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Tree Growth Based Optimization Algorithm for Parameter Extraction of Different Models of Photovoltaic Cells and Modules

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ABSTRACT Among all renewable energy sources, solar cells are considered the most popular solution for a clean source of energy and have a wide range of applications from few watts to Megawatt industrial and domestic loads. Building a precise mathematical model based on nonlinear equations for solar cells as well as photovoltaic (PV) modules is an essential issue for reasonable performance assessment, control and optimal operation of PV energy systems. In the current study, a novel optimization algorithm, Tree Growth Algorithm (TGA), is applied for accurate and efficient extraction of the unknown solar cell and PV module parameters. TGA is applied for estimating the unidentified parameters of PV models. Single diode model (SDM), double diode model (DDM) and three diode model (TDM) are investigated in the mathematical models of both solar cells and PV modules. The obtained results from the application of TGA to achieve this objective are compared with different algorithms reported in the literature. Moreover, the results demonstrated that the proposed algorithm of TGA superior to other reported methods. The good matching of the *I-V* characteristic curve of the computed parameters with those of the measured data from the manufacturer's PV modules/cells datasheet proved that the proposed TGA may function as a competitor to the methods provided in literature for parameters' identification of PV of solar cells.

INDEX TERMS Solar cells, tree growth algorithm, parameter estimation, PV modeling, optimization.

I. INTRODUCTION

Environmental protection concerns and the huge increase in the demand for electric energy make the usage of renewable sources of energy to be the tendency worldwide. Therefore, the policy of the majority of countries is to promote the utilization of renewable energy sources, as a solution to meet the ever-increasing energy needs without causing any adverse effects on nature [1]–[4]. Among a large number of renewable sources of energy, the most important one is solar or photovoltaic (PV) energy due to its multiple fields of use and its neatness. However, based on the high capital investment cost of PV systems, the best configuration of these systems should be a guarantee to increase their efficiency [5].

An essential aspect of improving the efficiency of photovoltaic systems is the optimal design of these systems. Therefore, reliable and optimal PV system modeling has to be provided to improve the overall PV system's operating characteristics [5]–[9]. The modeling process can be separated into two independent phases. The first is the preparation of the PV system mathematical model, whereas the second stage is the techniques of extraction parameters [10]–[12]. Many models of PV solar cells describe the non-linear performance of the solar PV system, the simplest one and most popular

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is the single diode model (SDM) [13]. Moreover, the double diode model (DDM) [14] and three diode model (TDM) are noteworthy models in the literature [4]. Apart from these basic and reference models detailed in the literature, many models are less described in the literature as the multi-diode model [15], the modified double diode model [16], and the reverse double diode model [17].

The single diode model is considered as a basic model of PV solar cells and considered as the most popularly applied model because of its smaller number of unknown parameters, its acceptable accuracy, and its simplicity. The double diode model is introduced as a mathematical model, including seven unidentified parameters that should be estimated. The three-diode model was represented in [4] by Khanna *et al.* as a model with ten parameters which increases the precision of the estimation's procedure and allows developing a PV cell model that will be convenient for manufacturing applications. Despite its complex design, the TDM is considered as the best model for PV solar cells. The reliable modeling of the PV system is a big challenge, which typically depends on the formulation of the mathematical simulation model and the exact estimation of the unknown parameters. The situation becomes unsatisfactory as the above simulation models are implicitly transcendent relationships and this debility is not explicitly solvable by applying conventional primary methods [18].

Recently, many research items have been conducted in the area of solar PV generating systems. The priority was given to find an estimation of the unknown parameters of the simulated PV system models i.e., finding optimal parameters' values of the solar cells as well as PV modules to derive precise non-linear *I-V* characterization curve and accurate design of the PV system. The PV parameter can be extracted by three common approaches: (1) analytical [19], (2) numerical extraction method [20], [67], [68], and (3) metaheuristic approaches [10]. The analytical approach is based on the derivation of mathematical equations which necessarily provide simple and rapid identification and calculation of the PV parameters. In the analytical methods, the main points of the *I-V* characteristic curves were utilized, i.e. the point of short circuit current, open-circuit voltage, and the maximum power. In spite of the simpleness and small time of calculations, the accuracy of the analytical approach is susceptible to deterioration if one or more of the key points of the *I-V* characteristics are incorrectly determined. Moreover, the analytical approach does not reflect the real operating conditions. Several analytical techniques have been reported in [19]–[22], such as the Lambert method-based W- function was used for the estimation of the values of the unknown parameters of the SDM and DDM of the solar PV cells. However, it was finally approved that these approaches are less accurate than numerical approaches [20]–[23].

Numerical calculation methods usually use non-linear algorithms, like Newton-Raphson methods (NRM) [23], Nelder-Mead simplex method [24], conductivity method (CM) [25] or the Levenberg–Marquardt (LM) algorithm to identify the parameters of the simulation models of the PV system [26]. Moreover, in Ref. [67], an accurate method has been applied based on Two-step linear least-squares (TSLLS). Also, the Reduced Forms (RF) based method has been presented in [68]. The numerical approaches for being applicable, need continuousness and differentiability conditions on the fitness functions, therefore they will face some shortage and challenges while solving the extraction of the PV cells parameter. A Newton-Raphson algorithm-based numerical approach has applied in [27] for the estimation of the parameter of the DDM of the PV cells. A simple and precise method to identify the design parameters of DDM has been proposed by Mares et al in [28]. In such a context, many numerical techniques are introduced in [21], [29], but regardless of the improvement in accuracy against the analytical approaches, the large number of unknown parameters in the numerical methods complicates the extraction's procedure.

Recently, meta-heuristic optimization methods have attracted considerable attention to the problems of the extraction of PV parameters to overcome the downsides of the analytical and numerical approaches. Meta-heuristic optimization methods characterized by their global search point and their capability to deal with the nonlinear problems without the need for the gradient calculation of the objective function and initialization constraints [30]–[35]. Several meta-heuristic algorithms are considered to solve the optimization problem that targets estimating the parameters of the PV cell, such as the genetic algorithm [30]–[32]. In the case of the genetic algorithm, significant weakness points were observed. The most important of which is the time of calculation and the low-speed of the convergence. Particle Swarm Optimization is another metaheuristic technique [33], [34]. In [34] the PSO was applied to find the parameters of solar cells considering SDM and DDM. In [35], the Simulated Annealing (SA) was suggested as an algorithm for extracting the parameters of the SD and DD models of the PV cell.

The Bacterial Foraging Algorithm with a new equation is proposed in [36] for the evaluation of the parameters of the PV cell models. In the same context, the Differential Evolution [5], [37], [38]; Teaching Learning Based Optimization [39]; Harmony Search [11]; Chaotic Gravitational Search algorithm [40]; biogeography-based optimization [41]; Moth- Flame optimization [42]; Bird Mating Optimizer [43]; Firefly algorithm [44]; cuckoo search [45]; imperialist competitive algorithm (ICA) [46] also are recommended to solve the PV estimation parameters. In [47], [48] the artificial bee colony is considered as an approach for finding a solution for this problem. In [49], [50] the Jaya algorithm and Improved Jaya algorithm are considered for PV parameter estimation.

The Chaotic Gravitational Search Algorithm and Chaotic Improved Artificial Colony Bee have been introduced in [40], [51] respectively, these algorithms use chaotic maps to provide precise evaluation for the PV unknown parameters. Moreover, applying of the Grasshopper Optimization

Algorithm (GOA) to extract the parameters of the three-diode PV model of a PV module has been introduced [69]. The researchers tested the GOA algorithm using two commercial PV modules of Kyocera KC200GT and Solarex MSX-60 PV cells [69]. Ref. [70] introduced the application of Biogeography-based heterogeneous cuckoo search (BHCS) algorithm to solve parameter estimation problems of different PV models. An interval branch and bound global optimization algorithm is applied for estimating the unknown PV parameters [71]. Ref. [72] proposed applying an advanced adaptive differential evolution technique on such a problem targeting finding an estimate of the PV module parameters considering the availability of minimum information from the manufacturer datasheet through the implementation of single-diode and double-diode models. Ref. [73] introduced an Improved Lozi Map based Chaotic Optimization Algorithm (ILCOA) algorithm for finding the unidentified parameters of the solar cell's models of SDM and DDM. A grey wolf optimization (GWO) algorithm is presented for the estimation of the unknown parameters of the PV module under changing weather conditions [74]. In Ref. [75], to extract PV model parameters, two parameters (parallel resistance and photo-generated current) are determining through analytical calculation and the rest of parameters are determined through the optimal design considering the sunflower optimization (SFO) technique. The application of a modified version of Whale optimization algorithm (WOA) for solving high-dimensional optimization problems and applied for solving photovoltaic model parameter estimation problems has been presented in [76]. An interval branch and bound global optimization algorithm is applied for estimating the unknown PV parameters in Ref. [71]. Ref. [77], A metaphor-less algorithm has been introduced for the photovoltaic cell parameter estimation for SDM, DDM and TDM. Ref. [78] proposed an Opposition-based Learning Modified Salp Swarm Algorithm (OLMSSA) for accurately identifying of the two-diode model parameters of the electrical equivalent circuit of the PV cell/module. A comprehensive overview of meta-heuristics methods for the estimation of the parameters of solar cells has been introduced in [82]. A categorized perturbation mutation-based particle swarm optimization algorithm has been applied to extract the parameters of Photovoltaic models has been introduced [80]. In [81], Flower pollination algorithm has been presented to estimate the parameters of DDM model for RTC France cell. In Ref. [82], Comparing solar cells parameters estimation through various optimization algorithms such as Artificial Bee Colony (ABC), Differential Evolution (DE), Harmony Search (HS), Gravitational Search Algorithm (GSA), Particle Swarm Optimization (PSO), Cuckoo Search (CS), Differential Search Algorithm (DSA), Crow Search Algorithm (CSA) and Covariant Matrix Adaptation with Evolution Strategy (CMA-ES) has been introduced. Ref. [82] concluded that the CMA-ES found the best results from such a group of algorithms. These techniques are efficient but suffer from a problem with accuracy. In this context, all the methods mentioned have been considered for SDM and DDM parameter estimation but only the PSO was applied for TDM parameter estimation. Although various meta-heuristic optimization methods are considered in order to find a solution for this problem. However, the research gaps may be summarized as: Shortcomings of reported results are the relatively high percentage of errors associated with the extracted parameters; low search speed with the application of most of the reported optimization techniques is also one of the shortcomings; In numbers of reported algorithms, improper tuning of many parameters, affects the balance between exploration and exploitation and may lead the search process to get trapped in local solution rather than global one; Many traditional optimization algorithms require the tendency data to pilot its search process; other optimization methods does it locate specific features of the objective function (e.g. convexity or continuity).

In any case, the essential point relevant to the extracting of the parameters of different models of PV panels still is an existing challenge, including the perspectives of not only the mathematical modeling but also the optimization techniques. So, the main features of the proposed optimization method in this paper are how simple the concept is, how easy the implementation is, and how efficient the computational. Searching for new algorithms is to compete with existing algorithms remains a major challenge for researchers.

In this paper, a recent metaheuristic optimization technique,

Tree Growth Algorithm (TGA), is proposed for solving the global optimization problems [52]. This paper is organized in the following manner: Section 2 introduces a brief explanation of the PV cell models. Section 3 presents the Trees Growth Algorithm in details including the formulation of the algorithm. Section 4 presents the simulation results and discussion for all case studies. Finally, the conclusion is presented in section 5.

II. MATHEMATICAL MODELLING

Single diode and double diode models are the most popularly used models when modelling and simulating PV solar cells and arrays [20], [29]. As previously explained in the literature survey, the one diode model is very simple but its accuracy is not so high. Accordingly, for more precise results, double diode, and three diode models are very essential as they help for satisfying the physical requirements of PV arrays and multi-crystalline cells like the effect of leakage circulating current and grain boundaries [29], [42]. Therefore, in this paper, the DDM and TDM are studied, and the results are compared with the results of the original SDM.

A. SINGLE DIODE MODEL (SDM)

The circuit configuration of the solar cell in SDM representation is shown in Fig. 1. The equivalent circuit includes an independent current source shunted by one diode and shunt resistance, the combination is connected with a series

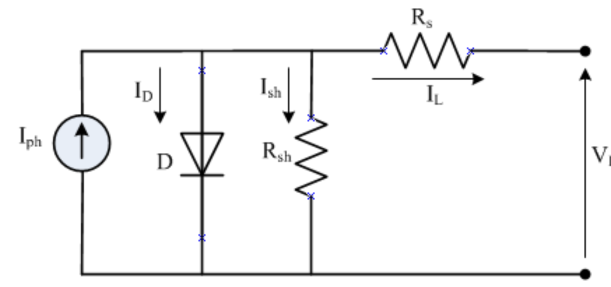

FIGURE 1. Equivalent circuit of the single diode model.

resistance R_s. By applying Kirchhoff's current low on the circuit of Fig. 1, the output load current I_L is defined as given in [20], [28],

$$I_L = I_{ph} - I_D - I_{sh} \tag{1}$$

where I_{ph} represents the photo-generated current (A), I_D is the diode current (A), and I_{sh} presents the current through the shunt resistance (A). Moreover, by the well-known Shockley equation, I_D is determined as follows [20]–[28],

$$I_D = I_{sd} \times \left[exp\left(\frac{V_L + R_s.I_L}{nV_t} \right) - 1 \right] \tag{2}$$

where I_{sd} denotes the reverse dark saturation current (A), V_L presents the generated voltage on the terminal of the solar cell (V), R_s is the series resistance (Ω), n represents the diode ideality coefficient, V_t presents diode thermal voltage (V), that is determined from the following expression [20]–[28],

$$V_t = \frac{k.T}{q} \tag{3}$$

where k denotes Boltzmann constant ($1.3806503 \times 10^{-23}$ J/K), q presents the charge of an electron ($1.60217646 \times 10^{-19}$ C), and T denotes the temperature of the solar cell in Kelvin. The current passing in the shunt resistor is expressed from the following formula [20]–[28],

$$I_{sh} = \frac{V_L + R_s.I_L}{R_{sh}} \tag{4}$$

where R_{sh} denotes the shunt resistance (Ω).

Considering the substitution from equation (2), (3) and (4) into equation (1), the load current I_L is redescribed as,

$$I_L = I_{ph} - I_{sd} \times \left[exp\left(\frac{V_L + R_s.I_L}{nV_t} \right) - 1 \right] - \frac{V_L + R_s.I_L}{R_{sh}} \tag{5}$$

Therefore, as given in equation (5), the unknown five parameters that have to be optimized in the case of SDM are (I_{ph}, I_{sd}, R_s, R_{sh} and n).

