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Electrical Parameters Identification of Three-Diode Photovoltaic Model Based on Equilibrium Optimizer Algorithm

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ABSTRACT Tremendous penetration of photovoltaic (PV) systems into the electric grids develops many challenges in the modern power systems. In the simulation analyses of PV systems, accurate modelling of PV modules plays a crucial role in enhancing the characteristics of such systems. Modelling of such PVs is represented by a non-linear I-V behavior, involving various unknown parameters because of the inadequate data offered in the datasheet of PV cells. This paper proposes a novel implementation of the equilibrium optimizer algorithm (EOA) to identify the nine-parameters of a three-diode (TD) model of a PV module. Soundness of the EOA-TD model is extensively confirmed by the simulation results that are carried out in different environmental conditions. The optimal parameters obtained using the proposed approach are compared with those realized using other optimization techniques-based TD models. To achieve a practical study, the simulation and experimental outcomes are checked for various commercial PV panels and the error among these results records a value less than 0.5%. Moreover, the optimal parameters attained using the EOA are competitive and very close to that realized using other approaches, where the offered EOA has exhibited a minimum fitness value of 1.14e-14 and 7.154 e-13 for Kyocera and Solarex marketable PV cells, respectively. The effectiveness of the proposed TD PV model is adequately assessed by evaluating its absolute current error (ACE) with the ACE in different PV models. The EOA technology is considered to be an accurate means of achieving the proper modelling of any commercial PV module.

INDEX TERMS Equilibrium optimizer algorithm (EOA), photovoltaic modeling, solar power, three-diode model.

NOMENCLATURE

Abbreviations

ACE	Absolute current error
DD	Double-diode
EOA	Equilibrium optimizer algorithm
MPP	Maximum power point
PV	Photovoltaic
PSO	Particle swarm optimization
RMSE	Root mean square error
SA	Simulated annealing
STC	Standard test condition
SD	Single-diode
TD	Triple-diode
WOA	Whale optimization algorithm

Symbols

a_i	ideality factor of diode i
E_g	Band gap energy (eV)
G	Solar irradiation (W/m^2)
I	Produced current of PV array (A)
I_{Oi}	Leakage current for diode i (A)
I_{mp}	Maximum output current of PV array (A)
I_{PV}	Photo-generated current (A)
I_{sc}	Short circuit output current of PV module (A)
K_i	Temperature coefficient of I_{sc} (A/°C)
K_v	Temperature coefficient of V_{oc} (V/°C)

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K_B Boltzmann's constant (1.38065e-23 J/K)
N_s Number of series cells in PV module
P_m Maximum output power of PV module (W)
q Electron charge (1.6022e-19 C)
R_s Series resistance (Ω)
R_p Parallel resistance (Ω)
T Cell temperature (K)
V Output voltage of PV module (V)
V_m Maximum output voltage of PV module (V)
V_{oc} Open circuit output voltage of PV module (V)
V_t Thermal voltage (V)

I. INTRODUCTION

Renewable energy systems have received great solicitude around the globe due to various strategic issues, including the rapid exhaustion of fossil fuels, climate interests, political concerns, and the potential trend to have a healthy environment [1]– [4]. The photovoltaic (PV) power system is considered as a competitive renewable power technology in the future. This interest is because of the recent cost saving in the components of such PVs, which reflects the enormous efforts exerted to develop the PV industry and to improve its efficiency [5]. Globally, the latest record of the PV market has reported that the PV installations realized 515 GW in 2018, which indicates a rise of 27% relative to 2016's statics. Note that, the global PV installations shall realize 2.5 TW by 2025, leading to a large-scale integration of the PV arrays into the power networks [5].

In the curved portion, there is a region of the $I - V/P - V$ characteristics called a power region, in which only one point can efficiently deliver the maximum output power from the PV module. This point illustrates the desired current/voltage, achieves the maximum output power. Notably, the tracking of maximum power point (MPP) is a dynamic process, where the operating point should be always adapted due to the constantly changing in the temperatures and irradiations [6].

In light of that, the huge-scale integration of PV power plants into the power grids/micro grids requires an accurate modelling of such PV modules/panels to investigate their impact on the system behavior under various environmental conditions, and during the grid disturbances. In addition, the precise mathematical model of such PVs is valuable in the dynamic analyses of power electronic converters that connected with such PVs, the MPP tracking techniques, and the simulation studies of such PV arrays and their power components. Modelling of such PV panel is represented by a non-linear $I - V$ curve, involving many ungiven parameters because of the limited data given in the PVs' datasheet [7].

The PV cell is a semiconductor diode whose positive-negative (PN) junction converts the incident light into electric power. The PV is made of different semiconductor materials like monocrystalline, polycrystalline, and silicon cells. Ideal PV model is performed by an electrical current source, named photo-generated current (I_{PV}), which relates to the solar irradiance falling on it. The real modeling of PV cell, which is a non-ideal diode, should involve the internal losses of such PVs, *e.g.*, electrical and optical losses [8]. The optical losses can be represented by the recombination and diffusion losses of the charge carriers in quasi-neutral, space charge, and deficiency zones of the PN junction [1], [4]. These losses are performed by utilizing a number of diode models, *i.e.*, single-diode (SD), double-diode (DD), or three-diode (TD) models. The SD PV model is used to address the losses in the quasi-neutral zone [1]. Due to the lower irradiance at the open-circuit voltage and the neglecting of recombination losses in the depletion zone, the SD model lacks precision [4]. The DD model can address the losses within the quasi neutral and space charge zones. Although this model is more accurate, it suffers from complexity, where it involves a high number of unknowns, *i.e.*, an additional diode leakage current and the diode coefficient of the second diode [4]. Recently, the TD model is proposed to express all PV losses in the three regions, resulting in a more significant PV model [9].

