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Opposition-Based Tunicate Swarm Algorithm for Parameter Optimization of Solar Cells

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ABSTRACT Parameter estimation of photovoltaic modules is an essential step to observe, analyze, and optimize the performance of solar power systems. An efficient optimization approach is needed to obtain the finest value of unknown parameters. Herewith, this article proposes a novel opposition-based tunicate swarm algorithm for parameter estimation. The proposed algorithm is developed based on the exploration and exploitation components of the tunicate swarm algorithm. The opposition-based learning mechanism is employed to improve the diversification of the search space to provide a precise solution. The parameters of three types of photovoltaic modules (two polycrystalline and one monocrystalline) are estimated using the proposed algorithm. The estimated parameters show good agreement with the measured data for three modules at different irradiance levels. Performance of the developed opposition-based tunicate swarm algorithm is compared with other predefined algorithms in terms of robustness, statistical, and convergence analysis. The root mean square error values are minimum (6.83×10^{-4}, 2.06×10^{-4}, and 4.48×10^{-6}) compared to the tunicate swarm algorithm and other predefined algorithms. Proposed algorithm decreases the function cost by 30.11%, 97.65%, and 99.80% for the SS2018 module, SolarexMSX-60 module, and Leibold solar module, respectively, as compared to the basic tunicate swarm algorithm. The statistical results and convergence speed depicts the outstanding performance of the anticipated approach. Furthermore, the Friedman ranking tests confirm the competence and reliability of the developed approach.

INDEX TERMS Machine learning, parameter extraction, photovoltaic cells, metaheuristics, tunicate swarm algorithm, opposition-based learning.

I. INTRODUCTION

In recent days, the availability of clean and sustainable energy is an important technical and scientific challenge for human society. These challenges spark the interest to develop renewable energy sources, e.g., solar, wind, geothermal, tidal, hydro energy, etc. [1]. Solar energy is an increasingly trendy way to supplement energy usage as it is the clean, amplest, and freely accessible energy source [2]. Thus, the global solar electricity market is rapidly growing and is projected to reach \$194 billion by 2027 [3]. The photovoltaic (PV) systems are employed to convert solar energy into electric energy. The importance of PV systems is estimated as a major stimulating topic by scientists/researchers and companies to progress their energy adaption and reduce the price [4]. Furthermore, the production firms require assurance of the maximum power production from PV power plants.

It is well known fact that the energy generation from PV power systems strongly depends on weather conditions, solar irradiance, and temperature [5]–[7]. Besides, these systems unavoidably undergo degradation along with the possible occurrence of electrical faults [8]. The effective

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modeling of the PV cells is needed to control and predict the performance of the solar systems at different working conditions. However, the modeling and parameter assessment of PV cells is a crucial task. The nonlinear dimensions and sporadic of meteorologic static make cell constraints difficult to identify [9]. Several models were developed based on the physical process and associated variables of PV cells. For example, single-diode, double-diode, and triple-diode models have successfully represented the PV systems' behavior single diode model (SDM) is majorly used to approximate equivalent circuit parameters because of ease and acceptance. The double diode model (DDM) is highly accurate for lower solar irradiance than SDM, but it consumes a longer time. The assessment of equivalent circuit parameters helps to determine the accuracy and dependability of the models. However, the model parameters are not accessible due to unbalanced operational cases like faults and aging. Therefore, the development of an active methodology to accurately extract these parameters turn out to be critical. The evolutionary algorithms were proposed to achieve more accurate and precise parameters from nonlinear implicit equations [10]. The bio-related algorithms are more accurate and powerful optimization algorithms to simplify nonlinear transcendental equations, as it does not include complex mathematics [12], [26], [27]. Previously, several algorithms have been utilized to enhance the parameter estimation accuracy for PV systems. These algorithms can be divided into two groups, deterministic and heuristic [11]. Both groups of algorithms have merits and demerits depending on the function. Deterministic algorithms include least squares [12], Lambert W-functions [13], and the iterative curve fitting methods. These algorithms impose several model restrictions as they are sensitive to the initial solution and generally converge at local optima. Heuristic methods are represented by particle swarm optimization (PSO) [14], chaos particle swarm optimization (CPSO) [15], harmony search (HS) [16], cuckoo search algorithm (CSA) [17], artificial bee colony (ABC) [18], cat swarm optimization (CSO) [19], modified generalized opposition based teaching learning based optimization (GOTLBO) [20], differential evolution (DE) [21], improved adaptive differential evolution (IADE) [22], genetic algorithms (GA) [23], simulated annealing (SA) [24], biogeography based optimization algorithm with mutation strategies (BBO-M) [25], Nelder-mead modified particle swarm optimization (NM-MPSO) [26], and pattern search (PS) [27]. Enhanced leader particle swarm optimization (ELPSO) is proposed [28] to avoid the premature convergence problem existing in basic version of PSO. Where five-staged mutation techniques are employed for generating the best leader in solution space. Simulation results depict that ELPPSO performed very well for solar cell, monocrystalline and thin film PV modules. Although the same author proposed another enhanced version of PSO as time varying acceleration coefficients particle swarm optimization (TVACPSO) [29] to solve the problem of local minimum occurring in standard version of PSO. Table 6 shows the comprehensive review of metaheuristic algorithms for parameter extraction of PV models (Appendix A). Comprehensive learning PSO algorithms were developed to identify the parameters of the dynamic models based on different experimental datasets [30], [31]. In the proposed marine predators algorithm (EMPA), the differential evolution operator (DE) is incorporated into the original marine predators algorithm (MPA) to achieve stable, and reliable performance while handling that nonlinear optimization problem of PV modeling [31]. The guaranteed convergence PSO (GCPSO) algorithm are proposed to estimate PV parameters of single and double-diode models on experimental data measured at different irradiance levels [32]. Kiani *et al.* proposed an exponential function-based dynamic inertia weight (DEDIW) strategy for the optimal parameter estimation of the PV cell and module that ensures a proper balance between exploitation and exploration stage to solve the premature convergence issue of conventional particle swarm optimization (PSO) algorithm [33]. A combination of Newton-Raphson method and heuristics algorithms for parameter estimation in photovoltaic modules was studied in detail [34], [35].

