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PV Model Parameter Estimation Using Modified FPA With Dynamic Switch Probability and Step Size Function

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ABSTRACT The development of highly efficient models of Photovoltaic (PV) cells and modules is essential for optimized performance, evaluation and control of solar PV systems. The accurate estimation of PV cells parameters is a challenging task because of their non-linear characteristics. In this paper, an improved variant of Flower Pollination Algorithm (FPA) is proposed for accurate estimation of PV cells and modules parameters. The proposed algorithm involves double exponential based dynamic switch probability and a dynamic step size function that mitigate the limitations of conventional FPA. The dynamic switch probability improves the overall performance of algorithm by maintaining a balance between local and global search, while dynamic step function controls the search speed which avoids premature convergence and local optima stagnation. Moreover, Newton Raphson Method is utilized for accurate computation of estimated current for optimum set of estimated parameters. The proposed methodology is evaluated using seven benchmark functions and three case studies; 1- RTC France silicon PV cell, 2- Photo-watt PWP-201 PV module and 3- a practical solar PV system (EAGLE PERC 60M 310W monocrystalline PV module) under different environmental conditions by estimating parameters for single and double diode models. The analysis of results indicates that, the proposed approach improves the convergence speed, precision, avoids premature convergence and stagnation in local optima of conventional FPA. Furthermore, comparative analysis of results illustrates that, the proposed approach is more reliable and efficient than many other techniques in literature.

INDEX TERMS Dynamic switch probability, flower pollination algorithm, parameter extraction problem, single and double diode models.

I. INTRODUCTION

Depleting conventional energy resources, increasing prices of fossil fuels and environmental threats have reduced the production of electrical energy. To overcome these issues, researchers are concerned to produce electric energy by using Renewable Energy Sources (RES) including solar, wind, biomass, tidal, hydro and geothermal [1]. Solar energy is considered as the best source to solve this issue due to its wide availability [2]. Photovoltaic (PV) systems do not require any fuel, moving parts of machinery and lubrication hence, its operational [3] and maintenance cost [4] is almost zero. Moreover, no greenhouse gas production as PV system directly converts solar energy into electric power.

A PV system is comprised of a series or parallel combination of various PV cells to produce required electric energy [5]. To increase the efficiency of a PV system or to understand the non-linear current-voltage (I-V) behavior of a solar PV system under changing environmental circumstances, an accurate modelling of PV cells or modules is essential and is a hot research topic these days [6], [7]. The studies pertaining to PV cell modeling generally performed in two

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steps: At first, an electrical equivalent mathematical modeling of PV cell/module is performed which may be based on single or multi diode model to accurately imitate the behavior of a PV cell or module [7]–[9]. Many researchers have worked to improve PV models using different approaches [10]. In [10], five parameter single diode PV model has been proposed which analytically depicts I-V and P-V behavior of PV module and its effects on maximum power point (MPP), short circuit current (I_{sc}) and open circuit voltage (V_{OC}) in different environmental conditions. Five accurate PV model parameters are based on nine coefficients. The second step is the selection of an effective computational intelligence approach (CIA) to estimate electrical equivalent model parameters of a PV cell or module. These techniques are broadly classified in two categories (1) analytical approaches (2) metaheuristic techniques [11]. Analytical approaches use datasheets provided by manufacturers to formulate functions [12]. These are not suitable for complex problems due to their complex mathematical formulation. These approaches do not give accurate results due to the need of approximations in calculations and dependency of equations on each other [13]. Metaheuristic techniques works by converting any problem into an optimization problem. These are more suitable to solve complex multimodal problems just like PV parameter estimation problem as they are efficient and require less information about initial conditions. Moreover, these techniques are reliable, simple and robust. Many techniques including Genetic Algorithm (GA) [14], Bacterial Foraging Algorithm (BFA) [15], Simulated Annealing (SA) [16], Particle Swam Optimization (PSO) [17], Harmony Search (HS) [18], Pattern Search (PS) [19], Artificial Bee Swam Optimization (ABSO) [20], Bird Mating (BM) [21], Differential Evolution [22], Cat Swarm Optimization (CSO) [23], Teaching Learning based ABC (TLABC) [24] and Salp Swarm Algorithm (SSA) [25] have been utilized for PV parameter estimation problem to find an optimal solution during an iterative process. However, such population-based algorithms have certain shortcomings for a complex and multi-modal problem like parameter estimation, GA is less accurate and more complex due to the selection of chromosomes from initial population [14], PSO is computationally fast but can converge prematurely [17] while SA requires absolute care in order to match temperature and cooling programs [16]. In [15], BFA is employed for parameter estimation of PV cell/module, it gives optimum results and undergoes fast convergence but involvement of many optimization parameters makes it more complex and requires more computational efforts. In [22], two diode model parameters of PV module are estimated for six modules (monocrystalline, multi-crystalline, thin film) using penalty based differential evolution which requires a smaller number of control parameters, improved accuracy of solutions and improved convergence rate but still needs some improvements. In [23], CSO has been used for parameter estimation of single and double diode model of PV cell and module. In [24], teaching learning operators are incorporated in ABC algorithm for the estimation of PV model parameters. In [25], SSA is an algorithm proposed for the parameter estimation of solar cell.