The mathematical PV modelling is expressed by a nonlinear I/V relationship, which involves an exponential function. The electrical modelling of PV cells is expressed by a I_{PV} paralleled by the diodes and a R_p, then connected to a series R_s. The non-ideal diode represents the internal losses in the PN junction of the PVs. These diodes can be modeled by a nonlinear exponential function with three designated parameters, *i.e.*, leakage current (I_o), ideality factor (a), and I_{PV}. The SD model includes five-parameters, *i.e.*, I_o, a, I_{PV}, R_s, R_p. The DD model is used to represent the extra losses plus SD losses, which is a seven-parameters model. The TD model is used to express all losses in the PVs, which is a nine-parameters PV model [1], [4]. It is indispensable to estimate the unknown parameters to realize an efficacious and a very precise PV model, which is beneficial in several simulation scenarios of PV arrays that integrated with the utility networks [9].

Various techniques have been utilized in obtaining the optimal design of ungiven parameters of such PV models. In literature survey, the SD and DD models of PV panels are commonly investigated owing to their low unknown parameters that can be extracted using iterative methods, analytical methods, and heuristic techniques. The analytical methods are presented to extract the PV parameters using various key-points which are available in the PV datasheet like the I_{sc}, V_{oc}, and P_m [9], [10]. Although these techniques have a rapid convergence, some approximations are coming in to reduce the number of unknown parameters, like neglecting R_p [9], the initial values of R_p [11] and I_o [12], Lambert function method [13], and using the linear least-squares approach [14]. However, it is hardly to achieve a precise PV model due to the inaccurate assumption of the formula or the inaccurate measurement of the key-points [15]– [17]. On the other hand, numerical methods such as deterministic and stochastic numerical optimization techniques were also presented to overcome the problems of analytical methods, achieving a precise PV model by minimizing the root mean square error (RMSE). Newton-Raphson method [18], Nelder-Mead simplex [19], and pattern search method [20] are deterministic numerical optimization techniques. Although, these methods have high computation efficiency and rapid convergence, they may fall into local optima, and hence the accuracy is very sensitive to the initial points. The stochastic approaches are used to identify the PV model parameters, such as genetic algorithm (GA) [21], [22], particle swarm optimization (PSO) [23], [24], teaching-learning optimization approach [25], [26], artificial bee colony [27], grey wolf optimization [28], whale optimization algorithm (WOA) [29], [30], Harris hawks optimization [31]. Although these methods are powerful approaches, they suffer from low convergence speed and require high numbers of iterations to achieve satisfactory responses. Moreover, more incorporated analytical and meta-heuristic techniques are developed for finding the seven-parameters of DD models [32], [33].

Furthermore, the iterative model method presents another approach to properly estimate the PV model parameters. An iterative model method is defined as a mathematical procedure that utilizes an initial value for generating a sequence to enhance an approximate solution for a problem. In [34], the iterative model method was applied to find the values of R_s and R_p, which are used in the PV model. Obtaining these parameters is vital to allow the peak of the mathematical $P-V$ curve very close to the measured data. In the iterative process, R_s is starting from zero and slowly incremented. Thereafter, other PV model parameters can be calculated using datasheet-based Equations at The STC for each value of R_s and R_p, as reported in [34]. Different iterative techniques were also presented to find the unknown parameters for different PV arrays, including Gauss Seidel method [35] and Newton Raphson method [36]. Note that, the classical approaches lack precision, resulting in inaccurate values of the PV parameters due to the nonlinear behavior and the multi-variable of PV models, besides the multi-modal problems that lead to various local optima [4].

On the other side, meta-heuristic approaches are the effective tools developed to optimally obtain the values of unknowns for the SD and DD PV models by minimizing the fitness functions. Recently, GA [21], simulated annealing (SA) [37], hybrid trust-region-reflective algorithm [38], WOA [39], hybrid firefly algorithm and pattern technology [40], water cycle algorithm [41], salp sawm algorithm [42], flower pollination algorithm [43], enhanced leader PSO (ELPSO) [44], and time varying acceleration coefficients PSO (TVACPSO) [45] are presented to minimize the RMSE for attaining the PV parameters. In addition, several fitness functions and many algorithms were implemented for solving the optimization problem, involving bacterial foraging algorithm [46], differential evolution [47], [48], and shuffled frog leaping approach [49]. Moreover, other approaches were presented in this sector, including penalty-based differential evolution to extract the PV parameters [50], parameter extraction of PV modules using mathematical techniques based on SD and DD models [51], and applying mathematical data for parameter extraction and model the PV system [52].

At present, the TD model has been addressed to show all losses in the PV cell. The analytical approaches used to achieve the nine-parameters are hardly to be employed because of the several variables and the lower number of nonlinear equations. Nowadays, the meta-heuristic approaches, including WOA [39], sunflower optimization algorithm (SOA) [53], [54], moth flame algorithm [55], coyote optimizer algorithm (COA) [56], Harris Hawk optimizer [57], and transient search algorithm [58] are the best choice to design the unknown parameters of TD model. Moreover, the experimental data of PV modules are applied to precisely attain the TD model using the RMSE concept. Till nowadays, application of new heuristic-based optimization approaches to properly determine the ungiven parameters of the TD model is highly appreciated and welcomed. This appears the main impetus to apply the equilibrium optimizer algorithm (EOA) to identify the nine-parameters of the TD-based PV panel.

The EOA is a new physics optimization approach simulated in 2019. It is motivated by physics-based dynamic mass balance on a control volume that is utilized to evaluate the dynamic and equilibrium states [59]. The EOA is a powerful heuristic approach that includes several advantages, like a lower number of variables to design, easier procedures, lower computation complexity, and rapid convergence speed. So, the EOA can be applied to solve different problems in the power systems.