In a very recent work, Kaur *et al.* proposed a bio-inspired metaheuristic optimization algorithm named tunicate swarm algorithm (TSA) [36]. It is demonstrated that the TSA can solve real case studies having unknown search spaces. It is also proposed that the TSA generates better optimal solutions than that of other competitive algorithms. However, the TSA endures some limitations, such as being slow to converge, being trapped at local optima, and longer computational time. The TSA consists these limitations because certain solutions are modified toward the best solution, while some solutions are not updated toward the best solution. It is possible to overcome these limitations by considering the opposite direction. The opposition-based learning (OBL) mechanism has received the most attention recently and is used to increase the efficiency of metaheuristic algorithms. It is interesting to note here that the OBL mechanism can search in the reverse direction to the current solution, which led to metaheuristic algorithms being searched throughout the search space. Therefore, the OBL-based technique can be integrated with the basic TSA for managing a good trade-off between exploration and exploitation.

To the best of our knowledge, the opposition based tunicate swarm algorithm (OTSA) has not been implemented yet for the parameter extraction of the solar cell. The no-free-lunch (NFL) theorem motivates us to design new optimization algorithms or to improve previously studied algorithms. It is widely known fact that the optimization algorithms cannot solve every problem because of diverse complexity and nature of different problems. Hence, it is needed to maintain good balance between exploration and exploitation of a search space.

This manuscript proposes an enhanced opposition based tunicate swarm algorithm (OTSA) for parameter estimation of PV panels. The exploration behavior of elementary TSA is

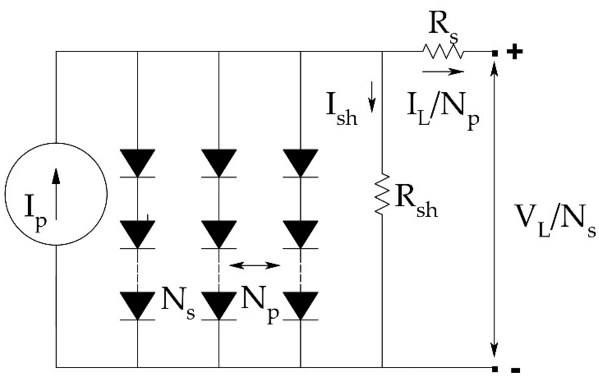

FIGURE 1. Equivalent circuit model of the photovoltaic panel.

enhanced to provide a good trade-off between exploration and exploitation capabilities. Section 2 represents the problem formulation followed by a mathematical model for solar PV cell/module. Section 3 represents the OTSA implementation to estimate the unknown optimized parameters. In section 4, the OTSA simulation results are discussed and compared with pre-existing metaheuristic algorithms. Finally, section 5 provides a conclusive remark to summarize the paper.

II. PROBLEM FORMULATION

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

A. EQUIVALENT CIRCUIT MODEL

Figure 1 illustrates the equivalent circuit model of the PV panel. The relation between current and voltage at the output terminal are expressed as:

$$^{I_l}/_{N_p} = I_p - I_{SD}\left[exp\left(\frac{q\left(V_l/N_s + R_sI_l/N_p\right)}{a_1k_BT}\right) - 1\right] - \frac{V_l/N_s + R_sI_l/N_p}{R_{sh}} \tag{1}$$

where N_s and N_p represent the number of solar cells connected in series and parallel, respectively. Only five parameters (I_p, I_{SD}, a, R_s and R_{sh}) are needed to evaluate the minimum value of root mean square error (RMSE), the summation of absolute error (SAE), and mean absolute error (MAE).

B. OBJECTIVE FUNCTION

In this work, the key deliverables are to optimize unknown specifications for a single-diode model (SDM) to reduce the error between experimental and estimated data. During optimization, unknown parameters $(I_p, I_{SD}, a, R_s, R_{sh})$ are used as a decision variable, while the cumulative squared error between simulated and measured data is used as an objective function. Furthermore, the proposed algorithm is validated by calculating the SAE and MAE. The objective function for error is expressed as [3], [4]:

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

$$SAE = \sum_{N=1}^{k} |I_{measured} - I_{estimated}| \tag{3}$$

$$MAE = \frac{1}{k}\sum_{N=1}^{k} |I_{measured} - I_{estimated}| \tag{4}$$

where V_l and I_l are the measured voltage and current of the PV module, respectively. The parameter 'k' is the number of experimental datasets. The best solution found by TSA is represented by a vector X. For the PV panel module model (5), as shown at the bottom of the page.

III. PROPOSED ALGORITHM

A. TUNICATE SWARM ALGORITHM

The TSA is a bio-inspired based metaheuristic algorithm for global optimization [36]. Tunicates can be noticed over many meters away as bright bio-luminescent and produce a pale blue-green light. Tunicates are shaped in one end closed cylinder and have a size of few millimeters. The presence of gelatinous tunic in each tunicate helps to combine all individual tunicates. Nevertheless, every individual tunicate takes water from the surrounding and thrusts as jet propulsion through open end atrial siphons. The jet propulsion actions of tunicates can be understood using the mathematical model and the following conditions: prevent collisions between candidate solutions, step more toward the location of the best solution, and stick close to the best solution.

1) REVENT COLLISIONS BETWEEN CANDIDATE SOLUTIONS

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:

$$\vec{A} = \frac{\vec{G}}{\vec{M}} \tag{6}$$

$$\vec{G} = c_2 + c_3 - \vec{F} \tag{7}$$

$$\vec{F} = 2 \times c_1 \tag{8}$$

$$M = \lfloor P_{min} + c_1 \times P_{max} - P_{min} \rfloor \tag{9}$$

$$\left\{\begin{matrix} f_{module}(V_l, I_l, X) = N_pI_p - N_pI_{SD}\left[exp\left(\frac{q\left(\frac{V_l}{N_s} + \frac{R_sI_l}{N_p}\right)}{ak_BT}\right) - 1\right] - \frac{\frac{V_lN_p}{N_s} + R_sI_l}{R_{sh}} - I_l \\ \left(X = I_p, I_{SD}, a, R_s, R_{sh}\right) \end{matrix}\right\} \tag{5}$$

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

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 neighbors:

$$\vec{PD} = \left|\vec{FS} - rand * \vec{P}_p(x)\right| \tag{10}$$

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, $\vec{P}_p(x)$ is the position of tunicates.

