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Parameter Extraction of Photovoltaic Module Using Tunicate Swarm Algorithm

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Abstract: In the renewable energy sector, the extraction of parameters for solar photovoltaic (PV) cells is a widely studied area of research. Parameter extraction is a non-linear complex optimization problem for solar PV cells. In this research work, the authors have implemented the Tunicate swarm algorithm (TSA) to estimate the optimized value of the unknown parameters of a PV cell/module under standard temperature conditions. The simulation results have been compared with four different, pre-existing optimization algorithms: gravitational search algorithm (GSA), a hybrid of particle swarm optimization and gravitational search algorithm (PSOGSA), sine cosine (SCA), and whale optimization (WOA). The comparison of results broadly demonstrates that the TSA algorithm outperforms the existing optimization algorithms in terms of root mean square error (RMSE) and convergence rate. Furthermore, the statistical results confirm that the TSA algorithm is a better algorithm in terms of average robustness and precision. The Friedman ranking test is also carried out to demonstrate the competency and reliability of the implemented approach.

Keywords: photovoltaic; TSA; parameter extraction; single-diode model; double-diode model; swarm intelligence

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1. Introduction

Solar energy is emerged as a potential renewable source of energy. For the eighth year in a row, solar power has received the greatest proportion of groundbreaking investment opportunities in renewable energy sources. Because of the high investment cost of PV-generating installations, it is necessary to estimate the behavior of the PV-system from the designing phase to assure efficient utilization of solar energy in electricity generation [1,2]. Solar energy is also reflected as an extremely capable renewable resource owing to its usage and non-polluting nature [1–3]. Moreover, its modularity and scalability have added to its extensive acceptance in power systems through different photovoltaic (PV) configurations [4]. For simulating, controlling, and evaluating the photovoltaic systems, modeling of the solar-cell installation must be done. Whenever photovoltaics start operating, the solar-cell parameters could be utilized for accounting for the detectability and analysis [3]. However, the practical aspect is that photovoltaic devices are majorly bare compared to several outer atmospheric belongings, and its photovoltaic arrays do not last always efficiently which will harm the production of sun-based devices [4]. Accordingly, this is a critical estimation of the practical performance of photovoltaic arrays in the process to achieve, enhance, and simulate these types of systems/devices. With this aim, we frequently use a reliable prototype to measure current and voltage files [5].

The importance of photovoltaics is estimated to be a major stimulating topic by scientists/researchers and firms to progress energy adaption and reduce costs [6–8]. To boost the systematic performance of photovoltaics, modeling the photovoltaic cells and their segments is a crucial part. The non-linear dimensions and sporadic nature of meteorologic static make it difficult to identify cell constraints [9]. Furthermore, the production firms require assurance of the performance of photovoltaic units for approx. twenty-five years; photovoltaic arrangements are dependent on location and unavoidably undergo degradation, along with possible occurrences of electrical faults. So, we can considerably work on a systematic model that predicts the practical behavior of the photovoltaic cell in possible working conditions [10].

Generally, PV systems are vulnerable to outside atmospheric aspects such as temperature and irradiance, which affect the effectiveness of solar energy [11]. Thus, it is essential to generate current–voltage modeling setups for enhancing and controlling PV arrangements [12]. Generally, single, double, and triple diode models are majorly used for photovoltaic cells [13–15], and are extensively used to specify the current–voltage connections. Parameters of the photovoltaics help to determine the accurateness and dependability of the models. However, due to unbalanced operational cases, such as faults and aging, the models' parameters are not accessible. Therefore, the development of an active methodology to accurately extract these parameters turn out to be critical. The single diode model (SDM) is majorly used in the approximation of these constraints because of ease and acceptance. The double diode model (DDM) is expected to be as accurate as SDM, especially in lower solar irradiance; nevertheless, it desires to exist for a long consuming time [16–20]. To get more accurate and precise parameters from nonlinear implicit equations with high accuracy, evolutionary algorithms [21–31] were proposed. The bio-related algorithms are more accurate and powerful optimization algorithms for simplifying nonlinear transcendental equations, as they do not include complex mathematics. In the proposed work, TSA is implemented for the parameter extraction of the solar cell/module, and the results clearly show the superiority of the TSA over particle swarm optimization (PSO). The reason for this is that PSO has the problem of getting stuck in the local optima solution due to poor exploration capabilities for searching for the optimal solution in the search space, while the searching mechanism of TSA provides a good trade-off between exploration and exploitation capabilities [18]. Hence, TSA provides a more optimal solution as compared with PSO and other existing algorithms.