This paper exhibits a new approach using the EOA to find the ungiven parameters of the TD PV model, achieving a precise electrical TD modelling of the PV modules that used in the power systems simulation analyses. The soundness of the EOA-based TD model is confirmed by the numerical results that are performed under different environmental conditions. The nine-parameters extracted using the proposed approach are paralleled to those achieved using other optimization techniques-based TD models. For achieving practical study, the numerical results are compared with their experimental outcomes for various commercial PV panels like KC200GT and MSX-60 and the error among these results records a value less than 0.5%. Moreover, the optimal parameters attained using the EOA are competitive and very close to that realized using other approaches, where the offered EOA has exhibited a minimum fitness value for Kyocera and Solarex marketable PV cells, respectively. The effectiveness of the proposed TD PV model is adequately assessed by evaluating its absolute current error (ACE) with the ACE in different PV models. The EOA technology is considered to be an accurate means of achieving the proper modelling of any commercial PV module. Notably, the EOA-based PV model parameters identification has not so far been pointed out in PV research literature.

II. TD MODEL OF PV MODULE

Fig. 1 depicts the TD modelling of a PV panel, which consists of a current source, three diodes that are in parallel connection, and series and parallel resistances [1], [39]. The leakage

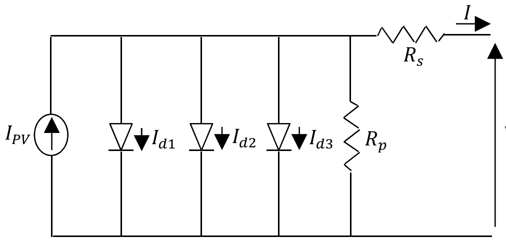


FIGURE 1. TD model of PV module.

currents of three diodes are I_{o1}, I_{o2}, and I_{o3}. In the first diode, the current (I_{o1}) expresses the current due to quasi-neutral regions of the emitter and bulk zones of the PN junction with ideality factor (a_1). In the second diode, the current (I_{o2}) relates to the recombination current in the space charge zone with ideality factor (a_2). In the third diode, the current (I_{o3}) expresses the grain boundaries with ideality factor (a_3). The R_s represents the material resistance of the PN junction. R_p is the parallel resistance of the solar cell [4]. The PV model has a nonlinear I-V curve that can be represented as follows [4], [9], [39]:

$$\begin{aligned} I = I_{PV} - I_{O1}\left\{exp\left[\frac{V+IR_s}{a_1V_t}\right]-1\right\} \\ - I_{O2}\left\{exp\left[\frac{V+IR_s}{a_2V_t}\right]-1\right\} \\ - I_{O3}\left\{exp\left[\frac{V+IR_s}{a_3V_t}\right]-1\right\} - \frac{V+IR_s}{R_p} \end{aligned} \tag{1}$$

where I_{PV} denotes the photo-generated current, I_{Oi} denotes the reverse current of a diode i, a_i is the ideality factor of a diode i, where i represents the diodes number, i.e., $i = 1, 2, 3$, and $V_t = N_sKT/q$ denotes the thermal voltage of PV panel. N_s represents the total cells in the PV module, K is the Boltzmann factor, T represents the panel temperature in Kelvin, and q is charge of electrons ($1.60217646e^{-19}$C).

As a rule, there are some key-points specified in the PV datasheet which are I_{sc}, V_{oc}, and P_m. Note that, various functions are developed to efficiently illustrate the I-V characteristic of various PV models at various temperatures and solar irradiations as follows [60], [61]:

$$I_{PV} = \left(I_{PV,n} + K_i\Delta T\right)\frac{G}{G_n} \tag{2}$$

$$I_O = I_{On}\left(\frac{T}{T_n}\right)^3 e^{\left\{\frac{qE_g}{aK}\left[\frac{1}{T_n}-\frac{1}{T}\right]\right\}} \tag{3}$$

$$E_g = E_{g,n}\left(1 - 0.0002677\right)\Delta T \tag{4}$$

$$R_p = R_{P,n}\frac{G}{G_n} \tag{5}$$

where, n denotes the nominal value at the STC. K_I is the coefficient of short circuit current, ΔT is the temperature difference, G is the irradiance, and E_g is the material band gap. $E_{g,n} = 1.211$ eV [4], [31]. Therefore, it is necessary to identify the ungiven parameters of such PV models. Here, the ungiven parameters are I_{PV}, R_s, R_p, I_{Oi}, and a_i, where $i = 1, 2, 3$.

III. PROBLEM FORMULATION

In order to estimate the electrical parameters of the TD model using an optimization technique, a definition of the fitness function is required, and then the optimization approach can be applied on it. In this study, a new fitness function is presented to extract the parameters of the TD model. Here, the current error, which is the difference between the modelled and practical currents, is proposed. The fitness function, ε, is depicted as follows:

$$\varepsilon = \sum_{k=1}^{N}\left|f_k\left(V,I,\phi\right)\right| + \sum_{k=1}^{N}f_k^2\left(V,I,\phi\right) + \sum_{k=1}^{N}f_k^4\left(V,I,\phi\right) \tag{6}$$

where N is the measured data samples, ϕ stands for a vector of design parameters that involves the unknown parameters of the TD model. The $f_k(V, I, \phi)$ is mathematically expressed as:

$$\begin{aligned} f_k\left(V,I,\phi\right) = I_{PV} - I_{O1}\left\{exp\left[\frac{V+IR_s}{a_1V_t}\right]-1\right\} \\ - I_{O2}\left\{exp\left[\frac{V+IR_s}{a_2V_t}\right]-1\right\} \\ - I_{O3}\left\{exp\left[\frac{V+IR_s}{a_3V_t}\right]-1\right\} \\ - \frac{V+IR_s}{R_p} - I_{measured} \end{aligned} \tag{7}$$

where $\phi = \left\{I_{PV}, I_{O1}, I_{O2}, I_{O3}, R_s, R_p, a_1, a_2, a_3\right\}$ $I_{measured}$ stands for the practical PV current. The EOA approach is used to minimize the fitness function, ε, to precisely extract the nine-parameters. The principle EOA is performed by using MATLAB software [62].

IV. EOA TECHNOLOGY

The EOA is a novel optimization algorithm, which was first presented by Faramarzi, Heidarinejad, *et al.* in 2019 [59]. It was motivated by physics-based dynamic mass balance on a control volume to determine the dynamic and steady states. In the EOA, the agent with its concentration represent the search agent. This search agent randomly updates its concentration based on the equilibrium candidate (best solution) to attain the equilibrium state (optimal solution) [59].