In 2012, Yang has proposed a new metaheuristic technique inspired by the pollination behavior of plants named Flower Pollination Algorithm (FPA) [26]. Its search mechanism is composed of biotic (global search) and abiotic (local search) pollination process. Due to its simple implementation and small number of controlling parameters it has been applied to many optimization applications [27]. However, like other metaheuristic algorithms FPA also have some limitations such as slow convergence at later stage of optimization algorithm, insufficient convergence proof and easily being trapped in local optima. To solve these issues, many researchers have proposed modified variants of FPA or had hybridized FPA with other algorithms [27]. In [28], Bee Pollinator Flower Pollination Algorithm (BPFPA) has been implemented on single and double diode models for parameter estimation problem by calculating currents of single and double diode models using an analytical approach while all other parameters are obtained using BPFPA in order to guarantee convergence to global optimum. In [29], FPA has been hybridized with Nelder Mead (NM) Simplex method and generalized opposition-based learning mechanism in order to improve convergence speed, stability and giving accurate results for parameter estimation problem. In [30], FPA has been hybridized with Clonal Selection Algorithm (CSA) to obtain better curve fitting and more accurate results for parameter extraction problem. In [31], [32], dynamic switch probability has been used to create balance between local and global search with p = 0.6 as an initial value. These papers do not briefly explain the effect of proposed methodology. In [33], local search ability is being improved by introducing a scaling factor through cloning method and switch probability is taken as 0.8 without any explanation. In [34], proposed methodology improves exploitative ability of FPA by introducing scaling factor and avoid local optima stagnation. This methodology is utilized for economic load dispatch problem. In [35], modified version of FPA have been used for optimal power flow problem. Proposed modification improves convergence speed by removing probability switch parameter and combining local and global search equations along with using opposition-based points as starting solutions. None of the modified versions of FPA have been used to solve parameter estimation problem because it is a complex multimodal problem.

The comprehensive review of literature shows that many researchers [36]–[41] have put their efforts in avoiding premature convergence, slow convergence rate and local optima stagnation problems of conventional FPA but they failed to prove efficient for parameter estimation problem because it is very sensitive due to minor changings in RMSE. All these variants improve performance of FPA with different search strategies but still FPA has a room for further improvements. Switching between global and local search is being carried out by switch probability (p) parameter and it is a user defined control parameter. It is usually taken as constant in standard

FPA but this paper is focusing on non-stationary switch probability. Constant probability value varies for every problem between [0,1] so it requires a hit and trial method to find out the suitable value of probability for a specific problem. Double exponential function with improved performance index function depending upon number of iterations has been used to improve search probability which is decrementing exponentially from higher value (causing global search) to smaller value (causing local search). Moreover, another controlling parameter proposed in [42] is the step function which describes the length of move of pollinators/search agents. As, one of the searching agents decided to move from one place to another then it must decide the length of its move. The step function provided in [42] is based on a user defined step size that could be between [0,1]. The step function used in this paper is also dynamic as its difficult to find the appropriate step size for a specific application. So, the step size proposed in this paper is made problem dependent. Initially, step size function starts searching with large step sizes which improves intensification around the found region and ended up to give optimal value by exponentially decreasing step size depending upon number of iterations. The obtained value of step function is introduced in updating position equations for global and local search of conventional FPA. Convergence speed has been improved along with balanced local and global search using exponential functions. In this paper, two modifications of FPA are proposed: dynamic switching probability and introducing step function in conventional FPA. The improvements made in conventional FPA solves the premature convergence problem, avoid local minima trapping, slow convergence rate problem and then it creates a balance between global and local search.