In this manuscript, we have discussed, initially, the problem formulation followed by a mathematical model for solar PV cell/module, as presented in Section 2. In Section 3, a brief introduction of the TSA algorithm is discussed and is implemented to estimate the optimized value of the unknown parameters of a PV module model. In Section 4, the simulation results of the TSA algorithm are discussed and compared with those of pre-existing metaheuristic algorithms. Section 5 entails the discussion and finally, the manuscript is concluded in Section 6.

2. Problem Statement

In a photovoltaic solar cell, the parallel circuits are formulated using single-diode and double-diode models. In the solar cell, the correlation between the current and voltage is represented using equivalent circuit models.

2.1. Photovoltaic Panel Module Model

The equivalent circuit of PV panel module is shown in Figure 1. The relation between the current and voltage at the output terminal for the PV panel module is expressed as:

$$I_l/N_p = I_p - I_{SD}\left[exp\left(\frac{q\left(V_l/N_s + R_s I_l/N_p\right)}{ak_B T}\right) - 1\right] - \frac{V_l/N_s + R_s I_l/N_p}{R_{sh}} \quad (1)$$

where N_s and N_p represent the number of solar cells connected in series and parallel, respectively. I_l stands for cell current in the output, I_p represents the photogenerated current, I_{SD} stands for the reverse saturation current. V_l, a, R_s, k_B, T and q are the cell output voltage, diode ideality constant, series resistance, Boltzmann constant (1.381×10^{-23} J/K), junction temperature (°K), and electron charge (1.602×10^{-19} C), respectively. It is depicted in Figure 1 that only five parameters (I_p, I_{SD}, a, R_s and R_{sh}) are needed to be estimated for the minimum value of RMSE.

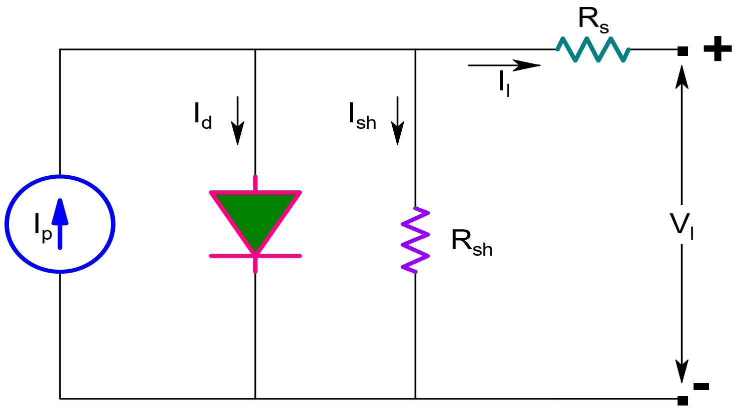

Figure 1. Single diode model of photovoltaic panel module.

2.2. Objective Function

The key deliverables in this work are the optimization of unknown specifications for both SDM and DDM models to reduce the error between the experimental and estimated data. The objective function for error used here is the same as the one that authors have used previously in [23–25]:

$$\text{RMSE} = \sqrt{\frac{1}{k}\sum_{N=1}^{k} f(V_l, I_l,)} \tag{2}$$

where V_l and I_l are the measured voltage and current of the PV module. The parameter k stands for the number of experimental data sets. The best solution found by the TSA is represented by a vector X.

For the PV panel module model,

$$\left(\begin{array}{c} f_{single}(V_l,\ I_l,\ X) = \ I_p - I_{SD}\left[exp\left(\frac{q\left(\frac{V_l}{N_s}+\frac{R_s I_l}{N_p}\right)}{a_1 k_B T}\right)-1\right] - \frac{\frac{V_l}{N_s}+\frac{R_s I_l}{N_p}}{R_{sh}} - \frac{I_l}{N_p} \\ (X = \ I_p,\ I_{SD},\ a,\ R_s,\ R_{sh}\ ) \end{array} \right) \tag{3}$$

3. Tunicate Swarm Algorithm

In [6], authors have proposed a new metaheuristic algorithm known as the Tunicate swarm algorithm. These are visible from a few meters' distance and create a pale blue–green bioluminescent light which is intense in nature. These are cylindrically shaped and must open at one end only when they grow to the size of a few millimeters. Each tunic consists of growing a gelatinous tunic which helps to join all individuals. These tunicates are opened at one end only, and they grow up to a few millimeters in size. In every tunicate, a gelatinous tunic grows, which helps all the individuals to join. Each tunicate, through atrial syphons, generates jet propulsion from its opening by receiving water from the adjacent sea. To understand the actions of jet propulsion using the mathematical model, the tunicate should fulfill three conditions: prevent collisions between candidate solutions, step more toward the location of the best solution, and stick close to the best solution. Figure 2 depicts the process flow chart of TSA for parameter extraction.