The design of EOA approach is analogous to that of the PSO technique, where the agent solution is similar to the position of a particle. In this regard, the concentration of each particle is updated using three parts. The first part is defined as steady-state concentration, which is known as some of the best solutions of the steady-state pool. The second part relates to a concentration variance between the agent and steady-state, which appears as a direct search technique. This phase acts as explorers, where the particles are promoted to the search space. The third part relates to the generation rate that has a crucial role in obtaining the solution, although it sometimes participates as an explorer as well. Each phase is briefly clarified as follows [59].

A. INITIALIZATION AND FUNCTION EVALUATION

In the EOA approach, the optimization process is started using the initial population similar to several meta-heuristic approaches. The initialization process of the agents can be updated by using the following formula:

$$C_i^{initial} = C_{min} + rand_i(C_{max} - C_{min}) \quad i = 1, 2, \ldots .n \tag{8}$$

where $C_i^{initial}$ denotes an initial concentration vector, C_{max} and C_{min} are the maximum and minimum limits, $rand_i$ denotes a random vector ∈ [0,1], and n represents the number of agents. These agents are assessed based on their fitness value, and then they are arranged to estimate steady-state candidates.

B. EQUILIBRIUM POOL AND CANDIDATES

The final convergence of the EOA is the steady-state that is required to find the optimal solution. At starting of the optimization process, no information exists in the steady-state. Also, some candidates are defined by four best particles set through the process and another agent whose concentration is an arithmetic mean of mentioned four particles. These agents are implemented to achieve a better exploration process. These agents are the steady-state candidates and they are utilized to arrange a vector, named the steady-state pool. Each agent updates its concentration with the course of the iteration with random chosen among candidates that are selected with similar probability.

C. EXPONENTIAL TERM

The exponential term, F, is used in the updating rule. The precise definition of F assists EOA to have an acceptable balance between exploration and exploitation. λ represents random vector ∈ [0,1], where the turnover rate varies with time.

$$\vec{F} = e^{-\vec{\lambda}(t-t_0)} \tag{9}$$

where t is the time that is a function of ($Iter$), and t_0 is the initial start time.

$$t = (1 - \frac{Iter}{Max_{iter}})^{(a_2 \frac{Iter}{Max_{iter}})} \tag{10}$$

where $Iter$ and Max_{iter} are the present and the total number of iterations, and a_2 denotes a constant value that managing the exploitation process. To guarantee the convergence rate along with enhancing the exploration and exploitation capability of the EOA, the following formula is considered:

$$\vec{t}_0 = \frac{1}{\vec{\lambda}} \ln\left(-a_1 sign\,(\vec{r} - 0.5)\left[1 - e^{-\vec{\lambda}t}\right]\right) + t \tag{11}$$

where a_1 denotes a constant value that controls exploration ability. r is a random vector that its value between 0 and 1. Eq. (11) is substituted into (9) and then,

$$\vec{F} = a_1 sign\,(\vec{r} - 0.5)\left[1 - e^{-\vec{\lambda}t}\right] \tag{12}$$

D. GENERATION RATE

The generation rate, G, plays a vital role in the EOA. It provides the accurate solution by enhancing the exploitation phase. The G is described as a function of time, and can be expressed in following formulas [63]:

$$\vec{G} = \vec{G_o} e^{-\vec{K}(t-t_0)} \tag{13}$$

where G_o denotes an initial value and K points out a decay constant. For a more systematic search, K is assumed to be equal to λ. Thus, the final set of G is:

$$\vec{G} = \vec{G_o} e^{-\vec{\lambda}(t-t_0)} = \vec{G_o}\vec{F} \tag{14}$$

where,

$$\vec{G_o} = \overrightarrow{GCP}(\vec{C}_{eq} - \vec{\lambda}\vec{C}) \tag{15}$$

$$\overrightarrow{GCP} = \begin{cases} 0.5r_1, & r_2 \geq GP \\ 0, & r_2 < GP \end{cases} \tag{16}$$

where r_1 and r_2 are random values in [0,1], $\overrightarrow{GCP}$ represents the generation rate control parameter that involves the possibility of G for the updating process, GP is the generation probability that determines how many particles utilize G to update their states, and C_{eq} is the equilibrium pool. To obtain a compromise balance between both of the exploration and the exploitation, $GP = 0.5$. The updated formula of the EOA is expressed as follows:

$$\vec{C} = \vec{C}_{eq} + \left(\vec{C} - \vec{C}_{eq}\right) . \vec{F} + \frac{\vec{G}}{\vec{\lambda}V}(1 - \vec{F}) \tag{17}$$

where V is regarded as a unit.

In (17), the first part denotes the steady-state concentration, and the other parts appear changing in the concentration. The second part is in charge of global searching the space in order to get the optimal solution. The third part is participated to achieve a more precise solution.

E. MEMORY SAVE OF PARTICLE

The memory save is added to assist each particle to follow its coordinates and also to inform the objective value. The technique looks like *pbest* rule in the PSO approach. For each particle, the objective function value of the agent is compared with the back-step iteration and shall be replaced if it realizes a better value. Although the technique helps in the exploitation process, it may fall into the local minimum point if the technique does not execute the global exploration process [64]. Fig. 2 demonstrates the flowchart of the offered EOA-based electrical parameters extraction of the PV model.

V. SIMULATION RESULTS

The EOA is applied to properly model the PV panels. Here, the proposed algorithm is employed to optimally design the parameters of a TD model of different PV modules. In this regard, two commercial PV panels are employed to test the validity of the EOA model, like KC200GT [65] and MSX-60 [66]. Table 1 indicates the electrical behaviors of such marketable PVs, which are measured under the STC.