This paper proposes a double exponential weight dynamic switch probability with exponential step size function FPA for parameter estimation of single and double diode models of PV cell, module and a practical system. The major contributions of this paper are listed as:

1. An improved variant of FPA is proposed to have fast convergence rate, avoids premature convergence and trapping in local optima hence providing accurate and optimal results for parameter estimation problem.
2. Accurate estimation of currents for best obtained parameters are calculated using Newton Raphson Method (NRM).
3. Proposed variant of FPA is validated using 4 unimodal and 3 multimodal test functions and three cases for parameter estimation problem: 1) RTC France silicon solar cell, 2) Photo-watt PWP201 PV module and 3) a practical test system having Eagle Perc 60M (310W) monocrystalline PV module under real environmental conditions.
4. The effectiveness of proposed approach is carried out by comparing obtained results and statistical analysis with the results of techniques available in literature.

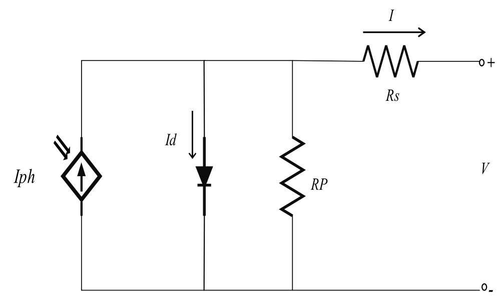

FIGURE 1. Electrical equivalent circuit of PV cell for single diode model.

The remaining paper is organized as follows: Section 2 illustrates Mathematical formulation of PV model. Section 3 presents problem and objective function formulation. Section 4 emphasizes on proposed approach to solve this parameter estimation problem. Section 5 demonstrates optimal results obtained for benchmark functions and parameter estimation problem using proposed approach and their comparison with different state of art algorithms. Finally, conclusion is presented in Section 6.

II. PV MODELLING

Single diode and double diode models are generally used by many researchers for PV modeling [8], [9], [18]. Single diode model comprises of five indefinite parameters while double diode model comprises of seven indefinite parameters and is relatively more complex in comparison with single diode model but it provides more accurate results. In this paper both single and double diode PV models are used for performance evaluation of proposed technique and the obtained optimal results are compared with various other techniques available in literature.

A. SDM MODELLING

Equivalent electrical circuit of a PV cell using single diode model is given in Fig. 1. It can be observed from this figure that I_{ph}, I_{rs}, R_s, R_p and n are the five associated parameters to be estimated and the output current I is calculated by applying KCL, [43]:

$$I = I_{ph} - I_d - I_p \tag{1}$$

where, I is the output terminal current, I_{ph} depicts photogenerated current, I_d shows diode current and I_p is the parallel resistor current. The diode current I_d is given by Shockley equation is:

$$I_d = I_{rs} \times \left[exp\left(\frac{q\times (V + IR_s)}{n \times k \times T} \right) - 1 \right] \tag{2}$$

where, I_{rs} is the reverse saturation current, R_s is the series resistance, V presents terminal voltage, n is called ideality factor, q represents electronic charge (1.60217646 $\times 10^{-19}$ C), T represents temperature in kelvin, k is called Boltzmann constant (1.3806503 $\times 10^{-23}$ J/K).

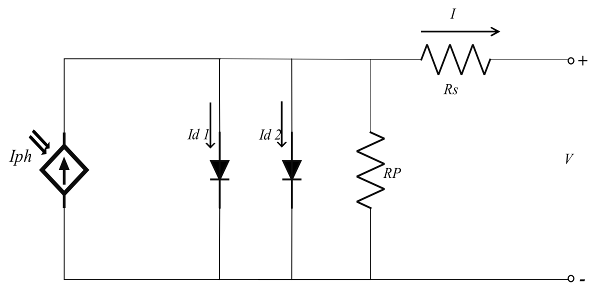

FIGURE 2. Electrical equivalent circuit of PV cell for double diode model.