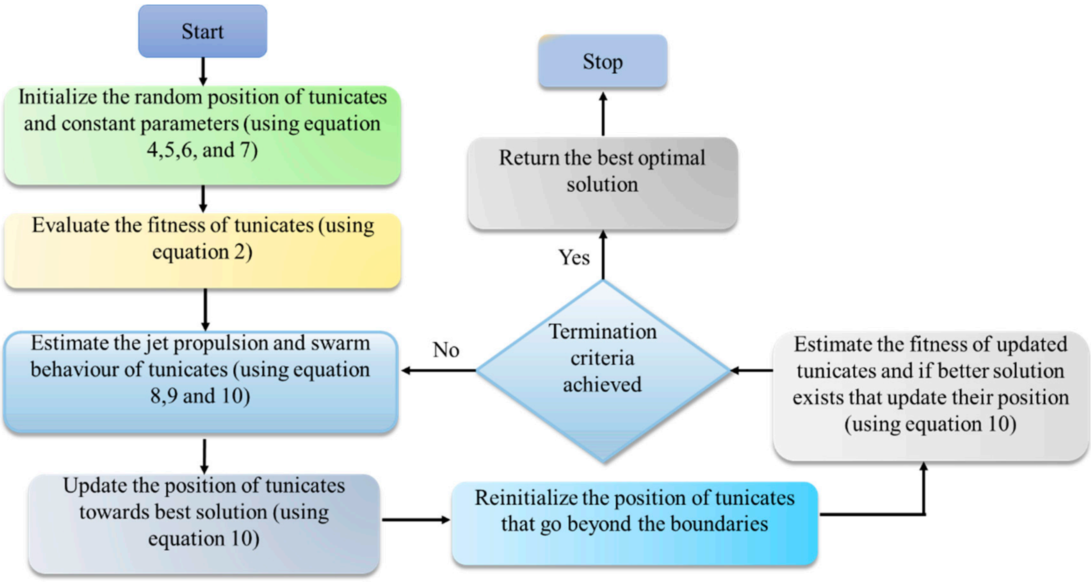

Figure 2. Process flow diagram of the Tunicate swarm algorithm (TSA).

3.1. Prevent Collisions between Candidate Solutions

We initialize the parameters $\vec{A}$ (constant), gravity force $(\vec{G})$, water flow advection in the deep ocean $(\vec{F})$, social force $\vec{M}$ and the maximum number of iterations:

$$\vec{A} = \frac{\vec{G}}{\vec{M}} \tag{4}$$

$$\vec{G} = c_2 + c_3 - \vec{F} \tag{5}$$

$$\vec{F} = 2 \times c_1 \tag{6}$$

$$M = \lfloor P_{min} + c_1 \times P_{max} - P_{min} \rfloor \tag{7}$$

where, c_1, c_2, c_3 are random numbers in the range [0,1], and P_{min} and P_{max} are considered as 1 and 4, respectively.

3.2. Step More toward the Location of the Best Solution

The search agents are moved in the direction of the finest neighbors after successfully preventing a conflict with the neighbors:

$$\vec{PD} = \left| \vec{FS} - rand \times \vec{P}_p(x) \right| \tag{8}$$

where $\vec{PD}$ is the total distance between the search agent and food source, *rand* is the random number in the range [0,1], x indicates the current iteration, $\vec{FS}$ indicates the position of the food source, and $\vec{P}_p(x)$ is the position of the tunicates.