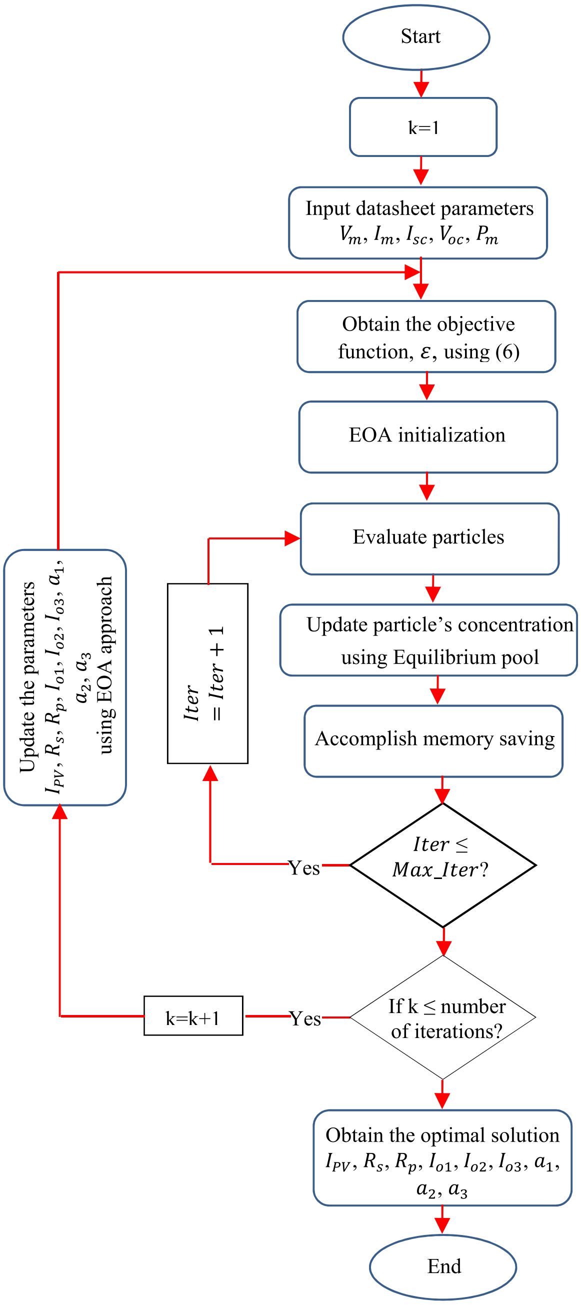


FIGURE 2. Flowchart of proposed EOA-based nine-parameters extraction.

TABLE 1. PV modules data.

Company	Kyocera [65]	Solarex [66]
Model	KC200GT	MSX-60
Cell Type	Multicrystal	Polycrystalline
P_m [W]	200	60
V_m [V]	26.3	17.1
I_m [A]	7.61	3.5
V_{oc} [V]	32.9	21.1
I_{sc} [A]	8.21	3.8
N_s [cell]	54	36
K_i [A/°C]	0.00318	0.00065
K_V [V/°C]	–0.123	–0.08

The EOA approach is used for minimizing the fitness function, $\boldsymbol{\varepsilon}$ that mentioned in Eq. (6), where the number of iterations is set 500. Based on the designer experience, the number of particles in the EOA is set 30. Notably, the control parameters of the EOA have been set using the trial and error method. After performing several runs, the EOA was terminated. Fig. 3(a) and (b) indicates the convergence curves of $\boldsymbol{\varepsilon}$ using the EOA approach for the two marketable PV modules. Note that, the EOA method has a rapid convergence speed. In addition, the graphs are smooth and terminated to a minimum

TABLE 2. Optimal parameters using the EOA-TD model.

	KC200GT	MSX–60
I_{PV}[A]	8.20131	3.79314
R_p [Ω]	331.2113	278.5781
R_s [Ω]	0.36742	0.17832
a_1	1.3124	1.381
a_2	1.201	1.0851
a_3	1.4541	1.4154
I_{01} [A]	2.781e–08	2.73e–08
I_{02} [A]	4.875e–10	3.45e–10
I_{03} [A]	4.759e–10	4.19e–10

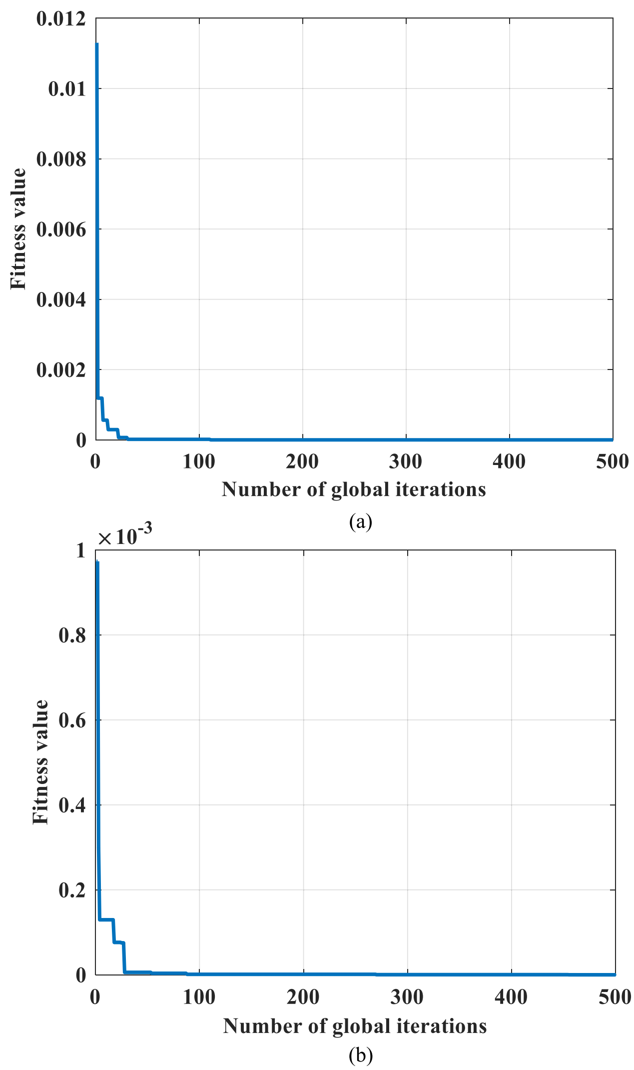


FIGURE 3. Convergence over iterations. (a) KC200GT. (b) MSX60.