By putting $V_t = {}^{k \times T}/_{q}$ in (2):

$$I_d = I_{rs} \times \left[exp\left(\frac{(V + IR_s)}{n \times V_t}\right) - 1\right] \quad (3)$$

$$I_p = \frac{V + IR_s}{R_p} \quad (4)$$

Substituting (3) and (4) in (1) gives:

$$I = I_{ph} - I_{rs} \times \left[exp\left(\frac{(V + IR_s)}{n \times V_t}\right) - 1\right] - \frac{V + IR_s}{R_p} \quad (5)$$

B. DDM MODELLING

Equivalent electrical circuit of a PV cell using double diode model is given in Fig. 2. It can be observed from this figure that $I_{ph}, I_{rs1}, I_{rs2} R_s, R_p, n_1$ and n_2 are the seven associated parameters to be estimated and the output current I is calculated by applying KCL [43]:

$$I = I_{ph} - I_{d1} - I_{d2} - I_p \quad (6)$$

$$I = I_{ph} - I_{rs1} \times \left[exp\left(\frac{(V + IR_s)}{n_1 \times V_t}\right) - 1\right] - I_{rs2} \times \left[exp\left(\frac{(V + IR_s)}{n_2 \times V_t}\right) - 1\right] - \frac{V + IR_s}{R_p} \quad (7)$$

where n_1, n_2 are called ideality factors while I_{rs1} and I_{rs2} are reverse saturation currents of diode 1 and diode 2.

This model gives more accurate results than single diode model because it involves two diodes. Second diode represents loss due to recombination [44], but it is computationally complex. Single and double diode equivalent circuits represent behavior of a PV cell. Solar modules are series or parallel combination of PV cells. Both single and double diode models are used to mimic behavior of PV module with a little variation in (5) and (7) as $V_t = {}^{N_s kT}/_{q}$ [45].

III. PROBLEM FORMULATION

Parameter estimation problem is considered as an optimization problem and is solved by estimating the parameters for single and double diode models so that the obtained I-V curve is in approximation with the experimental I-V curve under same operating environmental conditions. The difference between estimated I-V data and experimental data should be minimum and this difference is calculated using different performance indexes like: Absolute Error (AE), Mean Absolute Error (MAE), Sum Squared Error (SSE), Root Mean Square Error (RMSE) and so on [20], [46]. These performance indexes are called as Objective Function (OF) that determines the degree of correspondence between measured and experimental I-V data. In this paper, the selected OF is the RMSE given in (8) which should have a minimum value and it is restricted by the bounds of estimated parameters as provided in Tables 1 and 2.

$$RMSE\,(X_o) = \sqrt{\frac{1}{N} \times \sum_{i=1}^{N} \left[(I_{measured} - I_{calculated})^2\right]} \quad (8)$$

where N presents the number of experimental I-V pairs, Xo denotes set of estimated PV model parameters, $I_{measured}$ is the experimental data of PV cell or module and $I_{calculated}$ is the estimated current obtained using Newton Raphson Method (NRM) at the best estimated set of parameters for single and double diode models.

Experimental I-V data for single and double diode models is obtained from [47], for each pair of I-V, current is estimated using (9) and (10) for single and double diode models respectively as:

$$I = I_{ph} - I_{rs} \times \left[exp\left(\frac{(V + IR_s)}{n \times V_t}\right) - 1\right] - \frac{IR_s + V}{R_p} \quad (9)$$

$$I = I_{ph} - I_{rs1} \times \left[exp\left(\frac{(V + IR_s)}{n_1 \times V_t}\right) - 1\right] - I_{rs2} \times \left[exp\left(\frac{(V + IR_s)}{n_2 \times V_t}\right) - 1\right] - \frac{V + IR_s}{R_p} \quad (10)$$

$$f\,(V, I, X_o) = I_{ph} - I_{rs} \times \left[exp\left(\frac{(V + IR_s)}{n \times V_t}\right) - 1\right] - \frac{V + IR_s}{R_p} - I \quad (11)$$

$$X_o = \left\{I_{ph}, R_s, I_{rs}, R_p \text{ and } n\right\} \quad (12)$$

$$f\,(V, I, X_o) = I_{ph} - I_{rs1} \left[exp\left(\frac{(V + IR_s)}{n_1 \times V_t}\right) - 1\right] - I_{rs2} \left[exp\left(\frac{(V + IR_s)}{n_2 \times V_t}\right) - 1\right] - \frac{V + IR_s}{R_p} - I \quad (13)$$

$$X_o = \left\{I_{ph}, R_s, I_{rs1}, R_p, n_1, I_{rs2}, n_2\right\} \quad (14)$$

These equations do not work with explicit solutions so, in this paper NRM is utilized to resolve this problem.