3.3. Stick Close to the Best Solution

The search agent could even establish its position as the leading search agent.

$$\vec{P}_p(x) = \begin{cases} \vec{FS} + \vec{A} \times \vec{PD}, \ if\ rand \geq 0.5 \\ \vec{FS} - \vec{A} \times \vec{PD}, \ if\ rand\ < 0.5 \end{cases} \tag{9}$$

The position of all the tunicates is updated with respect to the position of the first two tunicates as follows:

$$\vec{P}_p(x+1) = \frac{\vec{P}_p(x) + \vec{P}_p(x+1)}{2 + c_1} \tag{10}$$

where $\vec{P}_p(x+1)$ represents the updated position of the tunicates.

3.4. Implementation of TSA for Parameter Extraction

Step 1. Initialize the population of search agents of the fifth order dimension in the search space. The fifth order dimension represents the photovoltaic current (I_p), series resistance (R_s), shunt resistance (R_{sh}), diode saturation current (I_{SD}), and diode ideality factor (a). The range of these parameters are [0–10, 0.001–2, 0–2000, 0–50, 0–100].

Step 2. Regulate the fitness of all agents in the search space using Equation (2).

Step 3. Update the position of the agents at every iteration using TSA. The algorithm is designed to work in the minimization mode; thus, the location of the particles that acquire minimum costs represents the optimized parameters of SDM with minimum RMSE.

4. Results and Discussion

We analyzed the feasibility of the TSA algorithm and evaluated it using mainly one polycrystalline PV module (Photowatt-PWP201) under standard temperature conditions (i.e., 1000 W/m^2 at 30 °C). As a result, the retrieved PV module parameters were monitored and used to create simulated I-V data. The reliability of the WOAPSO is evaluated and compared with six metaheuristics algorithms, i.e., GSA [7], SCA [8], GWO [9], PSO [10], WOA [11], PSOGSA [12], as well as other algorithms existing in the literature. For the experiment, the sample size and the objective function evaluations are set between 30 and 50,000, respectively. Furthermore, a minimum of 30 separate runs are carried out to prevent contingency.

The efficiency of the proposed method is evaluated based on distinct empirical tools such as the internal absolute error (IAE), the Relative Error (RE), the precision of the curve fitting, and the global minimum convergence patterns. The experimental values of current and voltage are taken from [13] by using Photowatt-PWP201 (Photowatt, Bourgoin-Jallieu, France). The Photowatt-PWP201 PV module is composed of 36 polycrystalline cells arranged in a series to generate current-voltage data under standard temperature conditions. The data collection consists of a total of 23 for the PV module. For a reasonable comparison, the search ranges (i.e., upper and lower bound) for each parameter are tabulated in Table 1, which are the same as those being used by investigators in [13–15]. The TSA algorithm is implemented on the MATLAB 2018a (MathWorks, Mexico) platform with Intel ® core ™ i7-HQ CPU, 2.4 GHz, 16 GB RAM laptop.

Table 1. Range of parameters for solar photovoltaic (PV) module.

Parameters	Photowatt-PWP201 PV Module	
	Lower Bound	**Upper Bound**
I_p (A)	0	10
I_{sd} (μA)	0	50
R_s (Ω)	0.001	2
R_{sh} (Ω)	0	2000
a	0	100

4.1. TSA for Parameter Extraction of Photowatt-PWP201 PV Module

This section discusses the evaluation efficiency of the TSA algorithm. Parameters of the Photowatt-PWP201 PV module were estimated under standard temperature conditions by utilizing the SDM model. The optimal values of the five parameters (I_p, I_{sd}, a, R_s, R_{sh}) for SDM of the solar PV module are presented in Table 2. The characteristics curves of current-voltage (I-V) and power-voltage (P-V) are redrawn by implementing the TSA algorithm under optimized parameters. Figure 3 demonstrates the estimated and experimental I-V and P-V characteristics curves. It can be observed that the estimated parameters show good agreement with the measured ones, which proves the efficient performance of the TSA.

Table 2. Comparison of TSA with other parameter estimation methods for Photowatt-PWP201 PV Module.