B. DOUBLE DIODE MODEL (DDM)

The circuit configuration of DDM is shown in Fig. 2. The DDM is recommended to account for the influence of current loss that happened inside the depletion region. The current drawn from the solar cell I_L is calculated by applying Kirchhoff's current law and Shockley formula on the circuit of Figure 2 [40], [42], [43].

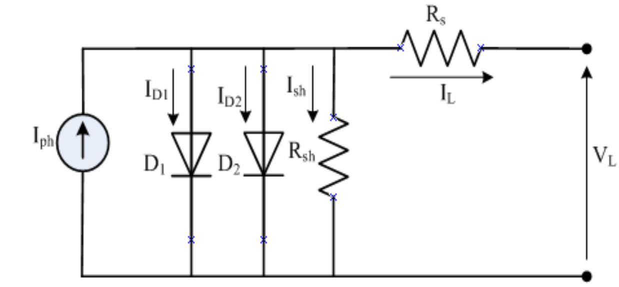

FIGURE 2. Equivalent circuit of the double diode model.

$$I_L = I_{ph} - I_{D1} - I_{D2} - I_{sh} \tag{6}$$

$$\begin{aligned} I_L &= I_{ph} - I_{sd1} \times \left[exp\left(\frac{V_L + R_s.I_L}{n_1 V_t} \right) - 1 \right] \\ &\quad - I_{sd2} \times \left[exp\left(\frac{V_L + R_s.I_L}{n_1 V_t} \right) - 1 \right] - \frac{V_L + R_s.I_L}{R_{sh}} \end{aligned} \tag{7}$$

where I_{sd1} denotes the diffusion current (A), and I_{sd2} is the saturation current (A). n_1 and n_2 denote the ideality factors of the diodes for diffusion and recombination, respectively. The DDM includes seven unknown parameters which should be identified (I_{ph}, I_{sd1}, $I_{sd2,}R_s$, R_{sh}, n_1 and n_2).

C. THREE DIODE MODEL (TDM)

For increasing the accuracy of the PV modeling, for taking into account the impact of the leakage currents and grain boundaries, the TDM is recommended [42]. As shown in Fig. 3, the circuit configuration of the TDM is the same as the DDM except the third diode is shunted with the last two diodes of the DDM. In this case, the load current drawn from the solar cell is identified as follows [42],

$$I_L = I_{ph} - I_{D1} - I_{D2} - I_{D3} - I_{sh} \tag{8}$$

$$\begin{aligned} I_L &= I_{ph} - I_{sd1} \times \left[exp\left(\frac{V_L + R_s.I_L}{n_1 V_t} \right) - 1 \right] \\ &\quad - I_{sd2} \times \left[exp\left(\frac{V_L + R_s.I_L}{n_1 V_t} \right) - 1 \right] \\ &\quad - I_{sd3} \times \left[exp\left(\frac{V_L + R_s.I_L}{n_1 V_t} \right) - 1 \right] - \frac{V_L + R_s.I_L}{R_{sh}} \end{aligned} \tag{9}$$

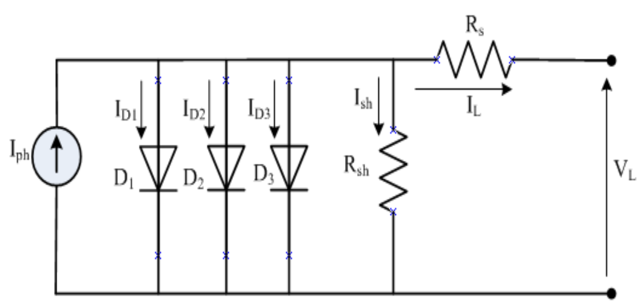

FIGURE 3. Equivalent circuit of three diode model.

where $I_{sd1}, I_{sd2,}$ and I_{sd3} represent the diffusion current, the recombination current and the current resulted from recombination in the defected region, respectively [42]. The other variables are defined in the previous sections. Accordingly, nine unknown parameters have to be determined.

D. PV MODULE MODEL

A typical solar PV module model based on a single diode is shown in Fig. 4. The model includes many solar cells arranged in series and/or in parallel connections to provide a certain value of the voltage and current from the module. N_s represent the number of series cells, where N_p denotes the number of cells connected in parallel connection. The output load current drawn from the PV module is calculated by the following expression as given in [28]–[30],

$$I_L = N_p . \left\{ \begin{array}{l} I_{ph} - I_{sd} \times \left[exp \left(\dfrac{V_L/N_s + R_s.I_L/N_p}{nV_t} \right) - 1 \right] \\ - \dfrac{V_L/N_s + R_s.I_L/N_p}{R_{sh}} \end{array} \right\} \tag{10}$$

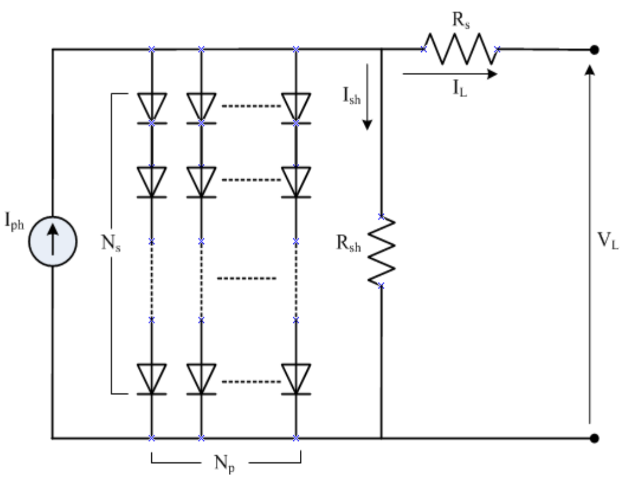

FIGURE 4. Equivalent circuit of solar PV module model.

The same as in the case of SDM, the module model includes five parameters (I_{ph}, I_{sd}, R_s, R_{sh} and n), which needs to be evaluated.

III. FORMULATION OF THE PARAMETER EXTRACTION PROBLEM

The unknown parameters of the solar cells can be estimated with the help of optimization techniques. The selected method of optimization will be applied to decrease the value of an early defined objective function by changing the unknown parameters within the predefined boundaries until the end criterion is achieved. The main objective in modeling PV solar cells is decreasing the gap between the commercial datasheet values and the estimated ones under different cell temperatures and intensity of solar radiation by determining the optimal solution of the optimization problem (i.e. the optimal value of the unknown parameters).

The essential requirements in any optimization problem that have to be determined to apply any optimization technique are the objective function, the search boundaries and the vector of solution (x). In this paper, the objective function is taken as the Root Mean Square Error (RMSE) among the measured data from experiment and the data that are extracted. The RMSE is calculated according to the following equation,

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} \left(fc \left(V_L^i, I_L^i, x \right)^2 \right)} \tag{11}$$

where $f(V_L^i, I_L^i, x)$ is the error function that represents the deviation between the measured data (experimentally collected or from manufacturer's PV cells/modules datasheet) and the computed ones. N denotes the number of data series (number of measurements). i denotes the order of measurement. x describes the parameters for estimation. C represents the diode model that is evaluated. The error function is described by equations (12), (13), (14) and (15) for SDM, DDM, TDM, and PV module model, respectively.

$$f_{SDM}(V_L, I_L, x) = I_{L,\text{meas}} - \left\{ \begin{array}{l} I_{ph} - I_{sd} \times \left[exp \left(\dfrac{V_L + R_s.I_L}{nV_t} \right) - 1 \right] \\ - \dfrac{V_L + R_s.I_L}{R_{sh}} \end{array} \right\} \tag{12}$$

$$f_{DDM}(V_L, I_L, x) = I_{L,\text{meas}} - \left\{ \begin{array}{l} I_{ph} - I_{sd1} \times \left[exp \left(\dfrac{V_L + R_s.I_L}{nV_t} \right) - 1 \right] \\ - I_{sd2} \times \left[exp \left(\dfrac{V_L + R_s.I_L}{nV_t} \right) - 1 \right] \\ - \dfrac{V_L + R_s.I_L}{R_{sh}} \end{array} \right\} \tag{13}$$

$$f_{TDM}(V_L, I_L, x) = I_{L,\text{meas}} - \left\{ \begin{array}{l} I_{ph} - I_{sd1} \times \left[exp \left(\dfrac{V_L + R_s.I_L}{nV_t} \right) - 1 \right] \\ - I_{sd2} \times \left[exp \left(\dfrac{V_m^i + R_s.I_L}{nV_t} \right) - 1 \right] \\ - I_{sd3} \times \left[exp \left(\dfrac{V_L + R_s.I_L}{nV_t} \right) - 1 \right] \\ - \dfrac{V_L + R_s.I_L}{R_{sh}} \end{array} \right\} \tag{14}$$

$$f_{module}(V_L, I_L, x) = I_{L,\text{meas}} - N_p . \left\{ \begin{array}{l} I_{ph} - I_{sd} \times \left[exp \left(\dfrac{V_L/N_s + R_s.I_L/N_p}{nV_t} \right) - 1 \right] \\ - \dfrac{V_L/N_s + R_s.I_L/N_p}{R_{sh}} \end{array} \right\} \tag{15}$$

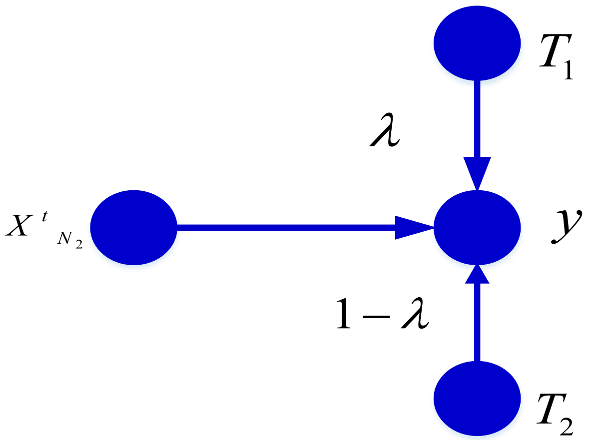

FIGURE 5. Linear combination.

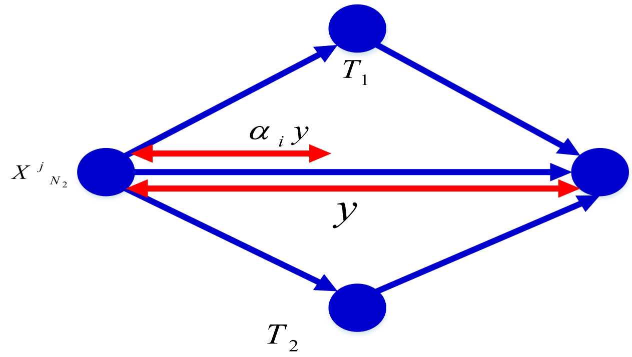

FIGURE 6. Moving between two adjacent trees.

where V_L, $I_{L,meas}$ and I_L denote the measured values of the solar cell generated voltage and current and the estimated currents, respectively. x is the vector of solutions that have the length of the unknown parameters. It should be noted that the second term of equations (12) to (15) are solved through the use of Newton-Raphson method.

The solution vectors are defined depending on the type of model as follows: For SDM, $x = (I_{ph}, I_{sd}, R_s, R_{sh}, n)$, for DDM $x = (I_{ph}, I_{sd1}, I_{sd2}, R_s, R_{sh}, n_1, n_2)$, for TDM $x = (I_{ph}, I_{sd1}, I_{sd2}, I_{sd3}, R_s, R_{sh}, n_1, n_2, n_3)$, and for module model, it is the same as SDM $x = (I_{ph}, I_{sd}, R_s, R_{sh}, n)$.

According to works of literature [41]–[43], the values of the upper and lower boundaries that control the search range of the unknown parameters are determined based on the results in Table 1. Tree Growth Algorithm has been proposed for extracting the optimum solution of the optimization problem (i.e. the value of unknown parameters) under different case studies while achieving the minimum value of the objective function.

TABLE 1. Search ranges of unknown parameters for SSD, DDM, TDM and module models.

Parameter	SDM/DDM/TDM		PV module model	
	Lower Bound	Upper bound	Lower bound	Upper bound
I_{ph} (A)	0	1	0	2
I_{sd} (μA)	0	1	0	50
R_s (Ω)	0	0.5	0	2
R_{sh} (Ω)	0	1000	0	10000
n_1, n_2, n_3	1	2	1	50

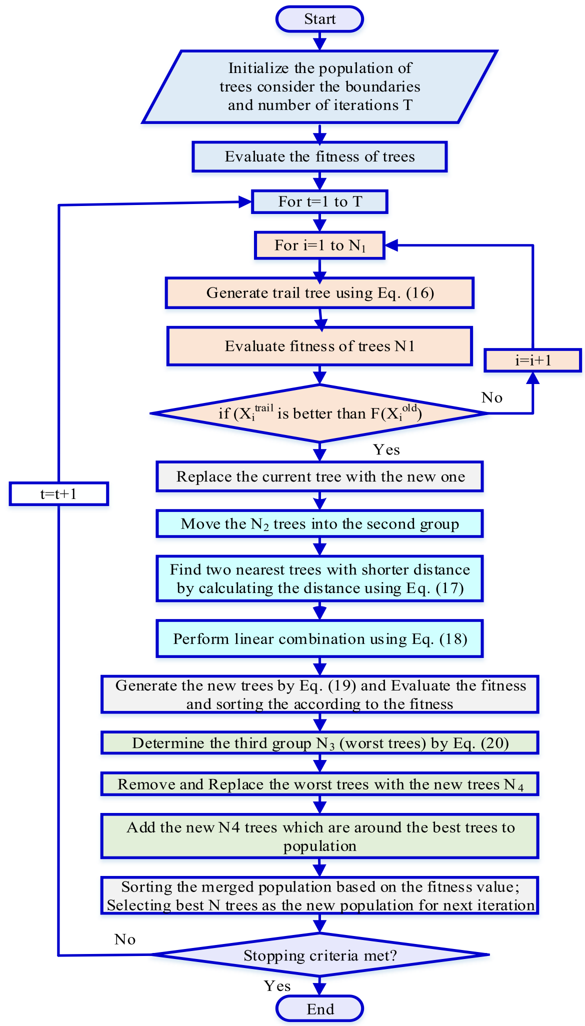

FIGURE 7. Flowchart of the proposed TGA.