TABLE 3. Comparison among PV models for KC200GT.

	WOA	SFO	COA	ELPSO	TVACPSO	EOA
I_{PV}[A]	8.231	8.212	8.1256	8.11	7.99	8.20131
R_p [Ω]	341.387	606.12	286.26	351.2	4.154	331.2113
R_s [Ω]	0.3421	0.237	0.273	0.248	0.314	0.36742
a_1	1.32	1.248	1.393	1.27	1.301	1.3124
a_2	1.236	1.991	1.048	1.10	1.84	1.201
a_3	1.0216	1.842	1.016	1.47	1.725	1.4541
I_{01} [A]	2.692e–8	4.3e-8	2.33e-8	2.54e-8	2.31e-8	2.781e–08
I_{02} [A]	4.67e–10	2.22e-10	1.865e-10	3.54e-10	3.41e-10	4.875e–10
I_{03} [A]	4.92e–10	1.35e-6	4.912e-10	3.48e-10	4.11e-10	4.759e–10
Fitness value	9.8488e-8	1.23e-12	5.48e-11	3.14e-10	2.19e-10	1.14e-14

TABLE 4. Comparison among PV models for MSX-60.

	WOA	SFO	COA	ELPSO	TVACPSO	EOA
I_{PV}[A]	3.756	3.801	3.706	3.59	3.41	3.79314
R_p [Ω]	277.37	578.34	258.93	378.1	384.27	278.5781
R_s [Ω]	0.195	0.205	0.171	0.181	0.194	0.17832
a_1	1.30	1.282	1.243	1.25	1.29	1.381
a_2	1.23	1.804	1.006	1.742	1.651	1.0851
a_3	1.03	1.436	1.075	1.02	1.12	1.4154
I_{01} [A]	2.19e–8	4.98e-8	2.042e-8	2.91e-8	2.64e-8	2.73e–08
I_{02} [A]	3.68e–10	7.24e-10	1.54e-10	1.45e-10	1.35e-10	3.45e–10
I_{03} [A]	3.97e–10	1.42e-7	1.37e-10	2.01e-10	2.7e-10	4.19e–10
Fitness value	7.31e-10	1.14e-11	3.41e-10	8.14e-10	3.69e-10	7.154e-13

objective value of 1.14e-14 and 7.154 e-13 for Kyocera KC200GT and Solarex MSX-60 PV cells, respectively. The optimization and numerical results are performed with the help of using MATLAB 2016b [62]. Furthermore, multiple runs around 50 of the EOA approach are executed to check the validity of the EOA technique. It is highly to mention here that the standard deviation value and variance value are close to zero, which reflect the excellence and the proper structure of the EOA technology. Table 2 clarifies the optimal variables of the PV model for KC200GT and MSX-60 PV modules. Tables 3 and 4 illustrate the optimal parameters that achieved using the EOA approach compared to that obtained using the WOA [39], SFO [54], COA [56], ELPSO, and TVACPSO for the two marketable PV modules. Notably, the optimal nine-parameters of the TD model using the EOA method are very near to that realized by using various algorithms for the two marketable PV modules. In addition, the proposed EOA-TD model has achieved a lower fitness value of 1.14e-14 and 7.154 e-13 for both marketable PV cells compared with other approaches. So, the EOA represents a competitive technology to precisely establish the TD model of any PV modules.

Table 5 clarifies the constraints of the proposed EOA-based TD model. Moreover, the numerical results that achieved using the proposed EOA-based PV model are compared with the practical results at various temperature and solar irradiation conditions. The *I-V* and *P-V* characteristics of the proposed EOA-based PV model are paralleled with the practical data of the marketable KC200GT PV panel at various temperatures, as depicted in Fig. 4(a)&(b). The results are achieved at constant $G = 1$ kW/m^2. Notably, the numerical results of the EOA model are concurred with the practical data. This reflects the high preciseness of the offered TD

TABLE 5. Constraints of the proposed EOA-based TD model.

	Lower boundary	Upper boundary
I_{PV}[A]	2.5	5
R_p [Ω]	200	400
R_s [Ω]	0.1	0.5
a_1	1.2	1.5
a_2	1	1.3
a_3	1	1.5
I_{01} [A]	1e-8	4e-8
I_{02} [A]	2e-10	5e-10
I_{03} [A]	1e-10	5e-10