These equations are solved by NRM given in Fig. 3 for $f\,(V, I, X_o) = 0$, The method also requires derivative equations for single and double diode models respectively as

TABLE 1. **Parameter boundary values for single diode model.**

Parameters	Case 1 (Cell)		Case 2(Module)		Case 3(Practical System)	
	Upper boundary	Lower boundary	Upper boundary	Lower boundary	Upper boundary	Lower boundary
I_{ph} (A)	1	0	1.2	0	11	0
I_{rs} (A)	1×10^{-05}	1×10^{-12}	1×10^{-05}	1×10^{-12}	1×10^{-05}	1×10^{-12}
n	2.5	0.5	2.5	0.5	2.5	0.5
R_s (Ω)	0.5	0.001	2	0.001	2	0.001
R_p (Ω)	100	0.001	5000	0.001	5000	0.001

TABLE 2. **Parameter boundary values for double diode model.**

Parameters	Case 1 (Cell)		Case 2(Module)		Case 3(Practical System)	
	Lower Boundary	Upper Boundary	Lower Boundary	Upper Boundary	Lower Boundary	Upper Boundary
I_{ph} (A)	0	1	0	1.2	0	11
I_{rs1} (A)	1×10^{-12}	1×10^{-05}	1×10^{-12}	1×10^{-05}	1×10^{-12}	1×10^{-05}
I_{rs2} (A)	1×10^{-12}	1×10^{-05}	1×10^{-12}	1×10^{-05}	1×10^{-12}	1×10^{-05}
R_s (Ω)	0.001	0.5	0.001	2	0.001	2
R_p(Ω)	0.001	100	0.001	5000	0.001	5000
n_1	0.5	2.5	0.5	2.5	0.5	2.5
n_2	0.5	2.5	0.5	2.5	0.5	2.5

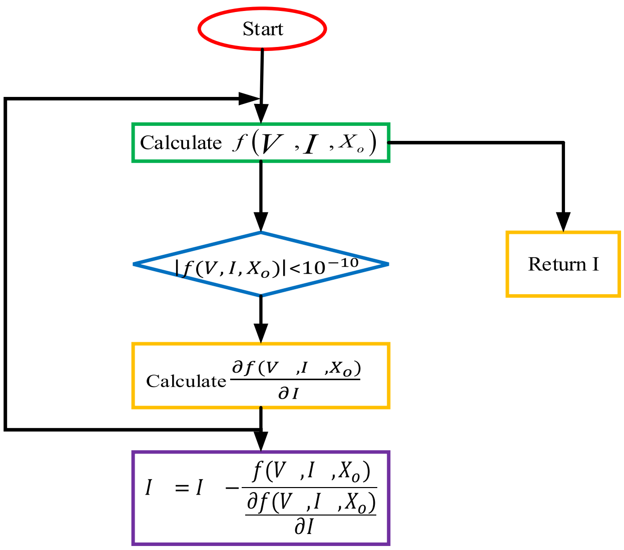

FIGURE 3. **Flowchart of NRM method.**

shown in (15) & (16) during consecutive iterations:

$$\frac{df\ (V, I, X_o)}{dI} = -\left(\frac{I_{rs} \times R_s \times \left[exp \times \left(\frac{(IR_s+V)}{n \times V_t}\right)\right]}{n \times V_t}\right) - \frac{R_s}{R_p} - 1 \tag{15}$$

$$\frac{df\ (V, I, X_o)}{dI} = -\left(\frac{I_{rs1} \times R_s \times \left[exp \times \left(\frac{(IR_s+V)}{n_1 \times V_t}\right)\right]}{n_1 \times V_t}\right) - \left(\frac{I_{rs2} \times R_s \times \left[exp \times \left(\frac{(IR_s+V)}{n_2 \times V_t}\right)\right]}{n_2 \times V_t}\right) - \frac{R_s}{R_p} - 1 \tag{16}$$

A stopping criterion of $f\ (V, I, X_o) < 10^{-10}$ is applied to add more accuracy in estimation of PV model parameters without increasing computational cost. Table 1 contains boundary limits for one diode models [8] while Table 2 contains boundary values for two diode models [8].