IV. TREE GROWTH ALGORITHM

In 2018, a new nature-inspired metaheuristic technique introduced by Cheraghalipour and his colleagues [53], known as Tress Growth Algorithm. The TGA has two stages: intensification and diversification of the algorithm. Intensification typically works by rebooting from high-quality solutions or by modifying the selection rules in favor of including attributes for these solutions. At this stage, we allow the best trees, which satisfy the absorption of light, to compete for the source of food. The modernist approach at this stage ensures that the movement of the trees is towards a better food source.

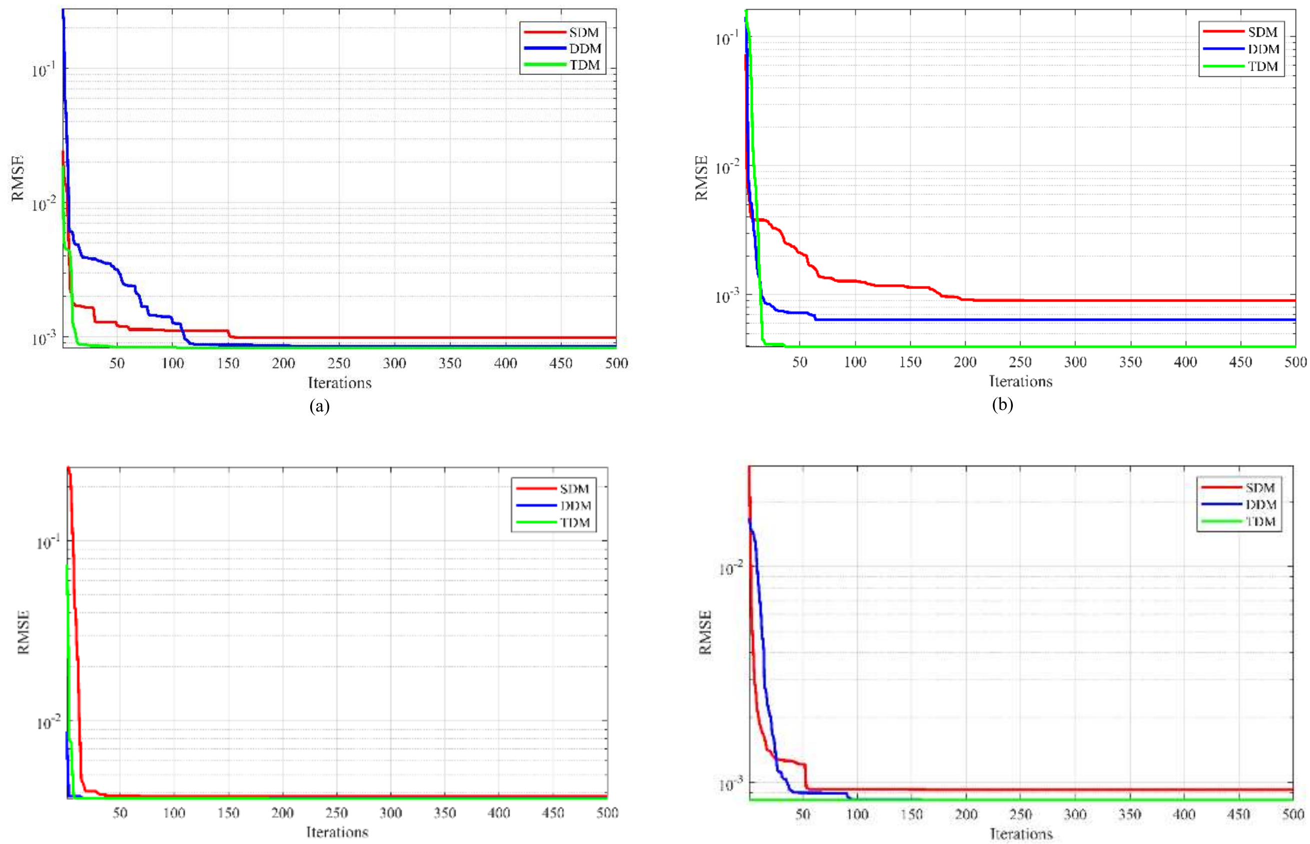

FIGURE 8. **Convergence trends of RMSE for the solar cells and PV modules under study using the proposed TGA-based models: (a) R.T.C. France solar cell, (b) PVM 752 GaAs thin-film cell, (c) Photowatt-PWP201 module, (d) Leibold Solar Module (STE 20/100).**

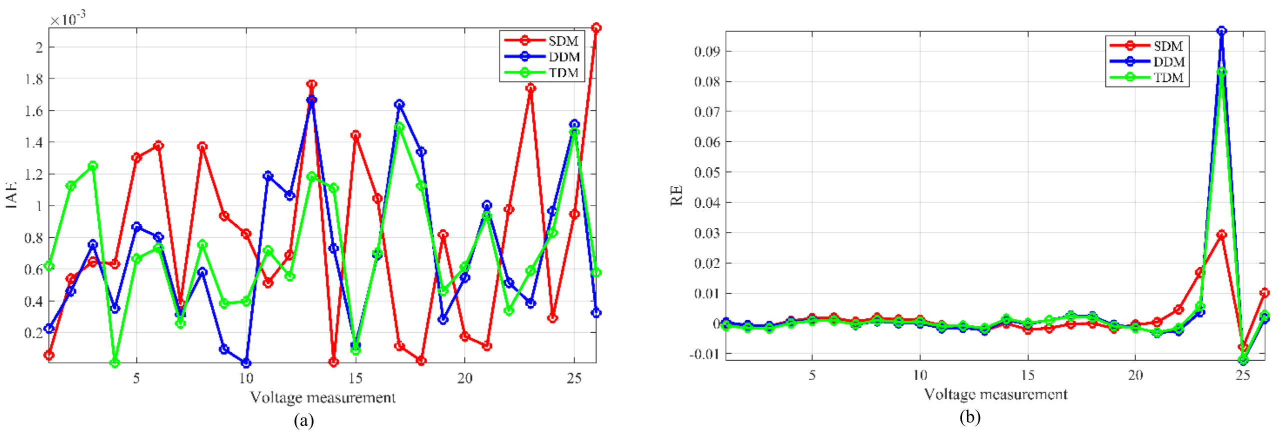

FIGURE 9. **(a) IAE values; (b) RE value; of RTC France solar cell.**

This means that in the intensification stage, we are moving only towards the optimum local or global optimum [53].

In the diversification phase, the other trees compete to absorb light and move towards new or virgin places (solutions) [53]. By adjusting the parameters, a balance can be obtained between Intensification and diversification. TGA performance and efficiency were tested in some standard and engineering problems.

Trees in forests are categorized into four groups. The first group is called the best tree group N_1, due to favorable conditions for growth, and the second one N_2 is defined as the competition for the light tree category. In the latter category, some trees move towards the best trees under various angles for reaching the light. The third group N_3 is called the replacement or removal group. The main goal of this group is to remove the bad and weak trees and reproduce new trees. After

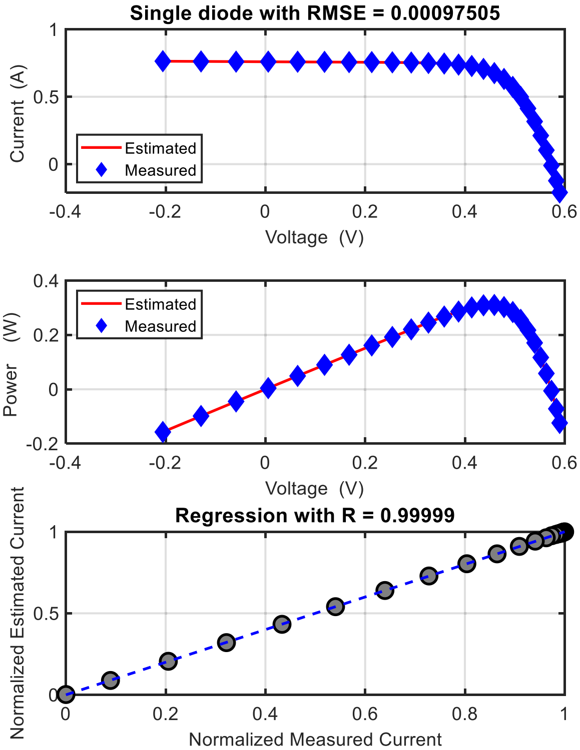

FIGURE 10. Characteristics of RTC France solar cells according to the experimental data and estimated data from SDM.

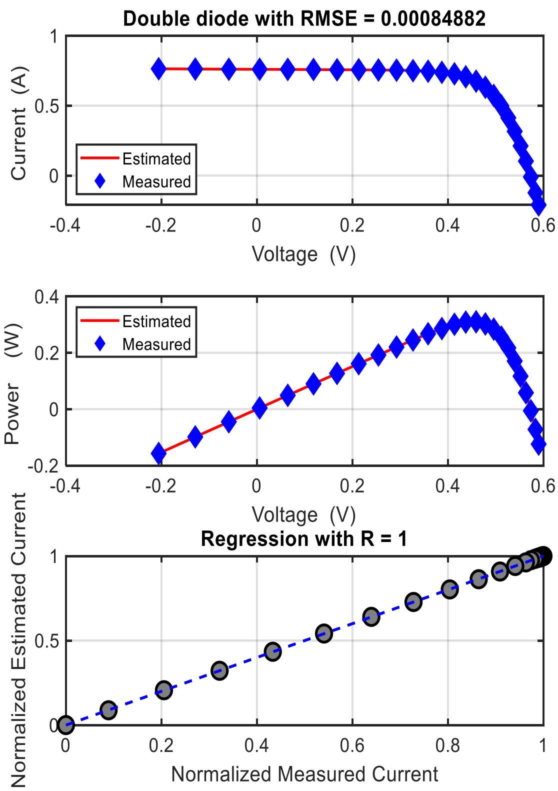

FIGURE 11. Characteristics of RTC France solar cells according to the experimental data and extracted data from DDM.

destroying the ancestor's worst trees, the reproduction period continues, where the last group N_4 is called the reproductive group [53].

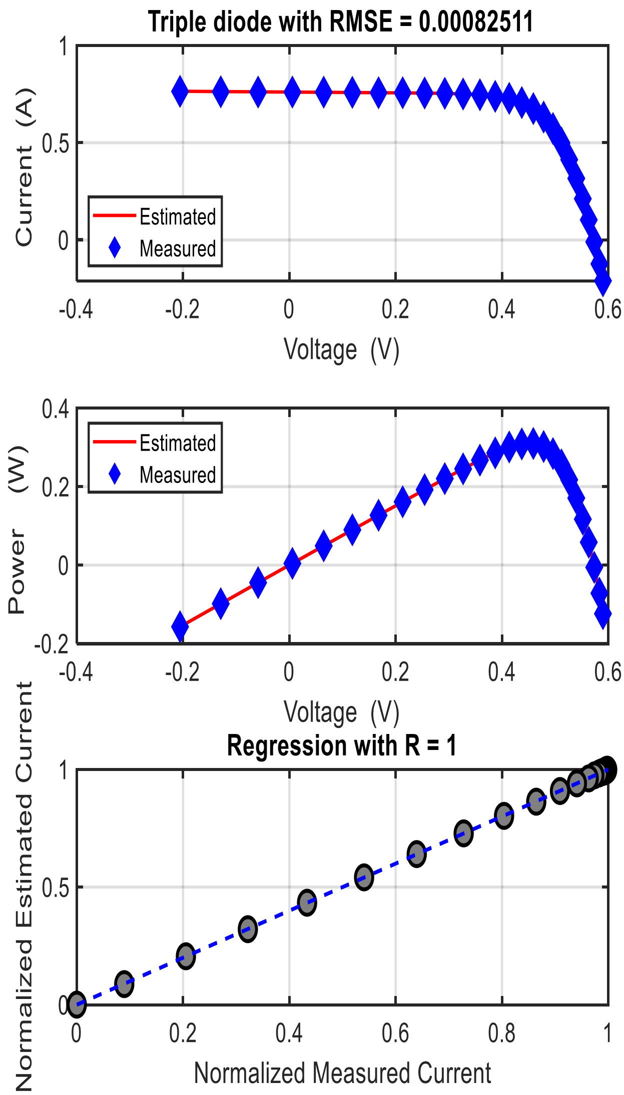

FIGURE 12. RTC France solar cells features as per experimental data and estimated data from TDM.

The principle of TGA is explained with the following steps: in the first step, the initial population of trees is created in a random form. The fitness value is determined for each tree and based on the fitness value, the trees are arranged in ascending order in the first group N_1. The new tree in N_1 is produced based on the following formula [52]:

$$X_i^{t+1} = \frac{X_i^t}{\theta} + rX_i^t \tag{16}$$

That θ is trees reduction rate of energy, as a result of old, increased growth and decreased food around. r is a number randomly distributed number in the interval [0, 1], X_i^t denotes the location of the solution(tree) in iteration t.

In the second step, the N_2 trees are moved in the second group, so the distance between the best near trees is determined using the following formula [53]:

$$D_i = \left(\sum_{i}^{N_1+N_2} (X_{N_2}^t - X_i^t)^2 \right)^{\frac{1}{2}} \tag{17}$$

TABLE 2. Estimated model parameters for SDM of R.T.C. France solar cell.

Algorithm	I_{ph} (A)	I_{sd} (μA)	R_s (Ω)	R_{sh} (Ω)	N	RMSE
TGA	0.760384664115839	0.230826252	0.0379916685433	53. 677883306	1.44792901564	9.750530454421328E-04
TSLLS [67]	0.76074014	0.31285196	0.036615485	55.907380	1.4777295	7.7301E– 04
RF [68]	0.76078797	0.31068442	0.036546948	52.889782	1.477105	77300627E-04
ABSO [47]	0.76080	0.30623	0.03659	52.2903	1.47583	9.9124E-04
HS [11]	0.7607	0.30495	0.03663	53.5946	1.47538	9.9510E-04
PSO [36]	0.7607	0.400	0.0354	59.012	1.5033	1.3900E-03
GA [32]	0.7619	0.8087	0.0299	42.3729	1.5751	1.8704E-02
An.5-Pt. [61]	0.7606	0.2417	0.0422	106.3829	1.4513	7.9602E-03
LW [62]	0.7611	0.2422	0.0373	42	1.4561	9.6964E-03
Newton [63]	0.7608	0.3223	0.0364	53.7634	1.4837	1.0072E-02
CM [28]	0.7608	0.4039	0.0364	49.5050	1.5039	2.8573E-03
PS [57]	0.7617	0.998	0.0313	64.1026	1.6	1.4940E-02

TABLE 3. Estimated model parameters for DDM R.T.C. France solar cell.