Algorithms	I_{ph} (A)	R_s (Ω)	R_{sh} (Ω)	I_{sd} (μA)	a	RMSE
WOAPSO [18]	1.5032	0.0213	668.27	0.024	1.502	8.86×10^{-4}
GSA	0.0278	2	1201.097	0.050	58.4588	8.80×10^{-3}
PSOGSA	0.0218	0.6430	1100.437	0.01	79.7893	7.156×10^{-3}
SCA	1.0063	0.0496	1107.399	0.039	1.0532	1.28×10^{-2}
WOA	0.0264	0.0113	588.5011	0.0424	1.4496	9.54×10^{-4}
TSA	0.0261	0.0017	2000	0.053	1.4727	5.06×10^{-4}

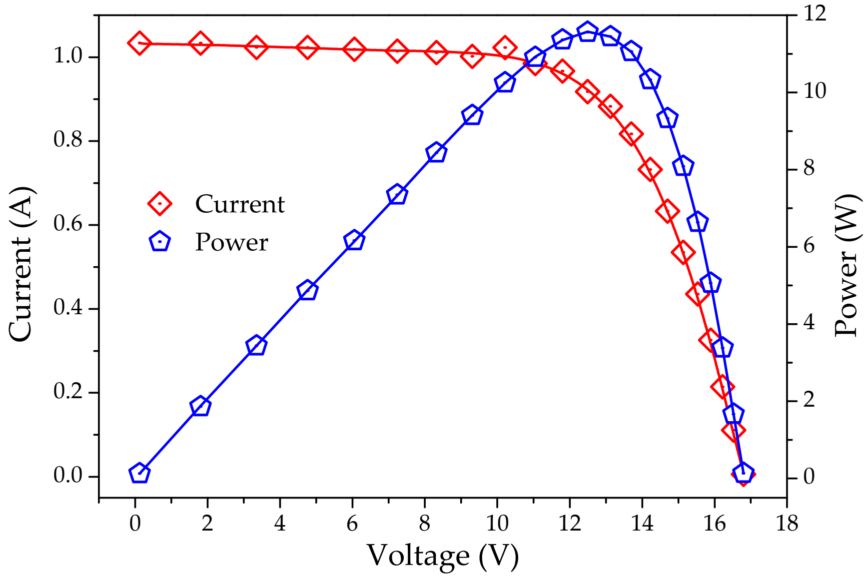

Figure 3. Current-Voltage (I-V) and Power-Voltage (P-V) characteristics curve for estimated and experimental values for single-diode model of Photowatt-PWP201 PV Module. Symbols represent measured data, and optimized data are represented by solid lines.

Table 3 represents the Internal absolute error (IAE) between the estimated and experimental data sets. Every determined value of IAE (at 1000 W/m^2 and 30 °C) is less than 0.0195, which indicates that the parameters optimized by the TSA are very precise. The error relating to the measurement results for each of the 23 pair points is determined by the IAE and Relative Error (RE). The IAE and RE values are calculated using Equations (11) and (12). The curve of IAE and RE between experimental and estimated values is shown in Figure 4.

$$\mathrm{IAE} = |I_{measured} - I_{simulated}| \tag{11}$$

$$\mathrm{RE} = \frac{(I_{measured} - I_{simulated})}{I_{measured}} \tag{12}$$

Table 3. The calculated current and absolute error results of TSA (Tunicate swarm algorithm) for solar PV (Photovoltaic) module.

Observations	V_L (V)	I_L (A)	I_{sim} (A)	IAE (A)	$P_{measured}$ (W)	$P_{simulted}$ (W)	IAE (W)
1	0.1246	1.0345	1.0335	0.001	0.1288	0.1256	0.0032
2	0.1248	1.0315	1.0335	0.002	0.1287	0.1226	0.0061
3	1.8093	1.03	1.0335	0.0035	1.8635	1.8765	0.013
4	3.3511	1.026	1.0234	0.0026	3.4382	3.4354	0.0028
5	4.7622	1.022	1.0234	0.0014	4.8669	4.8766	0.0097
6	6.0538	1.018	1.019	0.001	6.1627	6.1456	0.0171
7	7.2364	1.0155	1.0142	0.0013	7.3485	7.3256	0.0229
8	8.3189	1.014	1.011	0.003	8.4353	8.4453	0.01
9	9.3097	1.01	1.002	0.008	9.4027	9.4124	0.0097
10	10.2163	1.0035	1.023	0.0195	10.252	10.245	0.007
11	11.0449	0.988	0.985	0.003	10.9123	10.9234	0.0111
12	11.8018	0.963	0.967	0.004	11.3651	11.3554	0.0097
13	12.4929	0.9255	0.918	0.0075	11.5621	11.5722	0.0101
14	13.1231	0.8725	0.883	0.0105	11.4499	11.445	0.0049
15	13.6983	0.8075	0.8173	0.0098	11.0613	11.0521	0.0092
16	14.2221	0.7265	0.7324	0.0059	10.3323	10.321	0.0113
17	14.6995	0.6345	0.633	0.0015	9.3268	9.313	0.0138
18	15.1346	0.5345	0.535	0.0005	8.0894	8.0754	0.014
19	15.5311	0.4275	0.4356	0.0081	6.6395	6.6367	0.0028
20	15.8929	0.3185	0.3256	0.0071	5.0618	5.0524	0.0094
21	16.2229	0.2085	0.2145	0.006	3.3824	3.3724	0.01
22	16.5241	0.101	0.111	0.01	1.6689	1.6564	0.0125
23	16.7987	0.008	0.006	0.002	0.1343	0.1347	0.0004
Sum of IAE				0.0594			0.0927