IV. FLOWER POLLINATION ALGORITHM

A. BASIC FPA

FPA was proposed by Yang [26] and it mimics the behavior of flower pollination process that involves transfer of pollens through pollinators. The only controlling parameter in conventional FPA is a probability factor p, which switches from 0 to 1 to decide for local or global process of pollination [26]. Pollination process takes place in two ways: Self-pollination and Cross-pollination. The process in which pollens are transferred to different plants is called Cross-pollination while in Self-pollination pollens are transferred within same plants. Similarly, the carriers that cause the pollination process are also of two types. One of the carriers of pollens is the wind which transfers pollens within flowers, this is called abiotic pollination. The other method of transferring pollens is called biotic pollination which is carried out through insects, birds and animals. Some species only go to specific plants in order to increase the production of same plants e.g., honeybees it is called flower constancy. The flower pollination process is based on survival of the fittest theory to produce optimum number of plants. Following are the rules that are developed to mimic the behaviour of FPA as:

Rule 1: Global pollination process is carried out by biotic and cross-pollination, and the pollinators can fly so long obeying levy flight.

Rule 2: Self-pollination and abiotic can be regarded as local pollination.

Rule 3: Flower constancy is similar to reproduction probability which is proportional to degree of correspondence between involved flowers.

Rule 4: A parameter called switching probability which decides about switching between local and global search. The value of this switching factor may vary from 0 to 1.

FPA starts with randomly generated solutions then local and global search operators update solutions iteratively [26]. If new solution is better than old one, it is replaced with new one otherwise it is discarded.

B. MATHEMATICAL MODELLING OF FPA

The mathematical modelling of FPA is provided in following steps:

Rule 1 and Rule 3 combined to give global pollination process [26]

$$X_i^{t+1} = X_i^t + L\left(X_i^t - g^*\right) \tag{17}$$

$$L = \frac{\lambda\Gamma(\lambda)sin\left(\Pi\lambda/_2\right)}{\Pi}\frac{1}{s^{1+\lambda}}, \quad (s \gg s_o > 0) \tag{18}$$

where, X_i^t represents the X_i solution at iteration number t, L mimics the Levy flight distribution feature because search agents took long steps to move from one place to other and its value should be L > 0, g^* represents the best solution from the present population in (17), s represents the step size of a Levy flight. Its value is calculated using Mantegna algorithm and given by (18) [26], where λ is set to 1.5 in this equation and Γ() is a gamma function and [26].

Rule 2 and 3 combined to give local pollination process [26].

$$X_i^{t+1} = X_i^t + \varepsilon\left(X_j^t - X_k^t\right) \tag{19}$$

where X_j^t and X_k^t are two random chosen solutions from a given set of solutions and ε is a random number varies from 0 to 1.

C. PROPOSED FPA

Switch probability switches pollination method between local and global pollination in conventional FPA. So, the convergence rate between local and global optimal solution can be controlled by this parameter and its value varies between (0,1). At lower values of p, the search strategy of algorithm is more prone towards local pollination which makes the solution being trapped in local optimum hence, it becomes difficult to converge at global solution. At higher values of p, position of search agents is more likely to be updated by global pollination equation which is affected by Levy flight distribution mechanism. Solution obtained by this is not so accurate because it does not allow search agents to gather around optimal value. So, the purpose of optimization is not achieved properly. To resolve this problem of FPA, a dynamic switch probability is proposed in this paper to obtain global optimal solution.