Algorithm	I_{ph} (A)	I_{sd1} (μA)	I_{sd2} (μA)	R_s (Ω)	R_{sh} (Ω)	n_1	n_2	RMSE
TGA	0.7607	0.16740	0.22083	0.0356	58.2574	1.4999	1.4999	8.488244232381E-04
ABSO [47]	0.76078	0.26713	0.38191	0.03657	54.6219	1.46512	1.98152	9.8344E-04
HS [11]	0.76176	0.12545	0.2547	0.03545	46.82696	1.49439	1.49989	1.2600E-03
PSO [36]	0.7623	0.4767	0.01	0.0325	43.1034	1.5172	2	1.6600E-03
GA [32]	0.7608	0.0001	0.0001	0.0364	53.7185	1.3355	1.481	3.6040E-01
ABC [48]	0.760813	0.192684	0.999587	0.036861	55.933515	1.438003	1.983721	9.8387E-04
SBMO [49]	0.760786	0.200798	0.74373	0.036917	55.104367	1.441256	1.947888	9.8485E-04
SSO [12]	0.760651	0.287201	0.065979	0.036255	55.853271	1.510345	1.433838	9.9129E-04
MSSO [12]	0.760748	0.234925	0.671593	0.036688	55.714662	1.454255	1.995305	9.8281E-04

TABLE 4. Estimated model parameters for TDM R.T.C. France solar cell.

Algorithm	I_{ph} (A)	I_{sd1} (μA)	I_{sd2} (μA)	I_{sd3} (μA)	R_s (Ω)	R_{sh} (Ω)	n_1	n_2	n_3	RMSE
TGA	0.7611	0.30477	0.25571	0.32399	0.0363	51.1400	1.9999	1.4623	2.00	8.251052783901371eE04
ABC [48]	0.7607	0.2000	0.5	0.2100	0.03687	55.8344	1.4414	1.9	2	9.8466E-04
OBWOA [19]	0.76077	0.2353	0.2213	0.4573	0.03668	55.4448	1.4543	2	2	9.8249 E-04
STBLO [61]	0.7608	0.2349	0.2297	0.2297	0.0367	55.2641	1.4541	2	2	9.8253 E-04

TABLE 5. Estimated model parameters for SDM of PVM 752 GaAs thin-film cell.

Algorithm	I_{ph} (A)	I_{sd} (μA)	R_s (Ω)	R_{sh} (Ω)	N	RMSE
TGA	**0.1007**	**2.8324E-04**	**0.5092**	**349.8888**	**1.9707**	**9.037521972258222E-04**
ELPSO [58]	0.115016	0	0.159052	14.429507	1.768590	2.5400E-2
CPSO [59]	0.116530	0	0.346578	14.241982	1.617093	2.5400E-2
BSA [58]	0.103903	84.90 E-06	0.5	100	1.858574	2.1469E-3
ABC [48]	0.103312	32.00 E-06	0.5	100	1.774159	2.0412E-3

Then the competition for light begins, and the current tree moves to win and reach the light. Therefore, the linear combination is calculated for the nearest two trees using the following formula:

$$y = \lambda T_1 + (1 - \lambda) T_2 \tag{18}$$

where λ is the variable that is used to control the impact of the nearest tree as shown in Fig. 5.

Finally, the movement of this tree between two neighboring trees with different angles is presented in Fig. 6, and mathematically described as follows [53]:

$$X_{N_2}^{t+1} = X_{N_2}^{t} + \alpha_i y \tag{19}$$

where α is the angle distributed and its value between 0 and 1.

In the third group, the worst N3 trees are removed and instead of them the new population (trees) N3 is generated as follows [53]:

$$N_3 = N - N_1 - N_2 \tag{20}$$

TABLE 6. Estimated model parameters for DDM of PVM 752 GaAs thin-film cell.

Algorithm	I_{ph} (A)	I_{sd1} (μA)	I_{sd2} (μA)	R_s (Ω)	R_{sh} (Ω)	n_1	n_2	RMSE
TGA	**0.1001**	**2.00 E-04**	**2.00 E-04**	**0.5111**	**960.4025**	**1.9306**	**1.9808**	**6.3867360483385E-04**
ELPSO [58]	0.103192	1.775 E-04	1.00 E-06	0.5	100	2.00	1.571052	0.002075
CPSO [59]	0.102688	1.00 E-06	1.00 E-06	0.500	100	1.572718	1.572718	0.002303
BSA [58]	0.102497	1.00 E-06	8.06 E-05	0.500	100	1.635590	1.872465	0.002178
ABC [48]	0.103252	1.00 E-05	1.00 E-06	0.500	100	1.792987	2.00	0.002044

TABLE 7. Estimated model parameters for TDM of PVM 752 GaAs thin-film cell obtained by TGA.

Tech.	I_{ph} (A)	I_{sd1} (μA)	I_{sd2} (μA)	I_{sd3} (μA)	R_s (Ω)	R_{sh} (Ω)	n_1	n_2	n_3	RMSE
TGA	0.1002	2.0068E-05	4.3812E-05	8.1610E-05	0.5439	700.3994	1.9057	1.9037	1.9060	3.9270534E-04

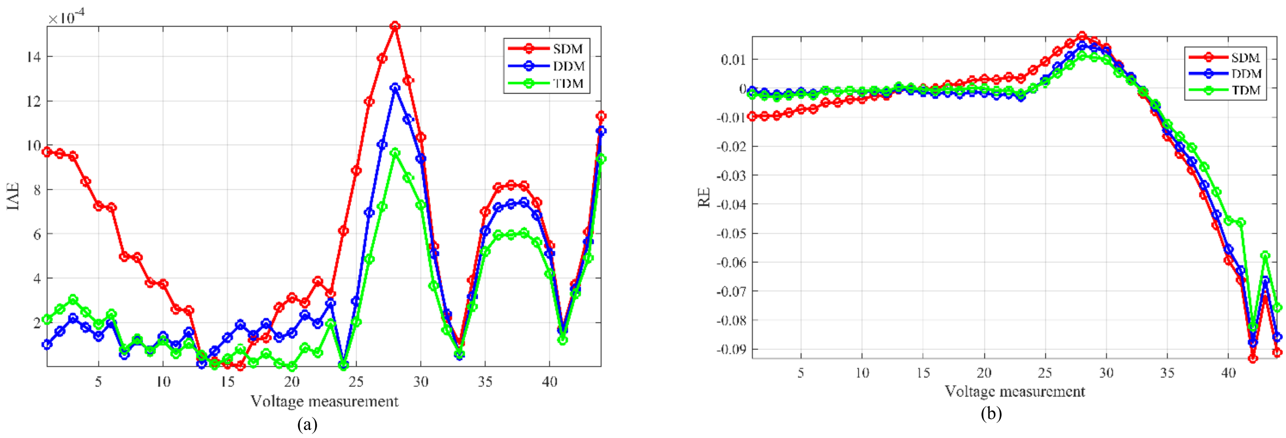

FIGURE 13. (a) IAE values; (b) RE values; PVM 752 GaAs thin-film cell.

TABLE 8. Estimated model parameters for SDM of the Photowatt-PWP201 module.

Algorithm	I_{ph} (A)	I_{sd} (μA)	R_s (Ω)	R_{sh} (Ω)	N	RMSE
TGA	**1.0263**	**9.5710**	**0.0298**	**6842.2**	**1.5255**	**0.003819491771269**
TSLLS [67]	1.0335685	2.2709763	1.2599674	687.87337	1.3069558	0.0021722792
RF [68]	1.032173	3.035367	1.218407	0.783516	1.336752	0.0021176
Newton [56]	1.0318	3.2875	1.2057	555.5556	1.3474016	0.7805
PS [32]	1.0324	3.1859	1.304	843.5233	48.2467	0.0127
OIS [60]	1.03674	3.1946	1.32897	1184.58	49.0435	0.004783
1DAB[62]	1.04276	3.4265	1.73762	948.845	49.2843	0.00536

TABLE 9. Estimated model parameters for DDM of the Photowatt-PWP201 module.

Algorithm	I_{ph} (A)	I_{sd1} (μA)	I_{sd2} (μA)	R_s (Ω)	R_{sh} (Ω)	n_1	n_2	RMSE
TGA	**1.0265**	**9.2998**	**2.2586E-02**	**0.0301**	**6719.0**	**1.5225**	**1.4164**	**3.7559306 E-03**
WDOWOAPSO [63]	1.03238234	1.72494775	0.787963228	1.23828868	744.71426	1.317304	1.317305	2.046535E-03
GCPSO [64]	1.03238233	2.51291639	1.0000574E-06	1.2392884	744.71539	1.317304	1.316939	2.0465E-03
TVACPSO [59]	1.031434	2.638124	1.00E-06	1.235632	821.65281	1.320998	2.777778	2.0530E-03
ABC-DE [65]	1.0318	0.32774	2.4305E-06	1.2062	845.2495	1.3443	1.3443	2.400E-03

TABLE 10. Estimated model parameters for TDM of the Photowatt-PWP201 module obtained by TGA.

Algorithm	I_{ph} (A)	I_{sd1} (μA)	I_{sd2} (μA)	I_{sd3} (μA)	R_s (Ω)	R_{sh} (Ω)	n_1	n_2	n_3	RMSE
TGA	1.0265	9.1105	2.0908 E-02	6.3250 E-02	0.0302	6021.9	1.5220	1.3011	1.5369	3.725913476 E-03

Finally, using the mask operator, the new trees in the fourth group are generated around the best trees. Next, the recently created N_4 trees are added to the population. The built-in population is saved based on their fitness value. Next, the best N trees are represented as a new population for the following iteration. Steps of the technique will be repeated until the

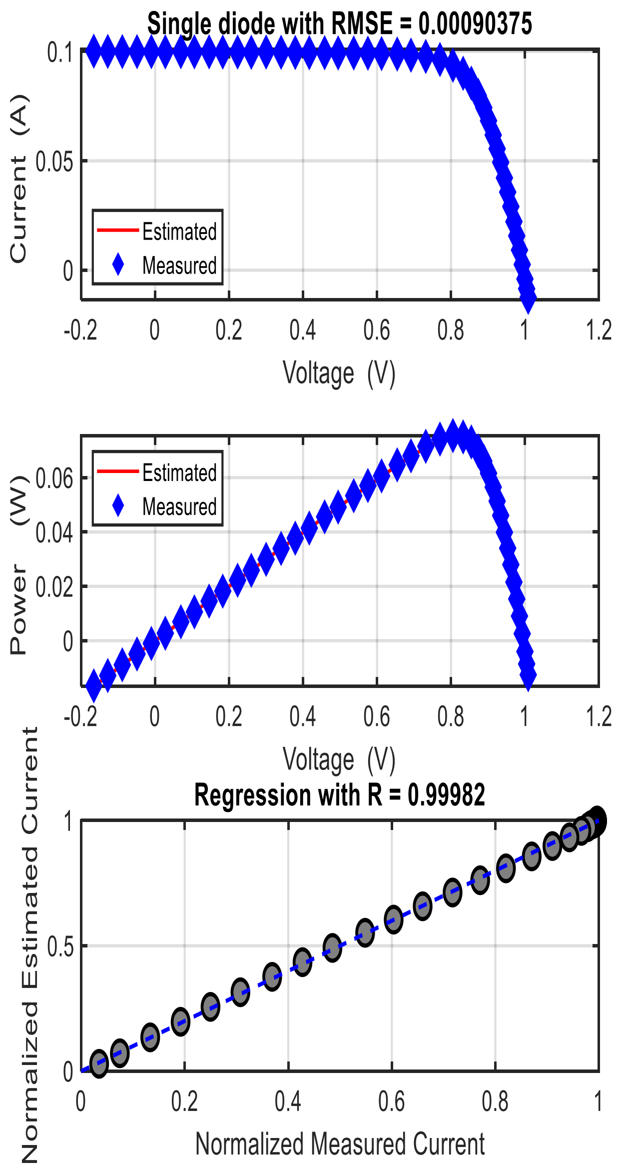

FIGURE 14. Comparison of the features of PVM 752 GaAs thin-film cell according to the experimental data and estimated data from SDM.

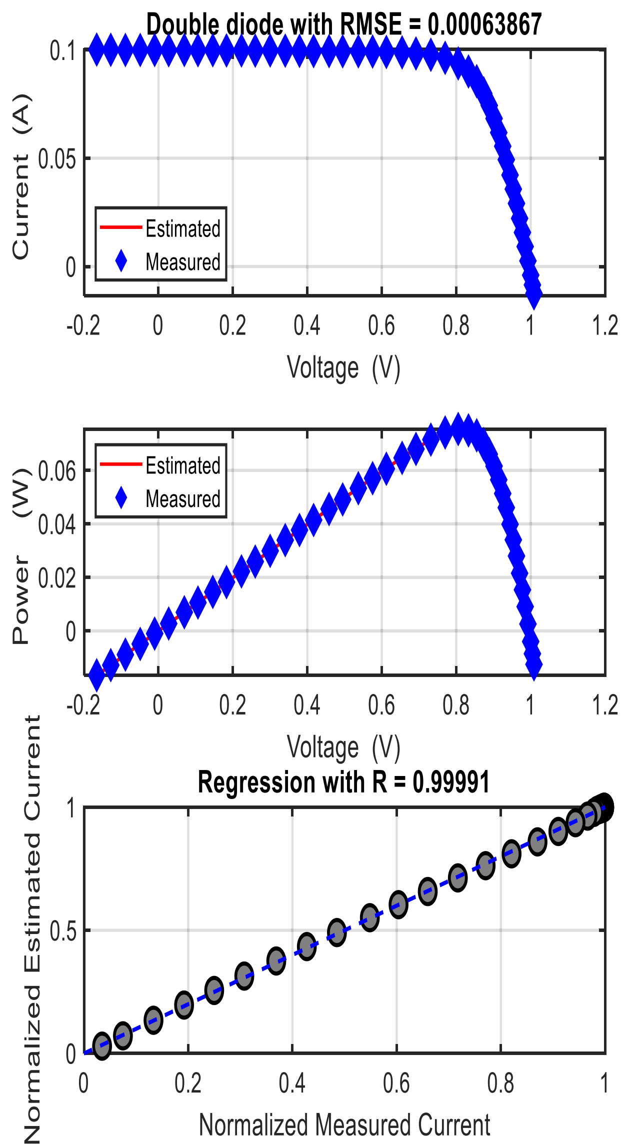

FIGURE 15. Characteristics of PVM 752 GaAs thin-film cell according to the experimental data and extracted data from DDM.

stopping criterion is met. Finally, the best global tree is identified as a superior solution. The flowchart of the recommended algorithm is presented in the following Fig. 7.