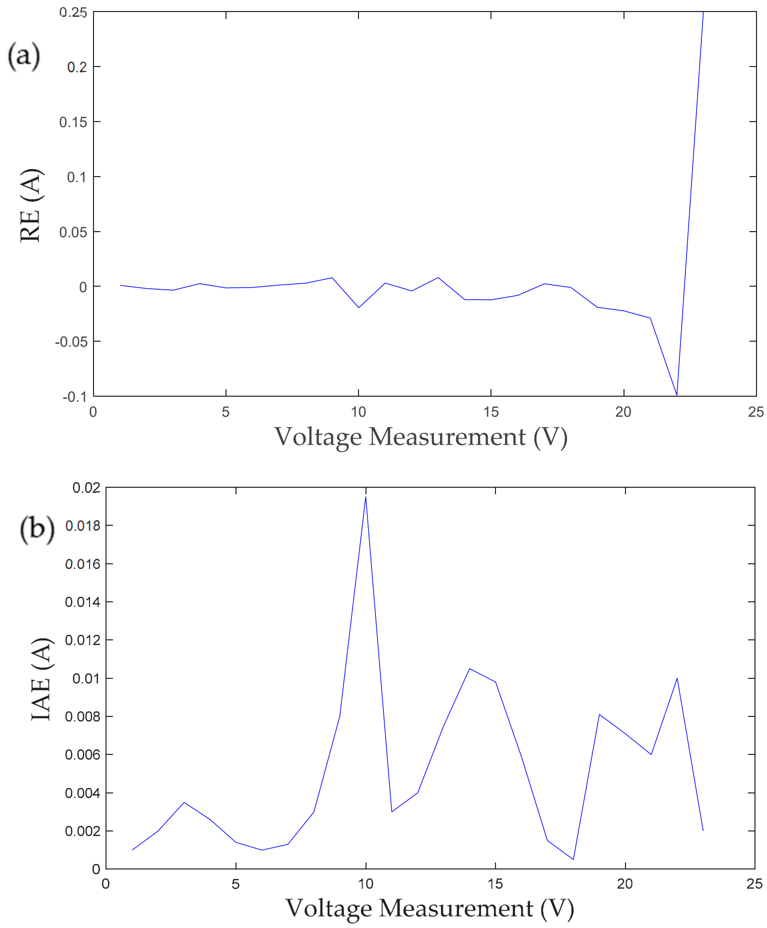

Figure 4. (**a**) Internal absolute error and (**b**) relative error curve between measured and estimated current for Photowatt-PWP201 PV Module.

4.2. Convergence Analysis

The convergence analysis was performed to examine the computational competence of the TSA. The convergence curves of the solar PV module are presented in Figure 5. It is depicted in Figure 5 that the TSA algorithm outperforms the GSA, PSOGSA, SCA, and WOA algorithms in terms of convergence speed and generates a precise solution for the identical number of function evaluations (i.e., 50,000).