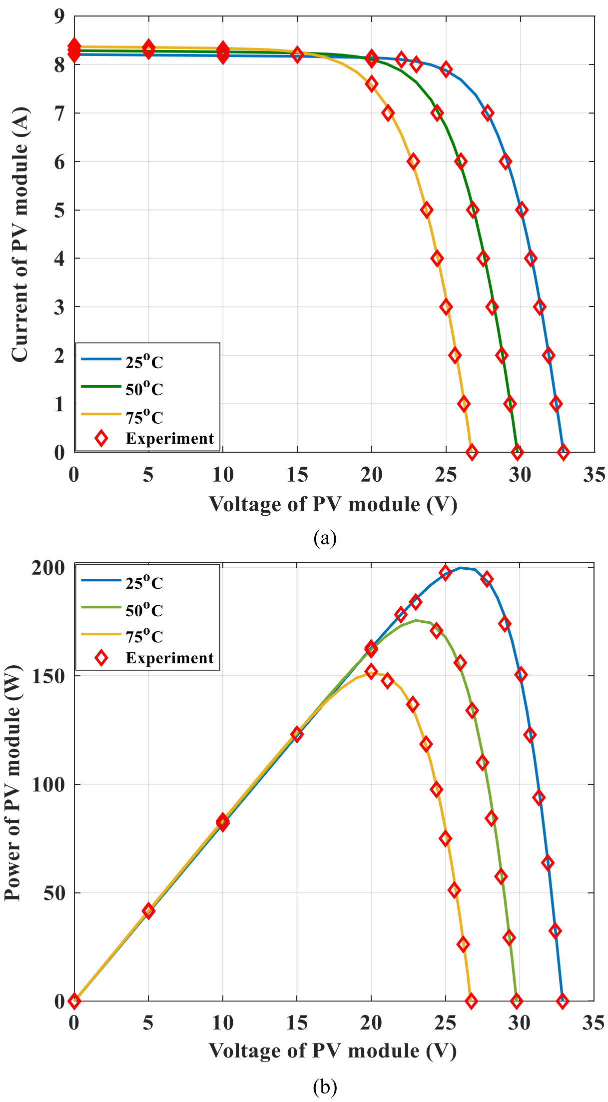
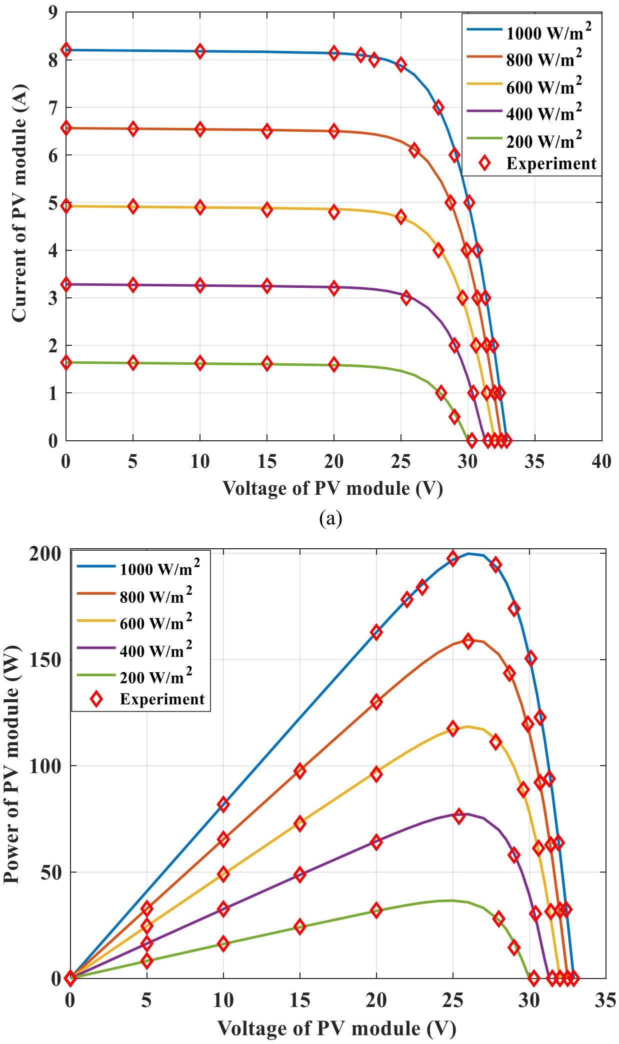


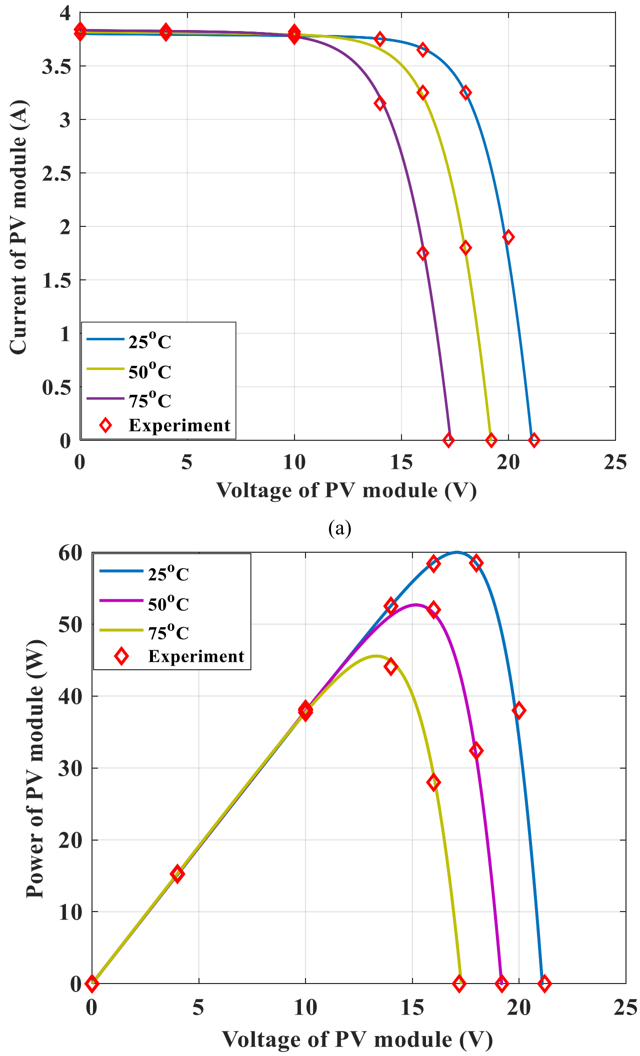
FIGURE 4. Simulation results and practical data of KC200GT at various T, $G = 1$ kW/m^2. (a) *current-voltage* ($I - V$) curves, (b) *power-voltage* ($P - V$) curves.

model of the PV panel. Furthermore, the PV characteristics of the EOA-PV model that compared with their practical data for KC200GT panel at several irradiations are illustrated in Fig. 5(a)&(b). It can be mentioned here that no change occurs between numerical and practical results. It appears a



(a)
(b)

FIGURE 5. Simulation results and practical data of KC200GT at various G, and $T = 25$ °C. (a) *current-voltage* ($I - V$) curves, (b) *power-voltage* ($P - V$) curves.