V. RESULTS AND DISCUSSION

The performance of the proposed producer based on the optimization technique has been validated through estimating the model parameters of two PV cells which are R.T.C. France solar cell, PVM 752 GaAs thin-film cell [48], [58] and two PV modules which are Photowatt-PWP201 module [48] and Leibold Solar Module (STE 20/100) [66]. The tests have occurred at the irradiance and temperatures of the datasheet of each other. As three different models are proposed in this study, the mathematical analysis is conducted to test the accuracy of each proposed model. The performance of these methods is evaluated based on several analytical tools including the Individual Absolute Error (IAE), Relative Error (RE), the accuracy of the curve fitting and convergence trends to the global minimum. The proposed TGA optimization algorithm is operated under the following control variables: maximum number of iterations 500 iteration; and 500 search agents. The proposed TGA based model is executed via MATLAB 2016a platform using an Intel ® core ™ i5-4210U CPU, 1.7 GHz, 8 GB RAM Laptop.

Fig. 8 shows the convergence curves for the fitness function (RMSE) for all case studies proposed in this work as obtained from the proposed TGA optimization method based on SDM, DDM, and TDM, respectively. It is seen from all figures that

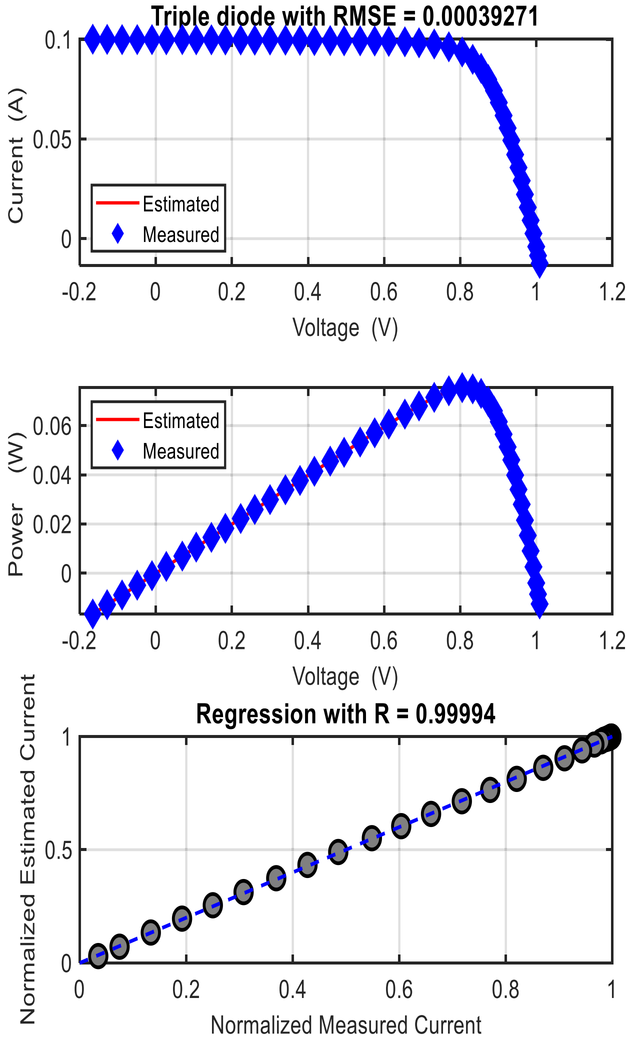

FIGURE 16. Characteristics of PVM 752 GaAs thin-film cell according to the experimental data and extracted data from TDM.

the TDM modeling method gives the minimum RMSE for the studied solar cells and PV modules. The time elapsed to reach the optimal solution for R.T.C. France solar cell is 7.4649 sec., 6.3421 sec, 5.2573 sec. based on SDM, DDM and TDM, respectively.

A. PARAMETERS OF R.T.C. FRANCE SOLAR CELL

In this section the experimental data of the commercial R.T.C. France solar cell based on manufacturer's PV cell datasheet was used. Moreover, the optimal values of the parameters for SDM, DDM, and TDM are extracted. The experimentally measured data manufacturer's PV cell datasheet includes 26 pairs of I-V points that are considered to extract the solar cell parameters, which have been used in Ref. [31]. The results obtained from the application of TGA considered for comparison with the results provided in the literature.

The ability of the TGA to estimate various parameters of the SDM is performed. The estimated parameters' results such as I_{ph}, I_{sd}, R_s, R_{sh}, and n are listed in Table 2. Such outcomes found through the TGA method are compared with the parameters obtained by alternative estimation methods such as: Two-Step Linear Least-Squares (TSLLS) method [67], Reduced forms RF [68], artificial bee swarm optimization (ABSO) [46], harmony search based algorithm (HS) [11], particle swarm optimization (PSO) algorithm [33], genetic algorithm (GA) [32], the analytical 5-point method (An.5-Pt) proposed in [54], the Lambert W (LW) function based-model [55], newton method [56], conductance method [26] and pattern search [57]. The results of the applied TGA algorithm have been compared with those of other techniques based on the criterion of the best optimal value of the objective function. The extracted parameters as well as the RMSE are reflected in Table 2. It was observed that, for the SDM, the TGA gives a very small value of RMSE, which approves that of ABSO, and HS and exceeds PSO, GA, An.5-Pt, LW, Newton, CM, and PS.

The values of the unknown parameters estimated by TGA in the case of DDM are depicted in Table 3. The extracted parameters compared with the values introduced in literatures; TSLLS [67], RF [68], ABSO [46], HS [11], PSO [32], GA [32], Artificial Bee Colony (ABC) [48],

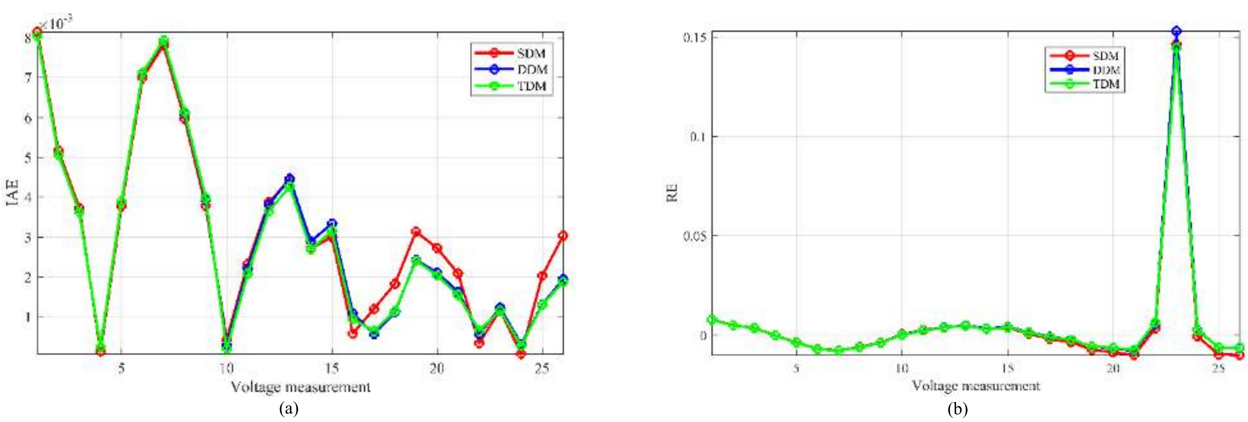

FIGURE 17. (a) IAE values; (b) RE values; for the Photowatt-PWP201 module.

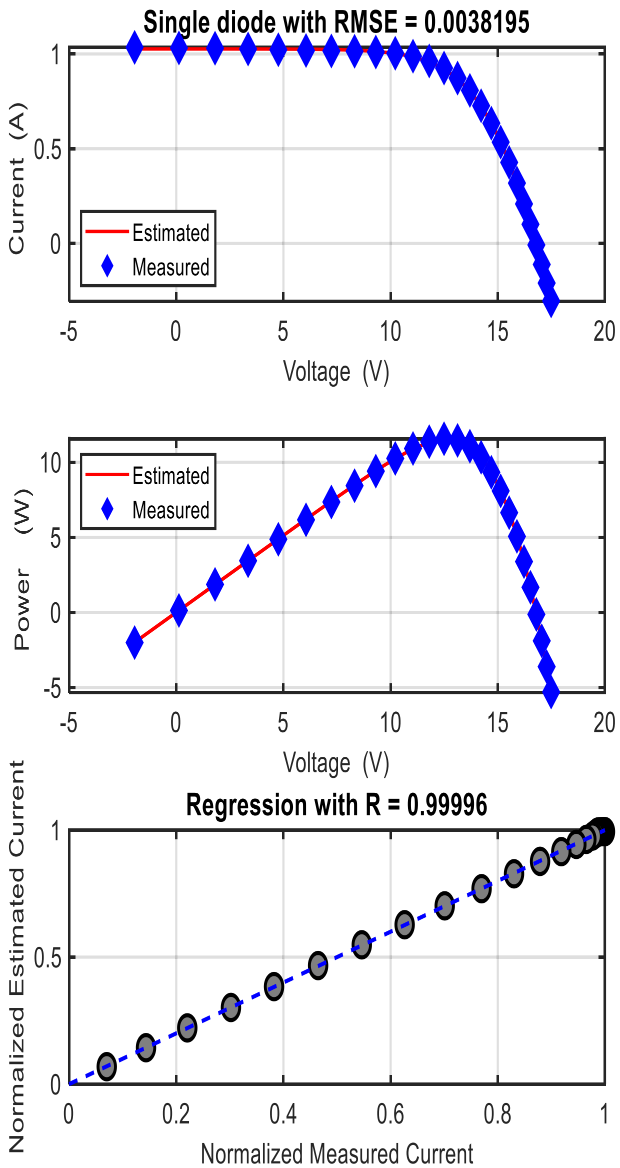

FIGURE 18. Characteristics of the Photowatt-PWP201 module according to the measured data and the estimated values from SDM.

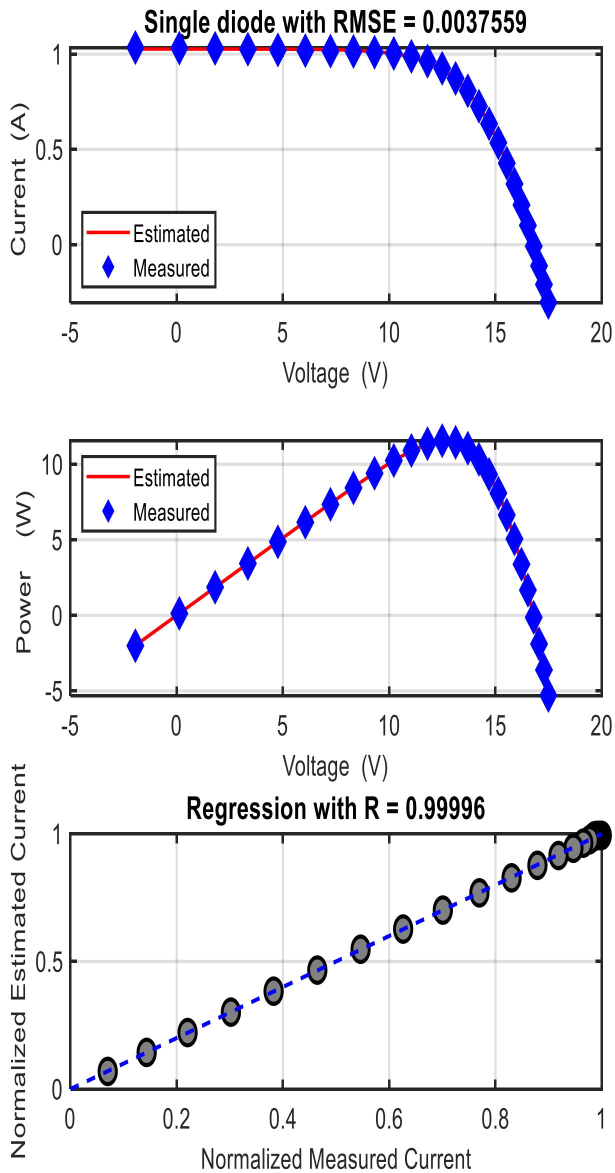

FIGURE 19. Characteristics of the Photowatt-PWP201 module according to the measured data and the determined values from DDM.

SBMO [42], SSO and MSSO [12]. The obtained results proved why the proposed method is supermum in extracting the unknown parameters with the lowest RMSE of 9.908952999628424E-04. Meanwhile, the worst RMSE of 1.8704E-02 was obtained by the method proposed in [32]. HS and ABSO introduced the best results after that obtained from the proposed TGA. while the results obtained in Refs. [67] based on TSLLS are the best ones and have super performance. This leads to enhancing the performance of the TGA in future work. Also, to search other optimization techniques in the future which improve the estimation performance.

Depending on the data reported in [18], the estimated parameters' values of the PV cell determined by the application of TGA based on the three diode model are shown in Table 4. Moreover, the nine parameters' values are considered for a comparison with the obtained values from literature; opposition based-learning whale optimization algorithm (OBWOA) [18], Artificial Bee Colony (ABC) [48], and Simplified Teaching-Learning Based Optimization (STBLO) [61]. From Table 4, it can be noticed that the RMSE value of the TGA is smaller than the other three optimization methods, while OBWOA comes in the second stage after our proposed technique.