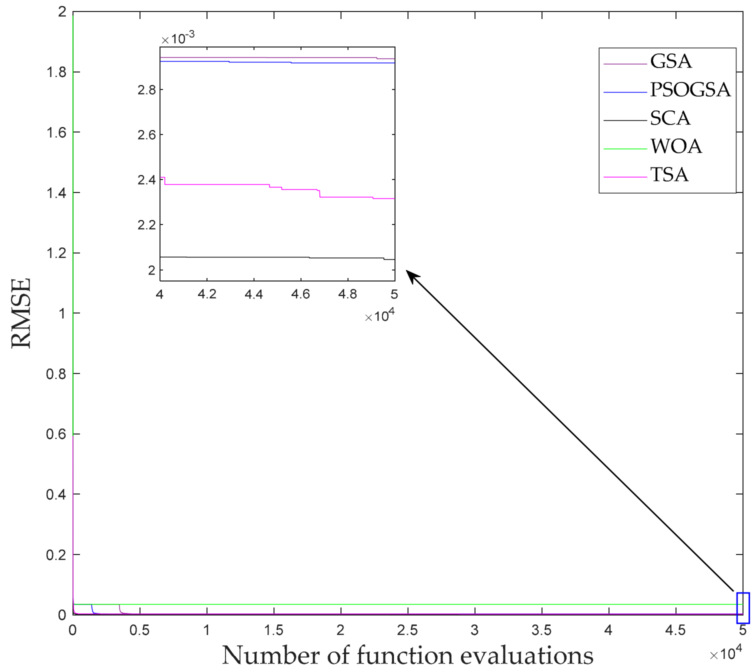

Figure 5. Convergence curve of TSA (Tunicate swarm algorithm) and the other four algorithms for single-diode model of Photowatt-PWP201 PV (Photovoltaic) Module.

4.3. Robustness and Statistics Analysis

This section presents the statistical evaluation based on mean, minimum, maximum, and standard deviation of the RMSE for all previously implemented methods and comparison concerning precision and consistency of the distinct algorithms in a total of thirty runs, as depicted in Table 4. The mean of the RMSE is calculated to evaluate the precision of the algorithms, and the standard deviation is calculated to evaluate the consistency of the parameter estimation methods.

Table 4. Statistical results of the root mean square error (RMSE) of different algorithms for Photowatt-PWP201 PV Modules.

	Algorithm	RMSE			
		Min	**Mean**	**Max**	**SD**
Photowatt-PWP201 Module Model	GSA	8.80×10^{-3}	2.65×10^{-1}	2.08×10^{-1}	5.85×10^{-3}
	PSOGSA	7.156×10^{-3}	6.47×10^{-3}	2.83×10^{-1}	1.81×10^{-2}
	SCA	1.28×10^{-2}	2.26×10^{-1}	6.35×10^{-1}	1.78×10^{-2}
	WOA	9.54×10^{-4}	2.35×10^{-2}	2.63×10^{-1}	2.83×10^{-2}
	TSA	5.06×10^{-4}	1.45×10^{-3}	2.34×10^{-2}	1.25×10^{-3}

In Table 4, it is depicted that the proposed TSA algorithm significantly outperforms the GSA, PSOGSA, SCA, and WOA algorithms for the solar PV module model. The statistical results presented in Table 4 indicate that TSA is the most accurate and reliable parameter optimization technique.

5. Discussion

The TSA algorithm is successfully developed and implemented for parameter extraction of the polycrystalline Photowatt-PWP201 PV module. The I-V and P-V curves obtained by the optimization process show excellent accord with the measured data. The IAE values (both current and power) validate the exactness of the optimized parameters. The statistical evaluation confirms that the standard deviation is very small, which confirms that the TSA is an accurate and useful parameter estimation technique. The average execution time of every algorithm on the Photowatt-PWP201 PV module is established and introduced in Figure 6. Compared to GSA, PSOGSA, SCA, and WOA, TSA requires a much lower time of about 11 s, while PSOGSA has the worst execution time of about 40 s. The Friedman ranking test results are shown in Figure 7. The best ranking is obtained by the TSA, followed by SCA, WOA, GSA, and PSOGSA.

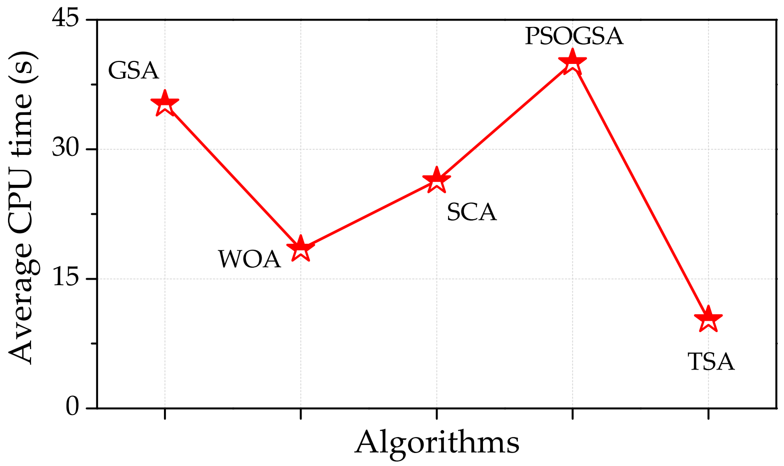

Figure 6. Comparison of the execution time of different metaheuristic algorithms.