3) STICK CLOSE TO THE BEST SOLUTION

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

$$\vec{P}_p(x) = \begin{cases} \vec{FS} + \vec{A} * \vec{PD}, & if\ rand \geq 0.5 \\ \vec{FS} - \vec{A} * \vec{PD}, & if\ rand < 0.5 \end{cases} \tag{11}$$

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

$$\vec{P}_p(x+1) = \frac{\vec{P}_p(x) + \vec{P}_p(x+1)}{2 + c_1} \tag{12}$$

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

B. OPPOSITION BASED LEARNING METHOD

The OBL method was first developed in 2005 [37]. This approach has been further introduced in [38] and shown to be a successful method of making the search patterns of meta-heuristics more real. This approach stems from the simultaneous estimate of the opposite pairs of the base agents to improve the likelihood of meeting a matching agent. The contrary of a real number $N \in [j_L, j_U]$ can be provided by $\vec{N}$ as follows:

$$\vec{N} = j_L + j_U - N \tag{13}$$

where j_L and j_U are known as the lower and upper bound of a real number. While in multi-dimensional space, N can be expressed as $N_k = \{N_{k1}, N_{k2}, N_{k3}, \ldots\ldots, N_{kt}\}$ and $N_{kt} \in [j_{Lt}, j_{Ut}]$, where $t = 1, 2, 3, 4, \ldots\ldots, n$ and the corresponding opposite points are as follows:

$$\begin{aligned} \bar{N} &= \left\{\bar{N}_{k1,}, \bar{N}_{k2}, \bar{N}_{k3}, \ldots \bar{N}_{kt}\right\} \\ \bar{N}_{kt} &= j_{Lt} + j_{Ut} - N_{kt} \end{aligned} \tag{14}$$

During the optimization process, opposite points $\bar{N}$ are replaced by the corresponding solution N based on the best fitness value. In other words, the position of the population is updated based on the finest values of $\bar{N}$ and N. Figure 2 illustrates the complete process of the opposition-based learning mechanism.

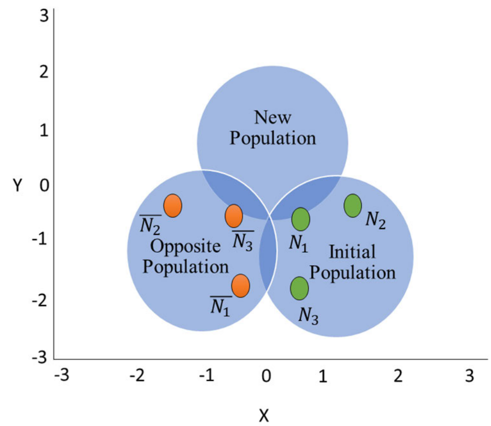

FIGURE 2. Illustration of opposition-based learning mechanism.

C. PROPOSED OPPOSITION-BASED TSA ALGORITHM

This section describes the proposed opposition-based TSA (OTSA) algorithm. The OBL mechanism is employed to enhance the performance of traditional TSA. The OTSA can also integrate the search capabilities of the classic TSA with OBL to maximize the exploration of solution space. The integration of OBL does not influence the basic functionality of TSA, and the precision of the optimal solution is enhanced. In this manner, OTSA can limit the number of the initial population, which improves the convergence to the optimal solution since it's exploring the solution space for an optimization problem.

Let us consider that a problem requires a population of 200 initial solutions. The OTSA can initialize 100 solutions in the specified order and compute their respective opposite solutions by utilizing the OBL principle. Only the top 100 solutions are identified in an iterative process before ranking them. However, the population setting in OTSA may also influence the occurrence of call functions needed throughout the optimization procedure. The computational effort generally depends on the implementation and evaluation of an optimization problem. This fact directly corresponds to the no-free-lunch (NFL) theorem [40], which specifies that the algorithms cannot be enhanced without any cost. However, the NFL has also noted that some algorithms are not suitable for solving all types of optimization problems. This is the primary motivation for the development of the proposed OTSA.

The proposed methodology enhances the basic version of TSA via two phases. In the first phase, the OBL mechanism is implemented to initialize the population to reduce the convergence rate and avoids the optimal local solution by searching for solutions in the entire search domain. In the second step, the population solution is updated, and the OBL mechanism is also used to check whether the opposite direction update is better than the existing update. The complete process flow of the proposed OTSA is shown in Figure 3.

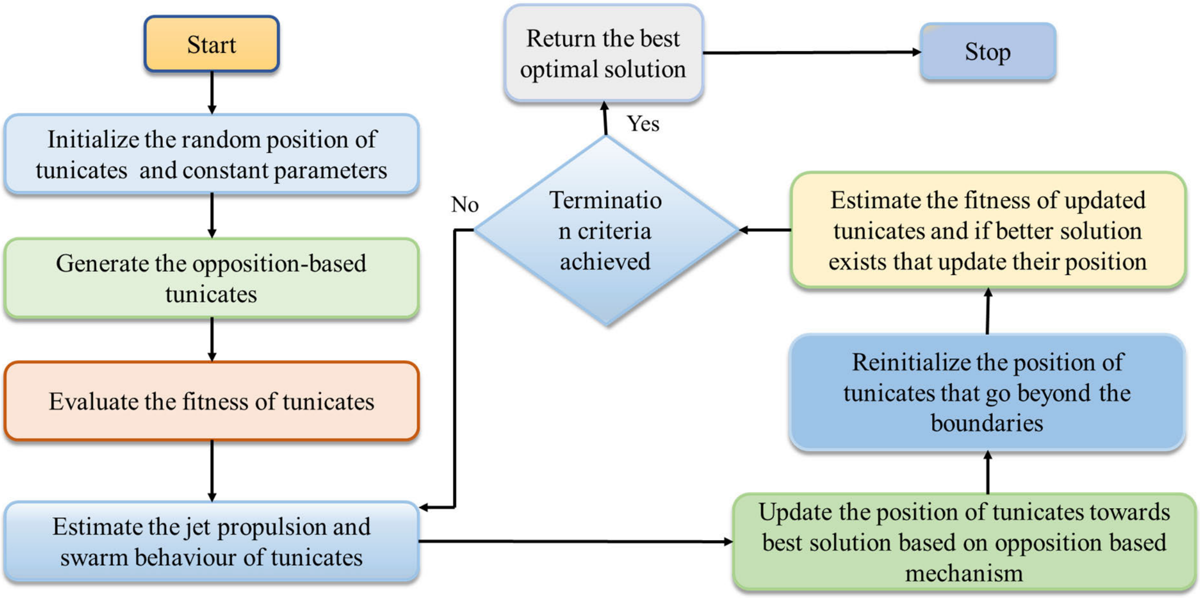

FIGURE 3. Process flow diagram of proposed OTSA.

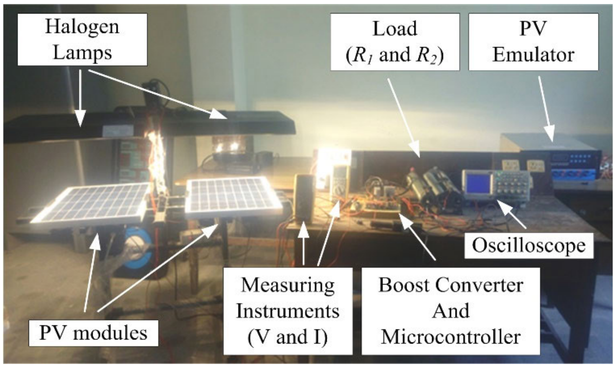

FIGURE 4. Experimental setup for measurements of SS2018 and Solarex MSX-60 PV modules.