To further examine the accuracy of the data obtained from the proposed TGA method, for the optimized parameters, the current was calculated based on the values estimated based on the three models considered for comparison with that taken from the experimental measurements. The error concerning the measured values for each of the 26 pair points

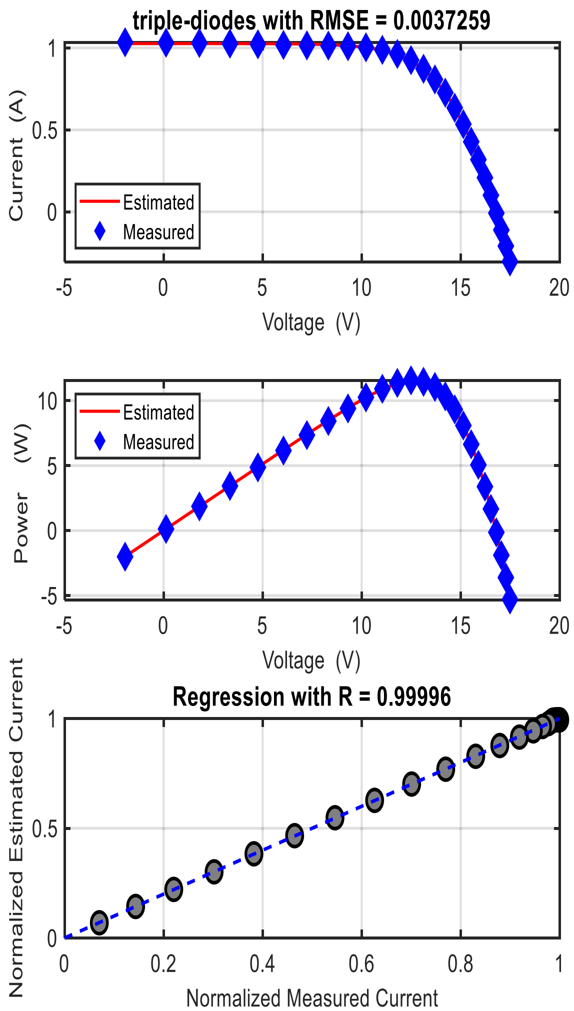

FIGURE 20. **Characteristics of the Photowatt-PWP201 module based on experimental data and calculated data from TDM.**

was evaluated by *IAE* and *RE*, calculated as given in Equations (21) and (22), respectively. The *IAE* and *RE* curves among the experimentally measured data and computed ones for the three modeling methods are indicated in Fig. 9(a) and (b), respectively.

$$IAE = |I_{measured} - I_{estimated}| \quad (21)$$

$$RE = (I_{measured} - I_{estimated}) / I_{measured} \quad (22)$$

Fig. 10 to Fig. 12 show a comparison between the I-V characteristics and P-V characteristics of the RTC France solar cell based on measurements and these considering the estimated parameters for single diode, double diodes, and triple diodes models, respectively. It is shown that the extracted and the actual results are exactly fitted and guarantee good correspondence for each modeling method. However, a small difference in the RMSE values for each other have appeared. The RMSE value of the triple diode model is better than the other two-based models. The figures also show the regression plot in each case, which measures the degree of matching between the actual data of the fuel cell and the target data. As seen from the regression curves of the three different models, the value of the coefficient of regression (R) equals 0.99999 for SDM and 1.00 for DDM and TDM, which proved a close matching between the measured and estimated data in the three models.

B. PARAMETERS OF PVM 752 GaAs THIN-FILM CELL

In this section, the measured data of the commercial PVM 752 GaAs thin-film cell, is operated at the radiation of 1000 W/m^2 and 25°C, were used, and the optimal parameters' values for SDM, DDM and TDM are extracted. The experimentally measured data, which consist of 44 *I-V* measured samples are obtained from [59]. The optimized results obtained from the TGA-based models were compared with those provided in other works.

The estimated parameters obtained depending on SDM, DDM, and TDM, as well as the value of the minimum RMSE in each case, are depicted in Tables 5, 6, and 7, respectively. For SDM and DDM, the values of the unknown parameters are compared with the values obtained by the application of different optimization methods: Enhanced leader particle swarm optimization (ELPSO) [58], conventional PSO

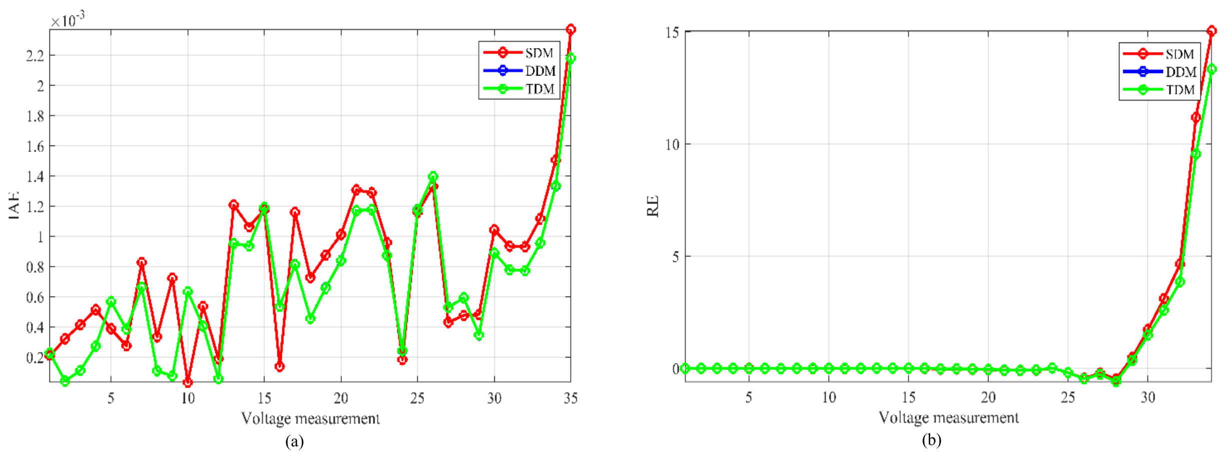

FIGURE 21. **(a) IAE values; (b) RE values; for LSM 20.**

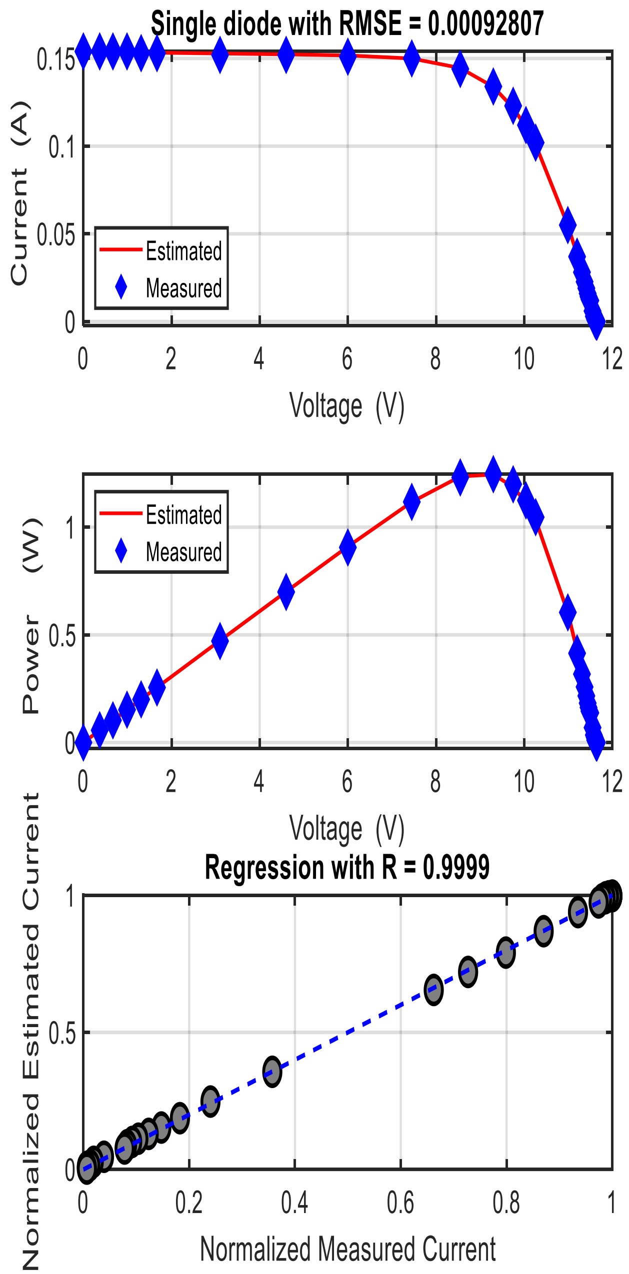

FIGURE 22. Characteristics of mono-crystalline Leibold Solar Module (LSM 20) based on experimental data and estimated data from SDM.

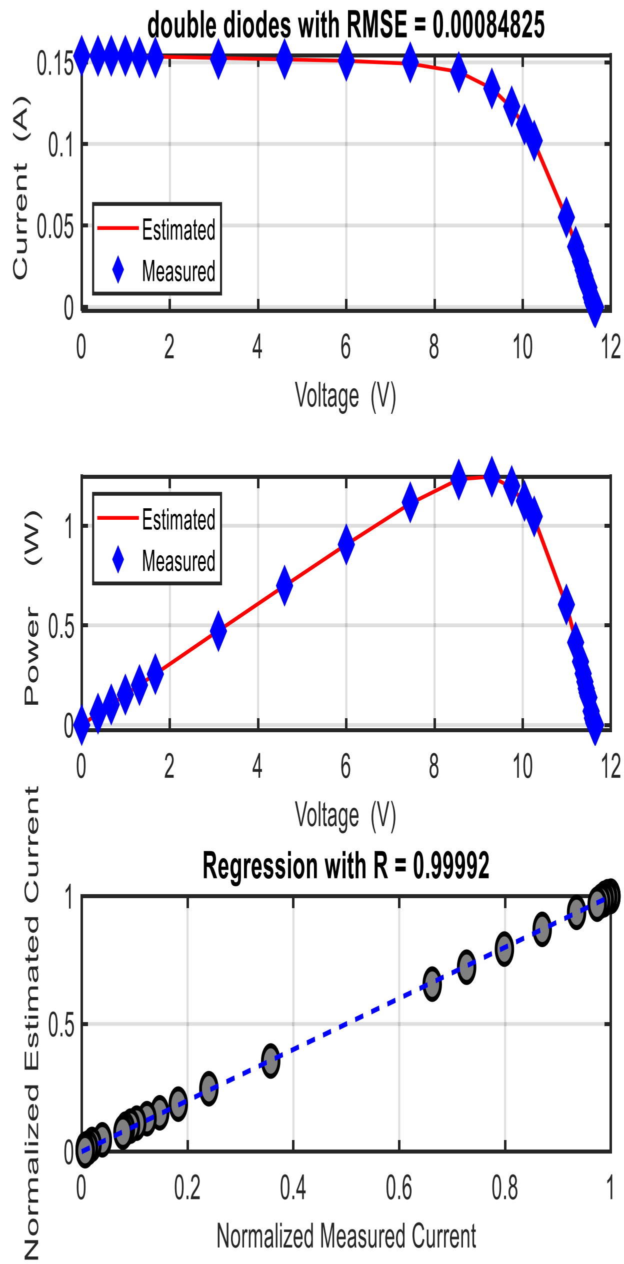

FIGURE 23. Characteristics of mono-crystalline Leibold Solar Module (LSM 20) based on experimental data and estimated data from DDM.

(CPSO) [59], backtracking search algorithm (BSA) [58] and artificial bee colony (ABC) [48].

From Tables 5 and 6, it is observed that for the SDM and DDM, the proposed TGA optimization method offers a better RMSE value which outperforms all methods included in the comparison. Because of the lack of data to compare with, the extracted parameters based on the TDM are presented in Table 7. The RMSE value in this model is the lowest when compared with the SDM and DDM results, which indicates a good match between the PV characteristics according to the determined parameters from estimation and the measured ones. The IAE and RE curves between the measured and extracted ones for the proposed models are shown in Figure 13(a) and (b), respectively. The *I-V* and *P-V* characteristics of the PVM 752 GaAs thin-film cell based on the experimentally measured data and the determined data through the application of the optimized parameters for the three alternative models are demonstrated in Figures 14-16. It can be noticed from the figures that the TDM gives the best results regard the SDM and DDM as the value of the coefficient of regression is 0.99994, which is the highest in the three cases.

C. PARAMETERS OF PHOTOWATT-PWP201 PV MODULE

Besides the studied PV cells, two different PV modules have been tested to identify their design parameters as

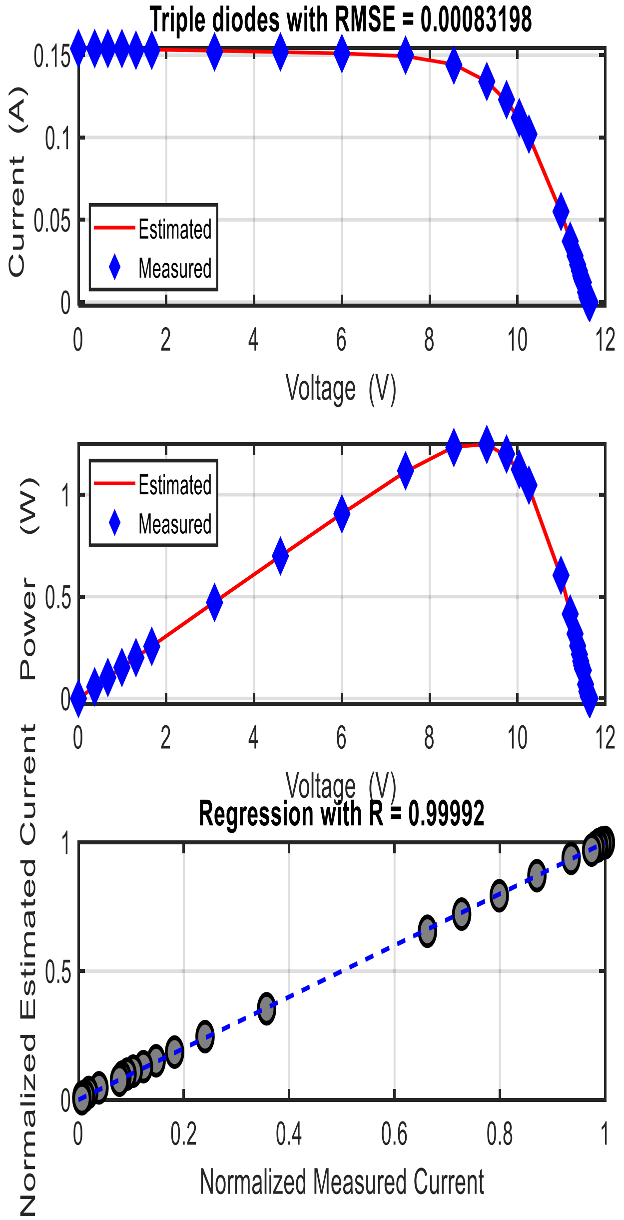

FIGURE 24. Characteristics of mono-crystalline Leibold Solar Module (LSM 20) according to the experimental data and the data are estimated from TDM.

well as examine the accuracy of the TGA-based models. Tables 8-10 summarize the results of the estimated parameters as well as the value of the RMSE for the SDM, DDM, and TDM of Photowatt-PWP201, which is designed from 36 series-connected polycrystalline silicon cells under module temperature of 45°C and solar radiation of 1000 W/m^2. The very low values of RMSE verifies the good operation of the proposed TGA method. The results proved that the suggested tree growth algorithm is competitive to be in use as an effective environment for estimating the parameters of PV solar cells and modules. For a single diode model, the results given by the proposed TGA are favored over that of Newton [56], PS [32], OIS [60], TSLLS [67], RF [68], and DAB [62]. The values of the PV module parameters in the DDM are more accurate than those obtained by WDOWOAPSO [63], GCPSO [64], TVACPSO [59] and ABC-DE [65] as validated by the lowest value of the RMSE. The determined values of the nine unknown parameters of the TDM are listed in Table 10, which proved the superiority of the three diode model over the other two methods. There is a hint here about the results in which the proposed algorithm results have higher values of I_{sd}, and R_{sh} as shown from tables 8, 9 and 10. while the results with the best RMSE confirm and validate of the extracting models. So, it is important for researchers to search for the parameters with a wide range of limits. Also, it is clear from the table, the TSLLS [67] and RF [68] methods have the priority rather than TGA and the other reported recent methods that encourage the researchers to enhance the performance of the optimization algorithms.