(a)
(b)

FIGURE 6. Simulation and practical results of MSX-60 at various T, $G = 1$ kW/m^2. (a) *current-voltage* ($I - V$) curves, (b) *power-voltage* ($P - V$) curves.

confirmation of the effectiveness of the EOA model. The PV characteristics of the MSX-60 PV panel that are realized at $G = 1$ kW/m^2 and various temperatures by the proposed model are compared with the practical results, as demonstrated in Fig. 6(a)&(b). Notably, the numerical outcomes of the proposed model coincide with the practical data. From the previous comparisons, it is noticed that the proposed PV model has a high efficacy.

It is worthy for mentioning here that all the practical data are attained on the outer surface of a Campus building roof. In this regard, the PV panel is located in an open glassed container. A circular hot water or cold water can flow in order to control the PV panel temperature. Many practical measurements were successfully carried out in June 2017, Cairo, Egypt. The PV panel is simply loaded by an adjustable resistance, which has a rated value of 39 Ω. A digital multimeter is utilized in recoding the values of PV's current and PV's voltage. These measurements were done at various temperature and irradiance conditions. The solar irradiance is measured with the help of using a Pyranometer SP-110-SS with a calibration factor of 5 W/m2 per mV and its uncertainty is ±5%. Besides, an infrared thermometer is performed to precisely record the temperature and its accuracy is ±1 °C, and its available range is [−32, 550 °C]. The real PV panel used in the experimental test is depicted in Fig. 7.

For an inclusive validation of the EOA PV model, the ACE, which is the difference between the modelled and practical currents, is used in the comparison between different approaches-based PV model. Fig. 8(a)&(b) points out the ACE of the EOA model compared with the WOA [39] and the iteration models [39] for both PV panels. It has obviously been noticed that the ACE of the EOA-TD model is lower than that obtained using other PV models. Hence, the EOA-TD model is preferable compared with the others models, particularly in the MPP operation and in the applications of PV panels. Thus, the superiority of the EOA-TD model distinguishes the proper design of the EOA technology.

FIGURE 7. Real PV panel used in the experimental test.

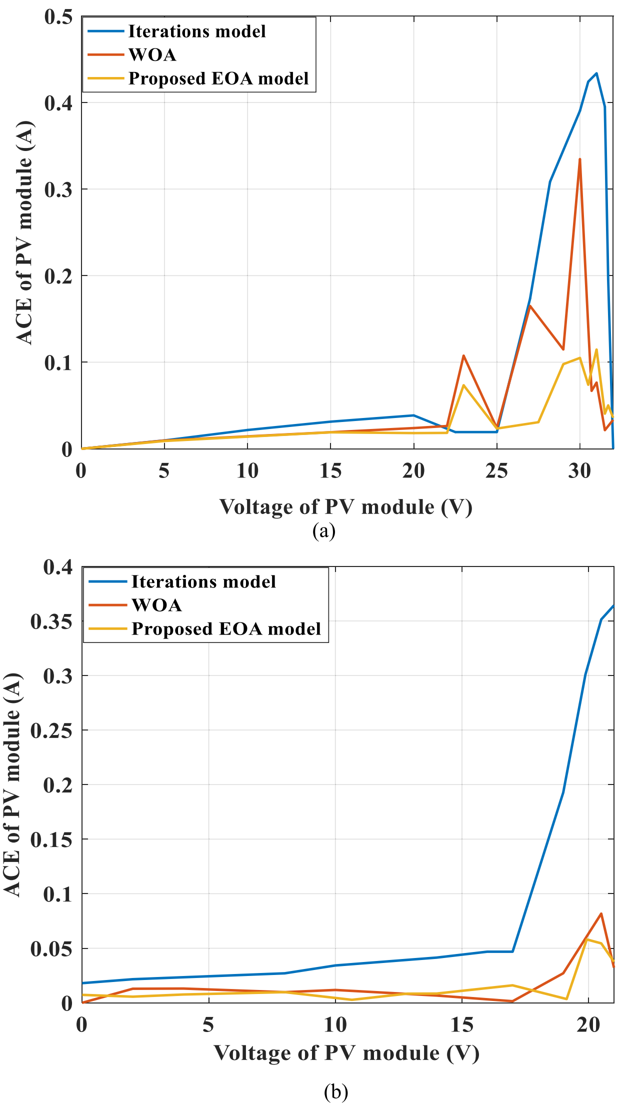


FIGURE 8. ACE (a) KC200GT, (b) MSX-60.

VI. CONCLUSION

As the TD model is a complex nonlinear model, the electrical nine-parameters are hardly achieved using mathematical methods. So, the optimization techniques present an alternative solution to overcome these problems. This article has exhibited a new fitness function and a novel implementation of the EOA technology to optimally design the undetermined parameters of the TD model-based PV panel. The EOA is inspired by physics-based dynamic mass balance on a control volume that is utilized to evaluate the dynamic and equilibrium states. The principle goal of this study is to achieve a precise PV model for commercial PV panels. The TD model of PV modules is mathematically simulated by a nonlinear I-V behavior, involving unknown parameters because of the shortage data offered in the PVs' datasheet. The main purpose of the optimization problem is to minimize the current error function, ε. The EOA technology was successfully employed for minimizing the ε, achieving the nine-parameters of the TD model. Several comparisons were made to confirm the effectiveness of the offered EOA-based PV model. The proposed approach was applied to extract the optimal parameters of the TD model for two commercial PV panels, which include different cells, power ratings, and voltage ratings. The PV model parameters, obtained using the EOA-based PV model, are close and competitive to that realized using other various approaches, where the EOA model has revealed a minimum fitness value of 1.14e-14 and 7.154e-13, respectively for both marketable PV panels. Moreover, the simulation outcomes of the offered EOA-based PV model are near to the practical data for these marketable PV modules under several temperatures and irradiances. The ACE of the EOA-based PV model with respect to the measured data records a value less than 5% compared with different PV models. In conclusion, the proposed EOA technology and the proposed fitness function, ε, can be applied to properly identify the unknown parameters of the TD model of any commercial PV panel, achieving a precise PV model. The precise PV model is very useful in the simulation analyses of the solar power systems. Furthermore, the proposed EOA algorithm can be further employed in solving different problems in various renewable energy conversion systems, microgrids, and smart grids.

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