IV. RESULTS AND DISCUSSION

A. EXPERIMENTAL SETUP

The proposed OTSA algorithm is validated by estimating the unknown parameters of SDM for three different PV modules under variable weather conditions. Figure 4 demonstrates the experimental setup for the measurement of PV modules' characteristics. First PV module consists of 36 serially connected solar cells (Solarex MSX 60 polycrystalline solar panel). This module is irradiated at different irradiance levels (500 W/m^2, 750 W/m^2 and 1000 W/m^2) at a constant temperature of 25°C. Second PV module comprises 36 serially connected polycrystalline cells (SS2018P PV module). The I-V characteristics are measured at different irradiance levels (720 W/m^2, 870 W/m^2, and 1000 W/m^2) at a constant temperature of 25°C. The data collection involves a total of 20 I-V measurements for solar cells and 27 for PV modules. The current and voltage for the solar PV module (SS2018P) are determined at variable resistive load (0.1–250 Ω, 2 A). Another PV module consists of 20 serially connected monocrystalline cells (Leibold Solar Module LSM 20). This module is irradiated at the temperature of 24°C under an irradiance level of 360 W/m^2 [5]. The measured values of current and voltage for all three PV modules are shown in Tables S2-S4 (supplementary file).

B. PARAMETER EXTRACTION BY OTSA ALGORITHM

The proposed OTSA algorithm is implemented on the MATLAB 2018a platform with Intel ® core ^{TM}i7-HQ CPU, 2.4 GHz, 16 GB RAM Laptop. To organize the experiment, the number of populations and the anticipated number of objective function evaluations are set at 30 and 50,000, respectively. Furthermore, a minimum of 30 distinct runs is conducted out to avert the contingency. The upper and lower bound limits of each parameter are tabulated in Table S1 for a rational evaluation.

1) PARAMETER EXTRACTION OF SOLAREX MSX 60 MODULE

For Solarex MSX 60 PV Module, the proposed algorithm is employed to extract parameters (I_p, I_{sd}, a, R_s, R_{sh}) of single diode model. The parameters are also extracted using different algorithms for comparison. Table 1 displays the optimized parameters, RMSE, SAE, and MAE values for irradiance level of 1000 W/m^2. The parameters and error magnitudes for other irradiance levels (500 W/m^2, and 750 W/m^2) are shown in Tables S5 and S6. It is found that the proposed OTSA algorithm generates the lowest RMSE, SAE, and MAE values of 2.057×10^{-4}, 5.77×10^{-8}, and 2.52×10^{-9}, respectively. The RMSE, SAE, and MAE values of the OTSA algorithm are smaller than the performance of the WOA [33], GWO [34], SCA [35],

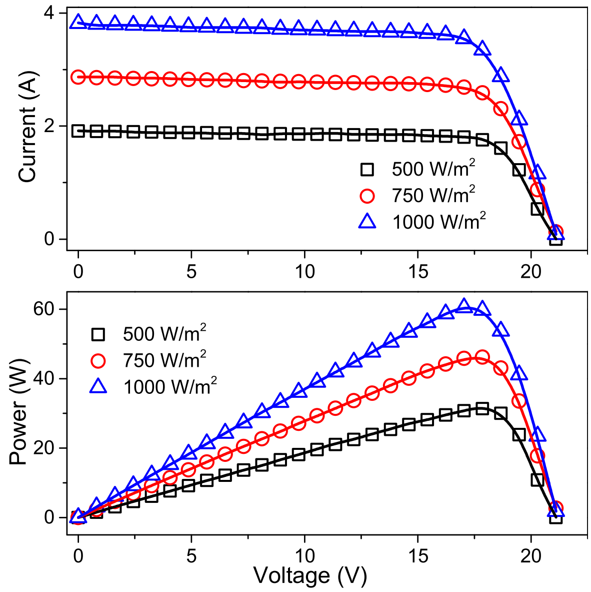

FIGURE 5. The I-V and P-V curves for the single-diode model of SolarexMSX 60 PV module at different irradiance levels. Measured data is represented by symbols, and optimized data is represented by solid lines.

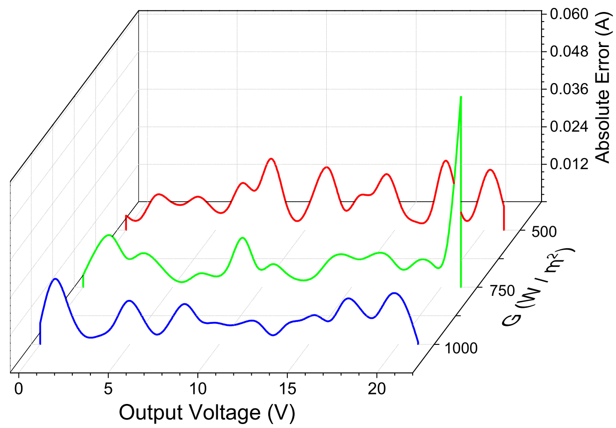

FIGURE 6. Internal absolute error between measured and simulated current for a single-diode model of SolarexMSX 60 PV module at different irradiance levels.

ALO [36], PSOGSA [37], TSA algorithms as well pre-existing algorithms. Here RMSE, SAE, and MAE values are acquired as the index for assessing the performance of algorithms. Figures 5(a&b) represent the simulated and measured current-voltage (I-V) and power-voltage (P-V) curves for different irradiance levels. The simulated data consists of the best-optimized parameters obtained by the OTSA algorithm. The measured data shows good agreement with the calculated one. The curves of internal absolute error (IAE) between experimental and simulated current for a single-diode model at different irradiance levels are shown in Figure 6.

2) PARAMETER EXTRACTION OF SS2018P MODULE

The efficiency of the proposed OTSA algorithm is further evaluated by another PV module (SS2018P PV).

