effectiveness of the PSCO algorithm in minimizing prediction errors and accurately estimating the target variables in the models.

Figure 11 and Figure 12 offer a comprehensive visualization of the absolute current errors generated by various algorithms when applied to the solar modules. These boxplots serve as valuable tools for assessing the performance and accuracy of each method. In each boxplot, a red horizontal line signifies the mean error specific to that particular algorithm. The Interquartile Range (IQR), representing the range of data dispersion between the upper and lower edges of the box, provides a clear measure of how the data is distributed. Additionally, outliers, those data points falling outside the whiskers of the boxplot, are prominently identified. Altogether, these boxplots provide a visual summary of data variability and offer profound insights into the performance of each algorithm.

These observations closely align with the data presented in both Table 5 and Table 6, further reinforcing the conclusions drawn from this research. They consistently show that errors associated with the PSCO algorithm are notably minimal. Roughly 75% of the data points closely approximate the true values, indicating an impressive level of accuracy. This consistency across the findings strongly emphasizes the efficacy of the proposed method in accurately estimating PSCO parameters. In conclusion, PSCO proves to be an effective and reliable choice for parameter estimation in photovoltaic models, offering precise and consistent results.

6. CALCULATION SPEED

In this segment, we assess the computational speed performance of optimization algorithms. We measured execution times for each algorithm concerning two solar PV types, and the findings are condensed in Table 7. Computation speed, quantified in seconds, is presented for all algorithms under uniform conditions, featuring a population size of 50 and a maximum iteration count of 1500. The algorithms also operated within the same predefined constraints, as detailed in Table 3.

Table 7 offers valuable insights into the comparative performance of various algorithms, measured in terms of

Table 7. Computation speed in seconds.

PV type	PSCO	EO	GWO	RUN	SMA	WOA	GBO
PHOTOWATT-PWP201	169.71	2.22	0.55	8.63	7.14	1.58	2.632
STP6-120/36	179.78	2.10	0.78	6.12	3.84	2.29	1.87

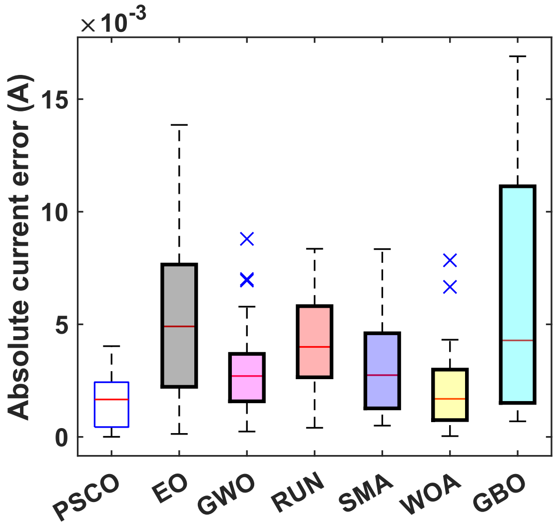

Figure 11. Boxplot absolute current error (Photowatt-PWP201 module).

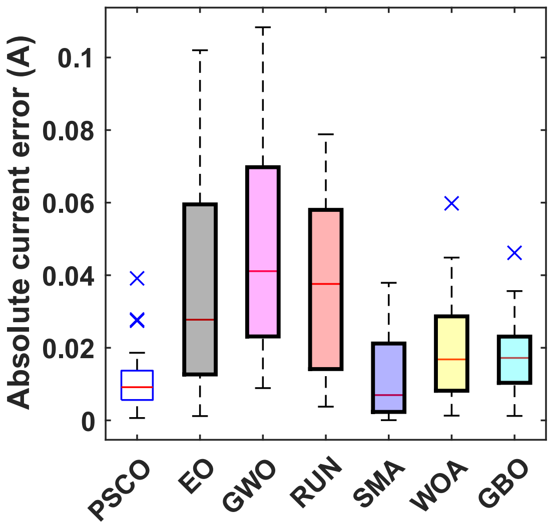

Figure 12. Boxplot absolute current error (STP6-120/36 module).

computation speed in seconds, for two distinct PV types: PHOTOWATT-PWP201 and STP6-120/36. The numerical results in this table underscore an essential trade-off between computation speed and accuracy, which is particularly pronounced in the case of the PSCO algorithm.

First, let's acknowledge that PSCO, with computation speeds of 169.71 seconds for PHOTOWATT-PWP201 and 179.78 seconds for STP6-120/36, takes significantly more time to process data than other algorithms. This might raise concerns about its efficiency, especially when time is a critical factor.

However, when considering the accuracy of parameter estimations, PSCO's performance tells a different story. Its remarkable accuracy is evident when we reflect on the results presented in Table 5 and Table 6. The RMSE, MSE, MAPE, Min-max, and power error indicators consistently demonstrate that PSCO surpasses the other six algorithms. For instance, the RMSE values for PSCO are remarkably low at 0.0145 A and 0.0019 A, and the power errors are the lowest at 0.16054 W and 0.01484 W. These results emphasize the strength of PSCO in providing precise parameter estimates.

While PSCO may be slower in terms of computation, it excels where it counts the most: accuracy. This contrast underlines the importance of carefully considering the specific needs of a project. In cases where precision is paramount, PSCO is an ideal choice.

As we look ahead to future work, our objective is to optimize the computational speed of the PSCO algorithm without compromising its remarkable accuracy. We are committed to striking a better balance between speed and precision while maintaining the high standards of transparency that our research is built upon. This includes providing real values that researchers can rely on to further the field of photovoltaic parameter estimation.

7. CONCLUSION

In conclusion, this study introduces the Particle Swarm Clustered Optimization (PSCO) algorithm, a novel approach that leverages clusters within the particle population for enhanced communication and information sharing at localized levels. The effectiveness of PSCO is vividly demonstrated through its application in parameter extraction for the TDM in STP6-120/36 and Photowatt-PWP201 PV modules. Notably, PSCO outperforms existing state-of-the-art algorithms, attaining impressively low Root Mean Square Error (RMSE) values of 0.0145 A and 0.0019 A. Moreover, it minimizes power errors to the greatest extent, achieving values as low as 0.16054 W and 0.01484 W, underlining its superior accuracy.

These results firmly establish the PSCO algorithm as an efficient and precise method for estimating parameters in photovoltaic models. The ability of PSCO to outshine its counterparts in accuracy and performance signifies its potential to revolutionize the field of photovoltaic modeling and drive further advancements in sustainable energy technologies. As the world continues to seek more efficient and reliable sources of renewable energy, the PSCO algorithm emerges as a promising tool to contribute to this important endeavor.

While the PSCO algorithm may have been slower in terms of computation, it excels where it matters most: accuracy. This highlights the need to consider a project's specific requirements carefully. In cases where precision is paramount, PSCO is an ideal choice. Looking forward, our objective is to optimize the computational speed of the PSCO algorithm without compromising its remarkable accuracy, addressing its initial slowness. We are committed to achieving a better balance between speed and precision while maintaining the high standards of transparency in our research. This includes providing real, dependable values to advance the field of photovoltaic parameter estimation.

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