The IAE and RE curves between the experimetnal data and the extracted values of the Photowatt-PWP201 module for the proposed models are presented in Fig. 17 (a) and (b), respectively. Moreover, the *I-V* and *P-V* curves of the Photowatt-PWP201 module, based on the experimentally measured data and that obtained by applying the optimized parameters for the three alternative models, are demonstrated in Fig. 18-20. It can be noticed from the figures that three models give a fine result that matches well with the measured data from experiment as the value of the coefficient of regression reached 0.99996, which is very close to unity.

D. PARAMETERS OF LEIBOLD SOLAR (LSM 20) PV MODULE

The second module, which was tested for estimating the unknown parameters using the proposed TGA is a mono-crystalline Leibold Solar Module (LSM 20) that consists of 20 cells in series and is worked under the temperature of 24°C intensity of solar radiation of 360 W/m^2. Table 11 shows the results of the parameters' estimation as well as the value of the RMSE for the SDM and DDM. It can be seen that the TDM gives the optimum values of the unknown parameters as verified by the lowest value of

TABLE 11. Estimated model parameters for SDM, DDM, and TDM of mono-crystalline Leibold Solar Module (LSM 20) based on TGA.

Technique	SDM	DDM	TDM
I_{ph} (A)	0.1541	0.1547	0.1549
I_{sd1} (μA)	1.6439E-02	1.3623E-04	1.3452E-04
I_{sd2} (μA)	-	3.6066 E-03	3.7056E-03
I_{sd3} (μA)	-	-	3.0909E-03
R_s (Ω)	0.2800	0.3078	0.3045
R_{sh} (Ω)	160.6005	98.8195	90.8629
n_1	1.3745	1.2763	1.7755
n_2	-	1.2587	1.5445
n_3	-	-	1.2486
RMSE	**9.28071173E-04**	**8.4825747E-04**	**8.3197747E-04**

the RMSE. The obtained results proved the ability of the proposed TGA in identiftion of the parameters of various PV cells and modules under different environmental operating scenarios.

The IAE and RE curves between the measured and extracted data of the mono-crystalline Leibold Solar Module (LSM 20) module for the proposed modeling methods are shown in Fig. 21 (a) and (b), respectively. Moreover, the *I-V* and *P-V* curves of the mono-crystalline Leibold Solar Module (LSM 20) based on estimated and measured data for the three different models are shown in Fig. 22-24.

VI. CONCLUSION

In this paper, the Tree Growth Algorithm is applied for the precise and fast extraction of the unknown parameters of the proposed semi-empirical mathematical models of solar cells and PV modules. Besides, the performance of the proposed technique was comprehensively examined in order to extract various commercial solar cells and typical PV modules using different diode models; a single diode model, a double diode model, and three diode modes. The obtained results considered for a comparison with other optimization algorithms.

The comparative results validated that the TGA technique can provide an accurate and efficient estimation of the parameters and it is best and in some cases comparable to different optimization methods. Moreover, the TDM based model has the best characteristics with the minimum RMSE. Furthermore, the convergence speed of the TGA based on TDM is better than with the other two models of SDM and DDM. So, the proposed TGA could be considered as a competitive algorithm the identification of the parameters of solar cells and PV modules. Moreover, the balance between intensification and diversification of the TGA can be obtained by well tuning of the parameters to apply it in its best condition. In future work, the application of the TGA and other algorithms for estimating the parameters of PV with partial shading conditions should be studied and analyzed. Moreover, enhancement of the estimation performance based on hybrid optimization algorithms also should be considered in future work.

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REFERENCES

[1] G. K. Singh, "Solar power generation by PV (photovoltaic) technology: A review," *Energy*, vol. 53, pp. 1–13, May 2013, doi: 10.1016/j.energy.2013.02.057.

[2] H. Tian, F. Mancilla, and E. Muljadi, "A detailed performance model for photovoltaic Systems," Nat. Renew. Energy Lab., Golden, CO, USA, Tech. Rep. NREL/JA-5500-54601, Jun. 2012. Accessed: Jun. 26, 2020. [Online]. Available: https://www.osti.gov/servlets/purl/1048979

[3] L. Peng, Y. Sun, and Z. Meng, "An improved model and parameters extraction for photovoltaic cells using only three state points at standard test condition," *J. Power Sources*, vol. 248, pp. 621–631, Feb. 2014, doi: 10.1016/j.jpowsour.2013.07.058.

[4] V. Khanna, B. K. Das, D. Bisht, Vandana, and P. K. Singh, "A three diode model for industrial solar cells and estimation of solar cell parameters using PSO algorithm," *Renew. Energy*, vol. 78, pp. 105–113, Jun. 2015, doi: 10.1016/j.renene.2014.12.072.

[5] K. Ishaque, Z. Salam, S. Mekhilef, and A. Shamsudin, "Parameter extraction of solar photovoltaic modules using penalty-based differential evolution," *Appl. Energy*, vol. 99, pp. 297–308, Nov. 2012, doi: 10.1016/j.apenergy.2012.05.017.

[6] K. Ishaque and Z. Salam, "An improved modeling method to determine the model parameters of photovoltaic (PV) modules using differential evolution (DE)," *Sol Energy*, vol. 85, no. 9, pp. 2349–2359, Jul. 2011, doi: 10.1016/j.solener.2011.06.025.

[7] K. Ishaque, Z. Salam, and H. Taheri, "Modeling and simulation of photovoltaic (PV) system during partial shading based on a two-diode model," *Simul. Model. Pract. Theory*, vol. 19, no. 7, pp. 1613–1626, Apr. 2011, doi: 10.1016/j.simpat.2011.04.005.

[8] K. Nishioka, N. Sakitani, Y. Uraoka, and T. Fuyuki, "Analysis of multicrystalline silicon solar cells by modified 3-diode equivalent circuit model taking leakage current through periphery into consideration," *Sol. Energy Mater. Sol. Cells*, vol. 91, no. 13, pp. 1222–1227, Aug. 2007, doi: 10.1016/j.solmat.2007.04.009.

[9] A. Kassis and M. Saad, "Analysis of multi-crystalline silicon solar cells at low illumination levels using a modified two-diode model," *Sol. Energy Mater. Sol. Cells*, vol. 94, no. 12, pp. 2108–2112, Dec. 2010, doi: 10.1016/j.solmat.2010.06.036.

[10] V. J. Chin, Z. Salam, and K. Ishaque, "Cell modelling and model parameters estimation techniques for photovoltaic simulator application: A review," *Appl. Energy*, vol. 154, pp. 500–519, Sep. 2015, doi: 10.1016/j.apenergy.2015.05.035.

[11] A. Askarzadeh and A. Rezazadeh, "Parameter identification for solar cell models using harmony search-based algorithms," *Sol. Energy*, vol. 86, no. 11, pp. 3241–3249, Nov. 2012, doi: 10.1016/j.solener.2012.08.018.

[12] P. Lin, S. Cheng, W. Yeh, Z. Chen, and L. Wu, "Parameters extraction of solar cell models using a modified simplified swarm optimization algorithm," *Sol. Energy*, vol. 144, pp. 594–603, Mar. 2017, doi: 10.1016/j.solener.2017.01.064.

[13] T. R. Ayodele, A. S. O. Ogunjuyigbe, and E. E. Ekoh, "Evaluation of numerical algorithms used in extracting the parameters of a single-diode photovoltaic model," *Sustain. Energy Technol. Assessments*, vol. 13, pp. 51–59, Feb. 2016, doi: 10.1016/j.seta.2015.11.003.

[14] T. Sudhakar Babu, J. Prasanth Ram, K. Sangeetha, A. Laudani, and N. Rajasekar, "Parameter extraction of two diode solar PV model using fireworks algorithm," *Sol. Energy*, vol. 140, pp. 265–276, Dec. 2016, doi: 10.1016/j.solener.2016.10.044.

[15] J. J. Soon and K. S. Low, "Optimizing photovoltaic model for different cell technologies using a generalized multi dimension diode model," *IEEE Trans. Ind. Electron.*, vol. 62, no. 10, pp. 6371–6380, Oct. 2015, doi: 10.1109/TIE.2015.2420617.

[16] B. Mazhari, "An improved solar cell circuit model for organic solar cells," *Sol. Energy Mater. Solar Cells*, vol. 90, nos. 7–8, pp. 1021–1033, May 2006, doi: 10.1016/j.solmat.2005.05.017.

[17] F. De Castro, A. Laudani, F. Riganti Fulginei, and A. Salvini, "An in-depth analysis of the modelling of organic solar cells using multiple-diode circuits," *Sol. Energy*, vol. 135, pp. 590–597, Oct. 2016, doi: 10.1016/j.solener.2016.06.033.

[18] M. Abd Elaziz and D. Oliva, "Parameter estimation of solar cells diode models by an improved opposition-based whale optimization algorithm," *Energy Convers. Manage.*, vol. 171, pp. 1843–1859, May 2018, doi: 10.1016/j.enconman.2018.05.062.

[19] E. I. Batzelis and S. A. Papathanassiou, "A method for the analytical extraction of the single-diode PV model parameters," *IEEE Trans. Sustain. Energy*, vol. 7, no. 2, pp. 504–512, Apr. 2016, doi: 10.1109/TSTE.2015.2503435.

[20] J. Ma, K. L. Man, T. O. Ting, N. Zhang, S.-U. Guan, and P. W. H. Wong, "Approximate single-diode photovoltaic model for EfficientI-VCharacteristics estimation," *Scientific World J.*, vol. 2013, pp. 1–7, Feb. 2013, doi: 10.1155/2013/230471.

[21] D. F. Alam, D. A. Yousri, and M. B. Eteiba, "Flower pollination algorithm based solar PV parameter estimation," *Energy Convers. Manage.*, vol. 101, pp. 410–422, Sep. 2015, doi: 10.1016/j.enconman.2015.05.074.

[22] S. Bogning Dongue, D. Njomo, and L. Ebengai, "An improved nonlinear five-point model for photovoltaic modules," *Int. J. Photoenergy*, vol. 2013, pp. 1–11, Jun. 2013, doi: 10.1155/2013/680213.

[23] M. Hejri, H. Mokhtari, M. R. Azizian, M. Ghandhari, and L. Soder, "On the parameter extraction of a five-parameter double-diode model of photovoltaic cells and modules," *IEEE J. Photovolt.*, vol. 4, no. 3, pp. 915–923, May 2014, doi: 10.1109/JPHOTOV.2014.2307161.

[24] X. Gao, C. Yao, X. Gao, and Y. Yu, "Accuracy comparison between implicit and explicit single-diode models of photovoltaic cells and modules," *Acta Phys. Sin.*, vol. 63, no. 17, Sep. 2014, Art. no. 178401, doi: 10.7498/aps.63.178401.

[25] F. Dkhichi, B. Oukarfi, A. Fakkar, and N. Belbounaguia, "Parameter identification of solar cell model using Levenberg–Marquardt algorithm combined with simulated annealing," *Sol. Energy*, vol. 110, pp. 781–788, Dec. 2014, doi: 10.1016/j.solener.2014.09.033.

[26] M. Chegaar, Z. Ouennoughi, and A. Hoffmann, "A new method for evaluating illuminated solar cell parameters," *Solid-State Electron.*, vol. 45, no. 2, pp. 293–296, Nov. 2000, doi: 10.1016/s0038-1101(00)00277-x.

[27] A. A. Elbaset, H. Ali, and M. Abd-ElSattar, "Novel seven-parameter model for photovoltaic modules," *Sol Energy Mater Sol Cells*, vol. 130, pp. 442–455, Jul. 2014, doi: 10.1016/j.solmat.2014.07.016.

[28] O. Mares, M. Paulescu, and V. Badescu, "A simple but accurate procedure for solving the five-parameter model," *Energy Convers. Manage.*, vol. 105, pp. 139–148, Nov. 2015, doi: 10.1016/j.enconman.2015.07.046.

[29] W. Gong and Z. Cai, "Parameter extraction of solar cell models using repaired adaptive differential evolution," *Sol. Energy*, vol. 94, pp. 209–220, Aug. 2013, doi: 10.1016/j.solener.2013.05.007.

[30] M. Zagrouba, A. Sellami, M. Bouaïcha, and M. Ksouri, "Identification of PV solar cells and modules parameters using the genetic algorithms: Application to maximum power extraction," *Sol. Energy*, vol. 84, no. 5, pp. 860–866, May 2010, doi: 10.1016/j.solener.2010.02.012.

[31] M. S. Ismail, M. Moghavvemi, and T. M. I. Mahlia, "Characterization of PV panel and global optimization of its model parameters using genetic algorithm," *Energy Convers. Manage.*, vol. 73, pp. 10–25, Sep. 2013, doi: 10.1016/j.enconman.2013.03.033.

[32] M. R. AlRashidi, M. F. AlHajri, K. M. El-Naggar, and A. K. Al-Othman, "A new estimation approach for determining the I–V characteristics of solar cells," *Sol. Energy*, vol. 85, no. 7, pp. 1543–1550, Jul. 2011, doi: 10.1016/j.solener.2011.04.013.

[33] H. Wei, J. Cong, X. Lingyun, and S. Deyun, "Extracting solar cell model parameters based on chaos particle swarm algorithm," in *Proc. Int. Conf. Electric Inf. Control Eng.*, Wuhan, China, Apr. 2011, pp. 398–402.

[34] M. Ye, X. Wang, and Y. Xu, "Parameter extraction of solar cells using particle swarm optimization," *J Appl Phys*, vol. 105, no. 9, pp. 94502–94508, May 2009, doi: 10.1063/1.3122082.

[35] K. M. El-Naggar, M. R. AlRashidi, M. F. AlHajri, and A. K. Al-Othman, "Simulated annealing algorithm for photovoltaic parameters identification," *Sol. Energy*, vol. 86, no. 1, pp. 266–274, Jan. 2012, doi: 10.1016/j.solener.2011.09.032.