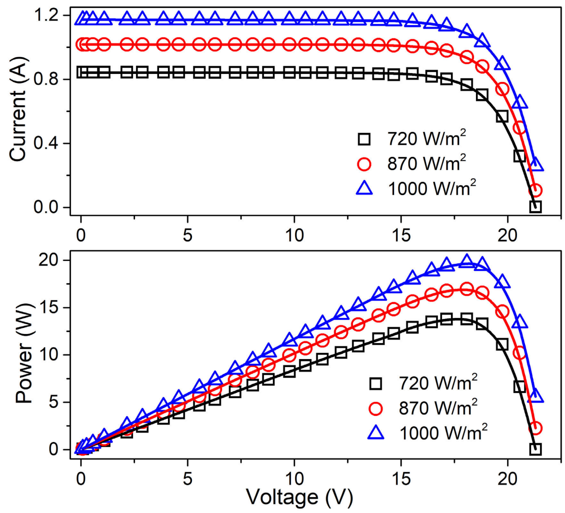

FIGURE 7. Characteristics I-V and P-V curves of simulated and experimental values at different irradiances for the single-diode model of SS2018P PV module. Symbols represent the measured data, while the solid lines represent the simulated data.

The parameters were estimated at different levels of irradiance by utilizing the SDM model. The optimized parameters, RMSE, SAE, and MAE values for irradiance level of 1000 W/m^2 are charted in Table 2. The parameters and error magnitudes for other irradiance levels (720 W/m^2, and 870 W/m^2) are shown in Tables S7 and S8. It is noticed that the proposed OTSA algorithm generates the lowest RMSE, SAE, and MAE values as compared to pre-existing algorithms. The characteristics curve of current-voltage and power-voltage for solar PV module is redrawn based on best-optimized parameters obtained by implementing the OTSA algorithm at different irradiance levels (1000 W/m^2, 870 W/m^2, and 720 W/m^2) is depicted in Figure 7. It is found that the calculated data obtained by the OTSA is very effective in keeping with the experimental data set. The curves of IAE between experimental and simulated current for a single-diode model at different irradiance levels are shown in Figure 8.

3) PARAMETER EXTRACTION OF LSM 20 MODULE

The proposed OTSA algorithm is also employed to analyze the monocrystalline LSM20 PV module. The parameters of the single diode model were estimated at an irradiance level of 360 W/m^2. Table 3 summarizes the optimized parameters, RMSE, SAE, and MAE values. Interestingly, the OTSA algorithm shows good performance for the monocrystalline PV module. These findings validate the applicability of OTSA for different types of PV cells. The error values (RMSE, SAE, and MAE) of the OTSA algorithm are smaller than that of WOA, GWO, SCA, ALO, PSOGSA, TSA, and pre-existing algorithms. The lowest RMSE, SAE, and MAE values are 4.48×10^{-6}, 1.69×10^{-4}, and 8.25×10^{-6}, respectively. The IAE values for current and power are calculated and shown in Table S4.

TABLE 1. Comparison of proposed OTSA with different parameter estimation methods for Solarex MSX-60 PV module (1000 W/m^2, 25 °C).

Algorithms	I_{ph} (A)	I_{sd} (µA)	R_s (Ω)	R_{sh} (Ω)	a	RMSE	SAE	MAE
NM [9]	3.8084	0.0005	0.3692	169.047	1.0003	9.613×10^{-2}	NA	NA
BC [38]	3.8080	0.0012	0.3160	146.080	1.0450	4.202×10^{-2}	NA	NA
SFLA [8]	3.80	0.2308	0.18	340.001	1.316	1.68×10^{-1}	NA	NA
ER-WCA [13]	3.812	1.399	0.2235	914.689	1.3325	1697×10^{-2}	NA	NA
WOA	1.131	0.6535	0.008	41.939	81.61	1.230×10^{-3}	1.41×10^{-4}	6.37×10^{-5}
GWO	3.39	0.293	0.001	180.89	56.50	8.129×10^{-2}	1.79×10^{-3}	3.14×10^{-3}
SCA	3.7705	0.0027	0.009	53.07	1.205	6.14×10^{-2}	1.06×10^{-4}	6.40×10^{-4}
ALO	3.368	0.145	0.03	4.66	65.83	9.703×10^{-2}	1.41×10^{-3}	4.09×10^{-3}
PSOGSA	0.7643	0.501	0.001	89.03	1.53	1.604×10^{-3}	1.10×10^{-4}	6.41×10^{-3}
TSA	3.395	1.775	0.237	894.82	93.87	8.774×10^{-3}	1.24×10^{-3}	4.21×10^{-3}
OTSA	3.3743	0.269	0.0003	1934.042	1.735	**2.057×10^{-4}**	**5.77×10^{-8}**	**2.52×10^{-9}**

TABLE 2. Comparison of proposed OTSA with different parameter estimation methods for SS2018 PV module (1000 W/m^2).

Algorithms	I_{ph} (A)	I_{sd} (µA)	R_s (Ω)	R_{sh} (Ω)	a	RMSE	SAE	MAE
WOA	1.099	7.79	0.172	1654.52	71.99	1.15×10^{-3}	4.62×10^{-4}	3.79×10^{-3}
GWO	1.092	2.08	0.257	661.6292	100	1.89×10^{-3}	1.78×10^{-4}	1.13×10^{-4}
SCA	1.102	0.01	0.558	354.70	40.11	2.18×10^{-3}	4.16×10^{-3}	1.70×10^{-3}
ALO	1.41	0.09	0.003	901.45	1.8	1.45×10^{-3}	4.41×10^{-4}	2.57×10^{-4}
PSOGSA	1.118	0.432	1.795	937.691	25.969	1.92×10^{-2}	7.41×10^{-3}	2.63×10^{-4}
TSA	1.099	5.60	0.911	884	19.2463	9.73×10^{-4}	8.14×10^{-5}	2.05×10^{-6}
OTSA	1.172	0.0731	0.0001	129.21	1.3	**6.83×10^{-4}**	**2.62×10^{-6}**	**4.99×10^{-5}**

TABLE 3. Estimated parameters of Leibold solar module (LSM 20) using different algorithm.