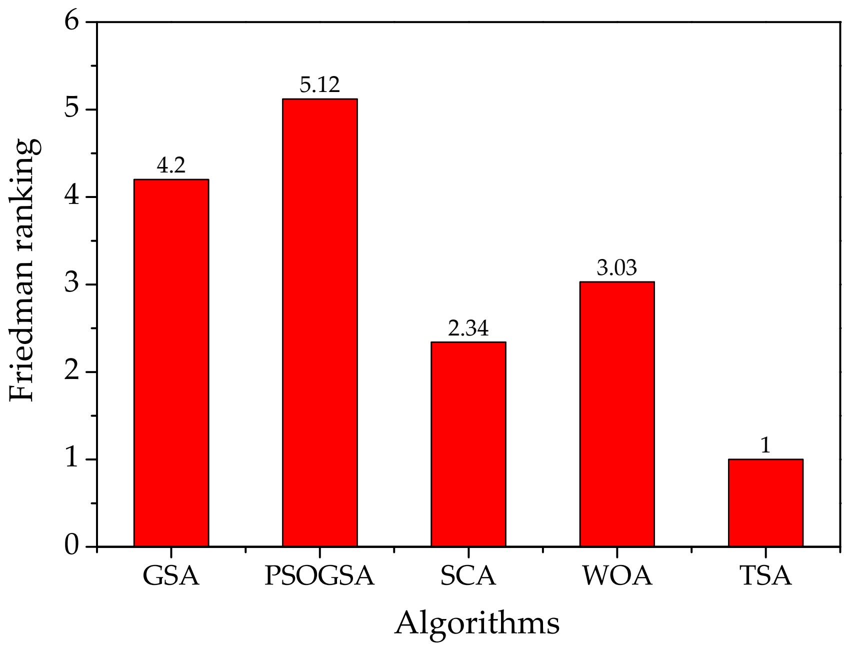

Figure 7. Ranking of TSA (Tunicate swarm algorithm) and other compared algorithms on Photowatt-PWP201 PV panel module according to the Friedman test.

6. Conclusions

In this research investigation, TSA was employed to estimate the Photowatt-PWP201 PV panel module parameters under standard temperature conditions. It should be noted the TSA technique is, for the first time, intended to reliably track the estimation of parameters for photovoltaic models. The observations based on the experimental findings are defined as follows:

- TSA is relatively accurate and reliable at delivering the solution in terms of the RMSE compared with other algorithms such as GSA, PSOGSA, SCA, and WOA.
- The I-V and P-V characteristic curves and IAE results indicate that TSA can generate the optimized value of the estimated parameters for all the solar PV cell models compared with other algorithms.
- The statistical analysis depicts the robustness of the TSA technique in parameter estimation problems under standard operating conditions.
- The convergence curves demonstrate that the TSA obtains the best estimated parameters in terms of RMSE (5.06×10^{-4}).
- From the above discussion, it can be concluded that the TSA is an effective and robust technique to estimate the unknown optimized parameters of the solar PV module model under standard operating conditions.

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Abbreviations and Symbols

The following abbreviations and nomenclature are used in this manuscript:

I_p	Photo Diode Current
I_{sd}	Reverse Saturation Current
R_s	Series Resistance
R_{sh}	Shunt Resistance
A	Diode Ideality Factor
RMSE	Root Mean Square Error
PV	Photovoltaic
I-V	Current-Voltage
P-V	Power-Voltage
MPPT	Maximum Power Point Tracking
V_{oc}	Open Circuit Voltage
I_{mpp}	Maximum Power Point Current
I_{sc}	Short Circuit Current
PSO	Particle Swarm Optimization
WOA	Whale Optimization Algorithm
SDM	Single diode Model
DDM	Double diode Model
IAE	Internal Absolute Error
RE	Relative Error
GSA	Gravitational Search Algorithm
SCA	Sine Cosine Algorithm
PSOGSA	Particle Swarm Optimization Gravitational Search Algorithm

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