[36] N. Rajasekar, N. K. Kumar, and R. Venugopalan, "Bacterial foraging algorithm based solar PV parameter estimation," *Solar Energy*, vol. 97, pp. 255–265, Nov. 2013, doi: 10.1016/j.solener.2013.08.019.

[37] H. V. Hultmann Ayala, L. D. S. Coelho, V. C. Mariani, and A. Askarzadeh, "An improved free search differential evolution algorithm: A case study on parameters identification of one diode equivalent circuit of a solar cell module," *Energy*, vol. 93, pp. 1515–1522, Dec. 2015, doi: 10.1016/j.energy.2015.08.019.

[38] C. Chellaswamy and R. Ramesh, "Parameter extraction of solar cell models based on adaptive differential evolution algorithm," *Renew. Energy*, vol. 97, pp. 823–837, Nov. 2016, doi: 10.1016/j.renene.2016.06.024.

[39] K. Yu, X. Chen, X. Wang, and Z. Wang, "Parameters identification of photovoltaic models using self-adaptive teaching-learning-based optimization," *Energy Convers Manage*, vol. 145, pp. 233–346, Apr. 2017, doi: 10.1016/j.enconman.2017.04.054.

[40] A. Valdivia-González, D. Zaldívar, E. Cuevas, M. Pérez-Cisneros, F. Fausto, and A. González, "A chaos-embedded gravitational search algorithm for the identification of electrical parameters of photovoltaic cells," *Energies*, vol. 10, pp. 1–25, Oct. 2017, doi: 10.3390/en10071052.

[41] Q. Niu, L. Zhang, and K. Li, "A biogeography-based optimization algorithm with mutation strategies for model parameter estimation of solar and fuel cells," *Energy Convers. Manage.*, vol. 86, pp. 1173–1185, Oct. 2014, doi: 10.1016/j.enconman.2014.06.026.

[42] D. Allam, D. A. Yousri, and M. B. Eteiba, "Parameters extraction of the three diode model for the multi-crystalline solar cell/module using moth-flame optimization algorithm," *Energy Convers. Manage.*, vol. 123, pp. 535–548, Sep. 2016, doi: 10.1016/j.enconman.2016.06.052.

[43] A. Askarzadeh and L. dos Santos Coelho, "Determination of photovoltaic modules parameters at different operating conditions using a novel bird mating optimizer approach," *Energy Convers. Manage.*, vol. 89, pp. 608–614, Jan. 2015, doi: 10.1016/j.enconman.2014.10.025.

[44] M. Louzazni, A. Khouya, K. Amechnoue, A. Gandelli, M. Mussetta, and A. Craciunescu, "Metaheuristic algorithm for photovoltaic parameters: Comparative study and prediction with a firefly algorithm," *Appl Sci*, vol. 8, pp. 1–22, Feb. 2018, doi: 10.3390/app8030339.

[45] J. Ma, T. O. Ting, K. L. Man, N. Zhang, S.-U. Guan, and P. W. H. Wong, "Parameter estimation of photovoltaic models via cuckoo search," *J. Appl. Math.*, vol. 2013, pp. 1–8, May 2013, doi: 10.1155/2013/362619.

[46] A. Fathy and H. Rezk, "Parameter estimation of photovoltaic system using imperialist competitive algorithm," *Renew. Energy*, vol. 111, pp. 307–320, Oct. 2017, doi: 10.1016/j.renene.2017.04.014.

[47] A. Askarzadeh and A. Rezazadeh, "Artificial bee swarm optimization algorithm for parameters identification of solar cell models," *Appl. Energy*, vol. 102, pp. 943–949, Feb. 2013, doi: 10.1016/j.apenergy.2012.09.052.

[48] D. Oliva, E. Cuevas, and G. Pajares, "Parameter identification of solar cells using artificial bee colony optimization," *Energy*, vol. 72, pp. 93–102, Aug. 2014, doi: 10.1016/j.energy.2014.05.011.

[49] K. Yu, J. Liang, B. Qu, X. Chen, and H. Wang, "Parameters identification of photovoltaic models using an improved JAYA optimization algorithm," *Energy Convers Manage*, vol. 150, pp. 742–753, Aug. 2017, doi: 10.1016/j.enconman.2017.08.063.

[50] L. Wang and C. Huang, "A novel elite opposition-based jaya algorithm for parameter estimation of photovoltaic cell models," *Optik*, vol. 155, pp. 351–356, Feb. 2018, doi: 10.1016/j.ijleo.2017.10.081.

[51] D. Oliva, A. A. Ewees, M. A. E. Aziz, A. E. Hassanien, and M. Peréz-Cisneros, "A chaotic improved artificial bee colony for parameter estimation of photovoltaic cells," *Energies*, vol. 10, no. 7, p. 865, Jun. 2017, doi: 10.3390/en10070865.

[52] D. Oliva, A. A. Ewees, M. A. E. Aziz, A. E. Hassanien, and M. Peréz-Cisneros, "A chaotic improved artificial bee colony for parameter estimation of photovoltaic cells," *Energies*, vol. 10, p. 865, 2017. [Online]. Available: https://www.mdpi.com/1996-1073/10/7/865, doi: 10.3390/en10070865.

[53] J. Too, A. Abdullah, N. Mohd Saad, and N. Mohd Ali, "Feature selection based on binary tree growth algorithm for the classification of myoelectric signals," *Machines*, vol. 6, no. 4, p. 65, Dec. 2018, doi: 10.3390/machines6040065.

[54] D. S. H. Chan, J. R. Phillips, and J. C. H. Phang, "A comparative study of extraction methods for solar cell model parameters," *Solid-State Electron.*, vol. 29, no. 3, pp. 329–337, 1986, doi: 10.1016/0038-1101(86)90212-1.

[55] C. Zhang, J. Zhang, Y. Hao, Z. Lin, and C. Zhu, "A simple and efficient solar cell parameter extraction method from a single current-voltage curve," *J. Appl. Phys.*, vol. 110, no. 6, Sep. 2011, Art. no. 064504, doi: 10.1063/1.3632971.

[56] T. Easwarakhanthan, J. Bottin, I. Bouhouch, and C. Boutrit, "Nonlinear minimization algorithm for determining the solar cell parameters with microcomputers," *Int. J. Sol. Energy*, vol. 4, no. 1, pp. 1–12, Jan. 1986, doi: 10.1080/01425918608909835.

[57] M. F. AlHajri, K. M. El-Naggar, M. R. AlRashidi, and A. K. Al-Othman, "Optimal extraction of solar cell parameters using pattern search," *Renew. Energy*, vol. 44, pp. 238–245, Aug. 2012, doi: 10.1016/j.renene.2012.01.082.

[58] A. Rezaee Jordehi, "Enhanced leader particle swarm optimisation (ELPSO): An efficient algorithm for parameter estimation of photovoltaic (PV) cells and modules," *Sol. Energy*, vol. 159, pp. 78–87, Jan. 2018, doi: 10.1016/j.solener.2017.10.063.

[59] A. R. Jordehi, "Time varying acceleration coefficients particle swarm optimisation (TVACPSO): A new optimisation algorithm for estimating parameters of PV cells and modules," *Energy Convers. Manage.*, vol. 129, pp. 262–274, Dec. 2016, doi: 10.1016/j.enconman.2016.09.085.

[60] M. Chegaar, N. Nehaoua, and A. Bouhemadou, "Organic and inorganic solar cells parameters evaluation from single I–V plot," *Energy Convers. Manage.*, vol. 49, no. 6, pp. 1376–1379, Jun. 2008, doi: 10.1016/j.enconman.2008.01.002.

[61] Q. Niu, H. Zhang, and K. Li, "An improved TLBO with elite strategy for parameters identification of PEM fuel cell and solar cell models," *Int. J. Hydrogen Energy*, vol. 39, no. 8, pp. 3837–3854, Mar. 2014, doi: 10.1016/j.ijhydene.2013.12.110.

[62] K. Bouzidi, M. Chegaar, and M. Aillerie, "Solar cells parameters evaluation from dark I-V characteristics," *Energy Procedia*, vol. 18, pp. 1601–1610, 2012, doi: 10.1016/j.egypro.2012.05.096.

[63] H. G. G. Nunes, J. A. N. Pombo, P. M. R. Bento, S. J. P. S. Mariano, and M. R. A. Calado, "Collaborative swarm intelligence to estimate PV parameters," *Energy Convers. Manage.*, vol. 185, pp. 866–890, Apr. 2019, doi: 10.1016/j.enconman.2019.02.003.

[64] H. G. G. Nunes, J. A. N. Pombo, S. J. P. S. Mariano, M. R. A. Calado, and J. A. M. Felippe de Souza, "A new high performance method for determining the parameters of PV cells and modules based on guaranteed convergence particle swarm optimization," *Appl. Energy*, vol. 211, pp. 774–791, Feb. 2018, doi: 10.1016/J.APENERGY.2017.11.078.

[65] O. Hachana, K. E. Hemsas, G. M. Tina, and C. Ventura, "Comparison of different metaheuristic algorithms for parameter identification of photovoltaic cell/module," *J Renew. Sustain. Energy*, vol. 5, no. 5, pp. 1–8, Sep. 2013, doi: 10.1063/1.4822054.

[66] F. F. Muhammad, A. W. Karim Sangawi, S. Hashim, S. K. Ghoshal, I. K. Abdullah, and S. S. Hameed, "Simple and efficient estimation of photovoltaic cells and modules parameters using approximation and correction technique," *PLoS ONE*, vol. 14, no. 5, May 2019, Art. no. e0216201, doi: 10.1371/journal.pone.0216201.

[67] F. J. Toledo, J. M. Blanes, and V. Galiano, "Two-step linear least-squares method for photovoltaic single-diode model parameters extraction," *IEEE Trans. Ind. Electron.*, vol. 65, no. 8, pp. 6301–6308, Aug. 2018.

[68] A. Laudani, F. Riganti Fulginei, and A. Salvini, "High performing extraction procedure for the one-diode model of a photovoltaic panel from experimental I–V curves by using reduced forms," *Sol. Energy*, vol. 103, pp. 316–326, May 2014, doi: 10.1016/j.solener.2014.02.014.

[69] O. S. Elazab, H. M. Hasanien, I. Alsaidan, A. Y. Abdelaziz, and S. M. Muyeen, "Parameter estimation of three diode photovoltaic model using grasshopper optimization algorithm," *Energies*, vol. 13, p. 497, Oct. 2020, doi: 10.3390/en13020497.

[70] X. Chen and K. Yu, "Hybridizing cuckoo search algorithm with biogeography-based optimization for estimating photovoltaic model parameters," *Sol. Energy*, vol. 180, pp. 192–206, Mar. 2019, doi: 10.1016/j.solener.2019.01.025.

[71] R. Chenouard and R. A. El-Sehiemy, "An interval branch and bound global optimization algorithm for parameter estimation of three photovoltaic models," *Energy Convers. Manage.*, vol. 205, Feb. 2020, Art. no. 112400, doi: 10.1016/j.enconman.2019.112400.

[72] P. P. Biswas, P. N. Suganthan, G. Wu, and G. A. J. Amaratunga, "Parameter estimation of solar cells using datasheet information with the application of an adaptive differential evolution algorithm," *Renew. Energy*, vol. 132, pp. 425–438, Mar. 2019, doi: 10.1016/j.renene.2018.07.152.

[73] N. Pourmousa, S. M. Ebrahimi, M. Malekzadeh, and M. Alizadeh, "Parameter estimation of photovoltaic cells using improved lozi map based chaotic optimization algorithm," *Sol. Energy*, vol. 180, pp. 180–191, Mar. 2019, doi: 10.1016/j.solener.2019.01.026.

[74] B. Nayak, A. Mohapatra, and K. B. Mohanty, "Parameter estimation of single diode PV module based on GWO algorithm," *Renew. Energy Focus*, vol. 30, pp. 1–12, Sep. 2019, doi: 10.1016/j.ref.2019.04.003.

[75] M. H. Qais, H. M. Hasanien, and S. Alghuwainem, "Identification of electrical parameters for three-diode photovoltaic model using analytical and sunflower optimization algorithm," *Appl. Energy*, vol. 250, pp. 109–117, Sep. 2019, doi: 10.1016/j.apenergy.2019.05.013.

[76] W. Long, T. Wu, J. Jiao, M. Tang, and M. Xu, "Refraction-learning-based whale optimization algorithm for high-dimensional problems and parameter estimation of PV model," *Eng. Appl. Artif. Intell.*, vol. 89, Mar. 2020, Art. no. 103457, doi: 10.1016/j.engappai.2019.103457.

[77] M. Premkumar, T. S. Babu, S. Umashankar, and R. Sowmya, "A new metaphor-less algorithms for the photovoltaic cell parameter estimation," *Optik*, vol. 208, Apr. 2020, Art. no. 164559, doi: 10.1016/j.ijleo.2020.164559.

[78] Abbassi, R. Abbassi, A. A. Heidari, D. Oliva, H. Chen, A. Habib, M. Jemli, M. Wang, "Parameters identification of photovoltaic cell models using enhanced exploratory salp chains-based approach," *Energy*, vol. 198, May 2020, Art. no. 117333, doi: 10.1016/j.energy.2020.117333.

[79] D. Oliva, M. A. Elaziz, A. H. Elsheikh, and A. A. Ewees, "A review on meta-heuristics methods for estimating parameters of solar cells," *J. Power Sources*, vol. 435, Sep. 2019, Art. no. 126683, doi: 10.1016/j.jpowsour.2019.05.089.

[80] J. Liang, S. Ge, B. Qu, K. Yu, F. Liu, H. Yang, P. Wei, and Z. Li, "Classified perturbation mutation based particle swarm optimization algorithm for parameters extraction of photovoltaic models," *Energy Convers. Manage.*, vol. 203, Jan. 2020, Art. no. 112138, doi: 10.1016/j.enconman.2019.112138.

[81] Ram, J. Prasanth, Dhanup S. Pillai, N. Rajasekar, and V. Kumar Chinnaiyan, "Flower pollination based solar PV parameter extraction for double diode model," in *Intelligent Computing Techniques for Smart Energy Systems*. Singapore: Springer, 2020, pp. 303–312, doi: 10.1007/978-981-15-0214-9_34.

[82] E. Cuevas, J. Gálvez, and O. Avalos, "Comparison of Solar Cells Parameters Estimation Using Several Optimization Algorithms," in *Recent Metaheuristics Algorithms for Parameter Identification* (Studies in Computational Intelligence), vol. 854. Cham, Switzerland: Springer, 2020, doi: 10.1007/978-3-030-28917-1_4.

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