Algorithms	I_{ph} (A)	I_{sd} (µA)	R_s (Ω)	R_{sh} (Ω)	a	RMSE	SAE	MAE
TGA [39]	0.1549	0.0016	0.280	160.60	1.37	9.28×10^{-4}	NA	NA
ACT [5]	0.1544	0.0025	6.394	1973.35	1.26	8.38×10^{-4}	24.25×10^{-3}	6.93×10^{-4}
SMA [40]	0.1550	0.001	7.295	1545.16	1.07	7.81×10^{-4}	NA	6.41×10^{-4}
WOA	0.066	0.706	0.119	1473.43	19.91	2.93×10^{-3}	3.38×10^{-4}	9.08×10^{-3}
GWO	0.083	0.015	0.242	15.04	45.71	2.92×10^{-3}	1.73×10^{-4}	8.64×10^{-6}
SCA	0.0730	0.01	0.304	26.3395	68.89	2.05×10^{-3}	3.09×10^{-4}	8.76×10^{-6}
ALO	0.1855	3.573	0.015	3.653	2.15	3.49×10^{-2}	2.46×10^{-3}	1.23×10^{-3}
PSOGSA	0.061	0.05	1.782	1865.467	1.66	1.72×10^{-2}	1.89×10^{-3}	9.07×10^{-3}
TSA	0.067	4.53	0.905	291.866	97.52	2.32×10^{-3}	1.84×10^{-4}	3.09×10^{-4}
OTSA	0.1546	0.0177	0.0009	685.75	1.46	**4.48×10^{-6}**	**1.69×10^{-4}**	**8.25×10^{-6}**

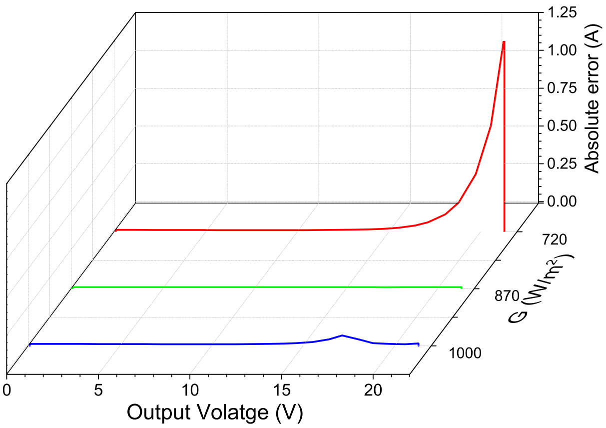

FIGURE 8. Internal absolute error between measured and simulated current for single diode model of SS2018P PV module at different irradiance levels.

A smaller magnitude of the IAE demonstrates the accuracy of optimized parameters produced by the OTSA algorithm. Figure 9 displays the measured and simulated I-V and P-V characteristic curves. The simulated curves are based on the best-optimized parameters obtained by the OTSA algorithm. It can be observed that estimated parameters show good agreement with the measured one, which proves the efficient performance of the OTSA.

C. CONVERGENCE ANALYSIS

The computational competence of OTSA is investigated through convergence analysis. The convergence curves of the single diode model for all three PV modules are presented in Figure 10. It is depicted in Figure 10 that the proposed OTSA algorithm outperforms the WOA, GWO, SCA, ALO, PSOGSA, and TSA algorithms in terms of convergence speed. The OTSA algorithm generates a precise solution for the exact number of function evaluations (i.e., 50000).

For the SS2018PV module, the RMSE values are 1.15×10^{-3}, 1.89×10^{-3}, 2.18×10^{-3}, 1.45×10^{-3}, 1.92×10^{-2}, 9.73×10^{-4}, and 6.83×10^{-4} for WOA, GWO, SCA, ALO, PSOGSA, TSA, OTSA respectively. The RMSE value is minimum for OTSA than that of others. It means that the OTSA decreases the function cost by 30.11 % compared to the basic version of TSA. Similarly, for the SolarexMSX-60 PV module, the RMSE values are 1.23×10^{-3}, 8.13×10^{-2}, 6.14×10^{-3}, 9.70×10^{-2}, 1.60×10^{-3}, 8.77×10^{-3}, and 2.06×10^{-4} for WOA, GWO, SCA, ALO, PSOGSA, TSA, OTSA, respectively. The OTSA algorithm generates a

TABLE 4. Statistical results of RMSE of different algorithms for all three models.

PV Module	Algorithm	RMSE			
		Min	Mean	Max	SD
Solarex MSX 60 PV module	WOA	1.23×10^{-3}	2.65×10^{-2}	2.47×10^{-1}	1.04×10^{-2}
	GWO	8.13×10^{-2}	4.50×10^{-4}	2.58×10^{-2}	5.81×10^{-3}
	SCA	6.14×10^{-2}	2.79×10^{-3}	4.08×10^{-1}	2.31×10^{-4}
	ALO	9.71×10^{-2}	1.46×10^{-3}	3.68×10^{-1}	3.31×10^{-3}
	PSOGSA	1.60×10^{-3}	2.47×10^{-3}	3.56×10^{-1}	5.47×10^{-3}
	TSA	8.77×10^{-3}	9.41×10^{-3}	3.13×10^{-1}	1.69×10^{-3}
	OTSA	$\mathbf{2.06\times10^{-4}}$	$\mathbf{2.98\times10^{-4}}$	$\mathbf{1.88\times10^{-3}}$	$\mathbf{1.06\times10^{-6}}$
SS2018P PV module	WOA	1.15×10^{-3}	7.32×10^{-3}	2.02×10^{-1}	1.03×10^{-3}
	GWO	1.89×10^{-3}	2.68×10^{-3}	2.22×10^{-1}	3.81×10^{-3}
	SCA	2.18×10^{-3}	2.74×10^{-3}	2.69×10^{-2}	3.63×10^{-4}
	ALO	1.45×10^{-3}	4.07×10^{-3}	1.31×10^{-2}	4.25×10^{-3}
	PSOGSA	1.92×10^{-2}	9.45×10^{-3}	3.50×10^{-1}	1.30×10^{-3}
	TSA	9.73×10^{-4}	7.75×10^{-3}	4.15×10^{-2}	2.06×10^{-4}
	OTSA	$\mathbf{6.83\times10^{-4}}$	$\mathbf{5.32\times10^{-4}}$	$\mathbf{1.02\times10^{-3}}$	$\mathbf{5.11\times10^{-6}}$
LSM 20 PV module	WOA	2.93×10^{-3}	2.62×10^{-3}	4.37×10^{-2}	2.61×10^{-3}
	GWO	2.92×10^{-3}	9.92×10^{-2}	2.04×10^{-1}	9.56×10^{-4}
	SCA	2.05×10^{-3}	4.31×10^{-3}	7.51×10^{-2}	1.21×10^{-3}
	ALO	3.49×10^{-2}	3.52×10^{-4}	5.71×10^{-2}	7.09×10^{-3}
	PSOGSA	1.72×10^{-2}	5.77×10^{-3}	7.75×10^{-2}	8.08×10^{-4}
	TSA	2.32×10^{-3}	6.65×10^{-4}	4.03×10^{-3}	5.57×10^{-4}
	OTSA	$\mathbf{4.48\times10^{-6}}$	$\mathbf{5.22\times10^{-5}}$	$\mathbf{1.05\times10^{-3}}$	$\mathbf{2.91\times10^{-6}}$

TABLE 5. Ranking of the proposed OTSA and other compared algorithms on three PV modules according to the Friedman test.

Algorithms	Friedman Ranking	Final Ranking
WOA	5.06	5
GWO	7.01	7
SCA	4.36	4
ALO	3.23	3
PSOGSA	6.05	6
TSA	2.22	2
OTSA	1	1

minimum RMSE value than that of others. It indicates that the OTSA decreases the function cost by 97.65% compared to the basic version of TSA. The proposed OTSA method also proves to be competent for the monocrystalline Leibold solar module. The RMSE values are 9.28×10^{-4}, 8.38×10^{-4}, 7.80×10^{-4}, 2.93×10^{-3}, 2.92×10^{-3}, 2.05×10^{-3}, 3.49×10^{-2}, 1.72×10^{-2}, 2.32×10^{-3} and 4.48×10^{-6} for WOA, GWO, SCA, ALO, PSOGSA, TSA, OTSA respectively. It implies that the OTSA reduced the cost function by 99.80% relative to the standard version of TSA.

D. ROBUSTNESS AND STATISTICAL ANALYSIS

This sub-section describes the statistical evaluations based on mean, minimum, maximum, and standard RMSE deviations

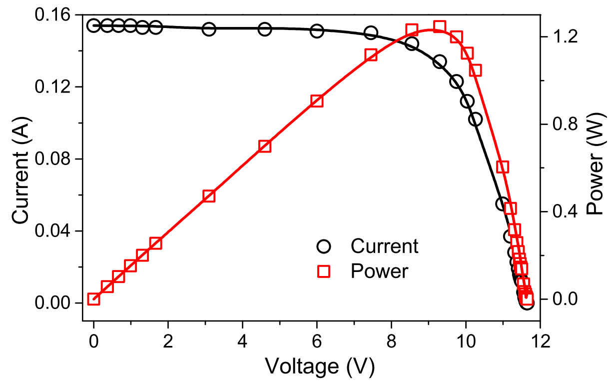

FIGURE 9. I-V and P-V curves for monocrystalline Leibold solar module (LSM 20). Open symbols represent the measured data, and solid lines show estimated data.

for OTSA and previously proposed methods. The comparative analysis with the accuracy and reliability of the different algorithms is performed in thirty tests and shown in Table 4. The mean of the RMSE is analyzed to assess the accuracy of the algorithms, and the standard deviation is determined to analyze the reliability of the proposed parameter estimation technique. The statistical analysis results depict that the proposed OTSA is the most precise

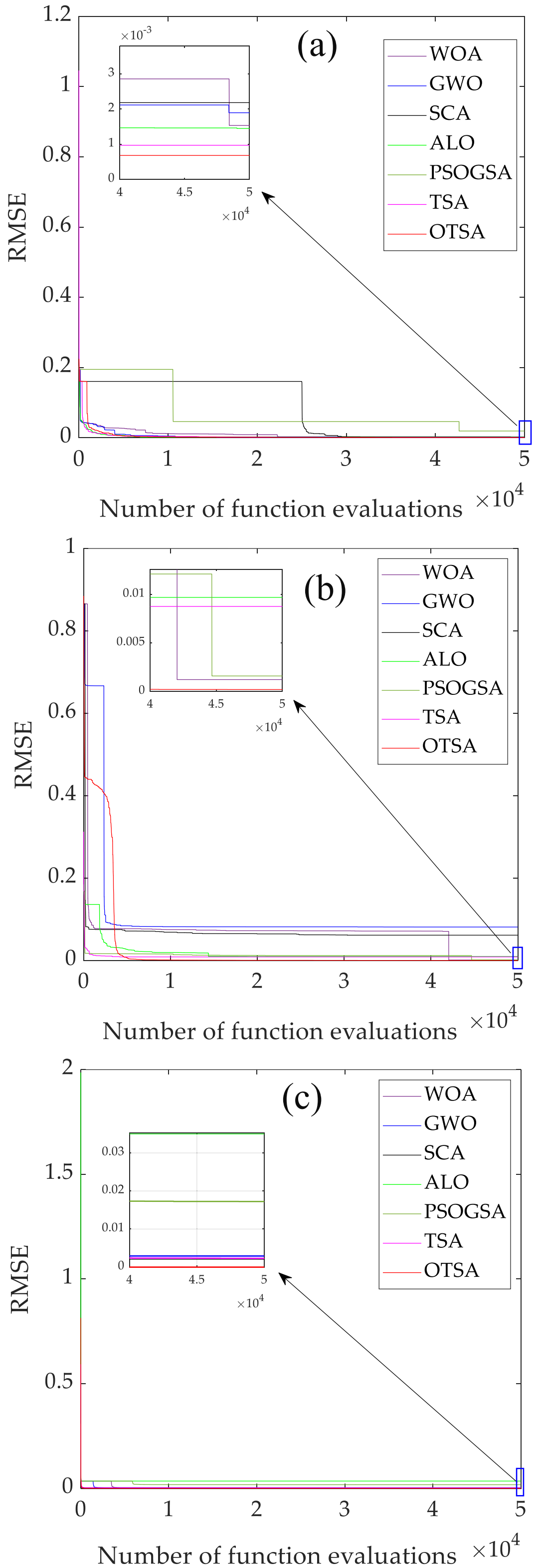

FIGURE 10. Convergence curve of WOAPSO and other six algorithms for single-diode model of (a) SS2018P PV module (b) SolarexMSX 60 PV module (c) monocrystalline LSM 20 PV module.

and effective parameter estimation technique as it has a very low standard deviation. A non-parametric test i.e., Friedman ranking test is performed to show the significant difference

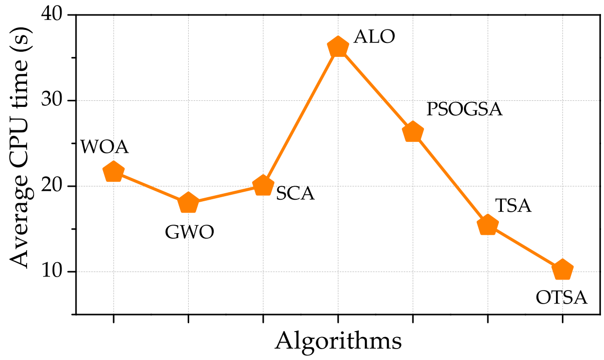

FIGURE 11. Comparison of the execution time of different algorithms.

between existing algorithms and proposed algorithm. The Friedman ranking test results are shown in Table 5. The best ranking is obtained by the OTSA, followed by TSA, ALO, SCA, WOA, PSOGSA, and GWO.

E. CPU TIME

The OTSA algorithm is successfully developed and implemented for parameter extraction of three PV modules (two polycrystalline and one monocrystalline). The I-V and P-V curves obtained by the optimization process show good agreement with the measured data. The IAE values (both current and power) verify the accuracy of optimized parameters. The statistical analysis shows that the standard deviation is very low for all three PV modules, which confirms that the OTSA is the precise and effective parameter estimation technique. The average execution time of each algorithm on the three PV models is determined and presented in Figure 11. Compared to WOA, GWO, SCA, PSOGSA, TSA, OTSA requires a much lower time of about 10 s, while ALO has the worst execution time of about 36 s. This study proves that the OBL mechanism increases the efficiency of the metaheuristic TSA algorithm. Furthermore, additional modifications can be done for solving the multi-objective problems.

V. CONCLUSION

In this study, a novel opposition-based tunicate swarm algorithm is successfully developed and analyzed. The proposed algorithm is anticipated to identify the unknown parameters of photovoltaic modules precisely and effectively. The proposed OTSA performed adequately and is reliable in terms of RMSE, SAE, and MAE compared to other methodologies such as WOA, GWO, SCA, ALO, PSOGSA, TSA, and similar approaches available in the literature. The implementation of OTSA leads to a reduction in cost function by 30.11%, 97.65%, and 99.80 % for SS2018, SolarexMSX 60, and LSM 20 PV module, respectively, as compared with the basic TSA. Based on the performance at different irradiation levels, the OTSA also establishes a more reliable efficacy. The OTSA algorithm produces the least value of RMSE even at 360 W/m^2. The convergence curves reveal that the OTSA algorithm obtains the finest values of estimated parameters for all three PV modules.

TABLE 6. Comprehensive review of application of meta-heuristic algorithms for parameter extraction of PV models.

Model	Parameters Extracted	Reference	Technique	Description
Double Diode	I_p, I_{sd1}, I_{sd2}, a_1, a_2, R_s, R_{sh}	[23]	Genetic Algorithm	Small deviation in the value of optimized parameters.
Single Diode	I_p, I_{sd}, a_1, R_s, R_{sh}	[49]		Reverse saturation current was highly accurate with slow extraction process.
Single Diode	I_{sd}, I_p, R_s, R_{sh}, a_1	[50]		Problem of local minima is found in non-convex cases.
Single and Double Diode	I_p, I_{sd1}, I_{sd2}, a_1, a_2, R_s, R_{sh}	[51]		Accurate optimized parameters are obtained for a wide range of radiation and temperature.
Single and Double Diode	I_p, I_{sd1}, I_{sd2}, a_1, a_2, R_s, R_{sh}	[52]	Particle Swarm Optimization	Accuracy and computational time of PSO technique is superior to GA.
Single and Double Diode	I_p, I_{sd1}, I_{sd2}, a_1, a_2, R_s, R_{sh}	[53]		The extracted parameters were further investigated to identify the various mechanisms affecting the cell performance.
Single Diode	a_1, R_s, R_{sh}	[54]		PSO technique produced precise PV cell parameters under varying radiation and temperature.
Single Diode	I_p, I_{sd}, a_1, R_{sh}, R_s	[55]		Improved overall searching capability under multiple local maxima.
Double Diode	I_p, I_{sd1}, I_{sd2}, a_1, a_2, R_s, R_{sh}	[56]		Extracted parameters gives a practical representation of the PV system.
Single Diode	a_1, R_s , R_{sh}	[57]		Proposed method eliminates the assumption in the ideality factor.
Single Diode	a_1, I_{sd}, R_s, R_{sh}, δ_s, Φ_{sh}	[58]	Differential Evolution Algorithm	Proposed technique has a high speed of convergence and easy to implement.
Double Diode	I_p, I_{sd1}, I_{sd2}, R_s, R_{sh}, a_1, a_2	[59]		Proposed two DE methods: boundary based, and penalty based to extract the parameters of PV module with a smaller number of control parameters.
Single Diode	a1, R_s, R_{sh}	[60]		Proposed a DE technique with improved ability to determine the parameters under different radiation and temperature.
Single and Double Diode	I_p, I_{sd1}, I_{sd2}, a_1, a_2, R_s, R_{sh}	[21]		Proposed method has improved convergence speed.
Single and Double Diode	I_p, I_{sd1}, I_{sd2}, a_1, a_2, R_s, R_{sh}	[24]	Simulated Annealing	Proposed method solves transcendental function of the I-V curve.
Single and Double Diode	I_p, I_{sd1}, I_{sd2}, a_1, a_2, R_s, R_{sh}	[27]	Pattern Search	Proposed method has higher accuracy as compared to other optimization methods.
Single Diode	a_1, R_s, R_{sh}	[61]	Bacteria Foraging Algorithm	Proposed a new objective function by taking the derivative of the basic current equation of single diode model.
Improved Single Diode	I_p, I_{sd}, a_1, R_{sh}, R_s, E_g	[17]	Cuckoo Search	The proposed method has the lowest root mean squared error value.
Single and Double Diode	I_p, I_{sd1}, I_{sd2}, a_1, a_2, R_s, R_{sh}	[62]	Harmony Search	Harmony search variants are proposed. The first variant finds the best harmonies in the harmony memory and the second helps in improving the probability of generating a harmony.
Single and Double Diode	I_p, I_{sd1}, I_{sd2}, a_1, a_2, R_s, R_{sh}	[63]	Artificial Bee Swarm Optimization	The proposed method is superior as compared to other optimization methods as it has the lowest root mean square error.
Single and Double Diode	I_p, I_{sd1}, I_{sd2}, a_1, a_2, R_s, R_{sh}	[64]	Bird Mating Optimizer	The proposed method was able to avoid premature convergence.
Single Diode	I_{sd}, I_p, R_s, R_{sh}, a_1	[65]		Can easily estimate the PV parameters with smaller number of control parameters.

Although the effectiveness of the proposed approach for estimating PV parameters has been demonstrated by statistical analysis, there are still a few constrained factors that could be further considered for future works. First, the proposed OTSA can be implemented for various other solar cell models to prove its capability. In particular, it can be used to observe the effect of unpredictable external factors like wind, rain, etc. Second, the feasibility of the proposed OTSA can be further enhanced based on other optimization techniques and concepts. The authors would like to mention that OTSA cannot be recognized as a ubiquitous method because no such approach exists that can solve all optimization problems as per the statement of the NFL theorem. The results confirm the OTSA efficiency comparing with state-of-the-art algorithms.

APPENDIX

See Table 6.

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