This paper presents double exponential-based switch probability with improved function of performance index which is non-linear and decreasing exponentially depending on the relationship between current iterations and maximum number of iterations. At smaller number of iterations, switch probability initially has maximum value causing global search. It avoids the solution being caught in local optima and fasten the convergence rate. At higher values of iteration switch probability has decreased to lower values causing local search which increases the convergence rate around optimal solution and improves convergence accuracy. Proposed switch probability function is shown in (20) as:

$$p_{(t+1)} = exp(-exp\,(-R) \tag{20}$$

$$R = p_{max} - \left(\frac{(p_{max} - p_{min})}{N_{iter}}\right) \times t \tag{21}$$

where, R presents performance index computed for every search agent at each iteration. N_{iter} is the maximum number of iterations, t represents current iteration, p_{max} and p_{min} are the maximum and minimum values of basic probabilistic value. Their values are taken as $p_{max} = 1$ and $p_{min} = 0$. At initial values of iterations, the proposed search strategy provides good exploration rate for search agents to explore more search space. At later values of iterations, lower values of p provide good precision in exploitation phase.

Moreover, in order to control the search speed, a dynamic step size function is also introduced in FPA along with previous modification. This user defined dynamic step size function given in [42] is decreasing exponentially with iterations to increase search accuracy around specified regions as:

$$stepsize_{t+1} = stepsize_t - e^{-t/(t+1)} \times \emptyset_{stepsize} \times stepsize_t \tag{22}$$

where, t is the current iteration, $\emptyset_{stepsize}$ is a user defined step size between (0,1) which controls the decrement speed of a function. Its larger values fasten the speed of decrement and lower values slower down the decrement speed. Value of $\emptyset_{stepsize}$ is obtained by hit and trial method to find the best value of step size to obtain optimal solution for specific optimization problem. This value could be different for different optimization problems, the fixed user defined step size requires computational effort to find optimum step size hence increases computational effort however, an inappropriate step size led to non-optimal solution. So, in this paper a new modification in (22) is proposed which makes step size as problem dependent rather than a user defined step size.

The modified form of (23) is given as:

$$stepsize_{t+1} = stepsize_t - e^{-t/(t+1)} \times \frac{1}{N_{iter}} \times stepsize_t \tag{23}$$

where, N_{iter} is the maximum number of iterations. Now the position of search agents for global or local search as given in (24) and (25) respectively are being updated depending upon

TABLE 3. Characteristics of benchmark functions.

Test Function	Iteration	Dimension	Range	Optimum	Category
$F_1(x) = \sum_{i=1}^{d} x_i^2$	1000	10	[-100, 100]	0	Unimodal
$F_2(x) = \sum_{i=1}^{d} \lvert x_i \rvert + \prod_{i=1}^{d} \lvert x_i \rvert$	1000	10	[-10, 10]	0	Unimodal
$F_3(x) = \sum_{i=1}^{d} \left(\sum_{j-1}^{i} x_j \right)^2$	1000	10	[-100, 100]	0	Unimodal
$F_4(x) = max\{\lvert x_i \rvert, 1 \leq i \leq d\}$	1000	10	[-100, 100]	0	Unimodal
$F_5(x) = \sum_{i=1}^{d} [x_i^2 - 10\cos(2\pi x_i) + 10]$	1000	10	[-5.12, 5.12]	0	Multimodal
$F_6(x) = -20exp\left(-0.2\sqrt{\frac{1}{d}\sum_{i=1}^{d} x_i^2}\right) - exp\left(\frac{1}{d}\sum_{i=1}^{d}\cos(2\pi x_i)\right) + 20 + e$	1000	10	[-32, 32]	0	Multimodal
$F_7(x) = \frac{1}{4000}\sum_{i=1}^{d} x_i^2 - \prod_{i=1}^{d}\cos\left(\frac{x_i}{\sqrt{i}}\right) + 1$	1000	10	[-600, 600]	0	Multimodal

the two modifications made in this paper as and the flowchart of proposed methodology is given in Fig. 4.

Global search,

$$X_i^{t+1} = X_i^t + L\left(X_i^t - g^*\right) \times stepsize_t \quad (24)$$

Local search,

$$X_i^{t+1} = X_i^t + \varepsilon\left(X_j^t - X_k^t\right) \times stepsize_t \quad (25)$$

V. RESULTS AND DISCUSSION

The performance of proposed technique is first evaluated using seven standard benchmark functions to obtain optimal solution and the characteristics of these benchmark functions is given in Table 3 [48]. Among the selected benchmark functions F1-F4 are unimodal while F5-F7 are multi-modal. Afterwards, the proposed FPA is applied on three case studies 1) RTC France silicon PV cell, 2) Photo-watt PWP-201 module and 3) a practical system EAGLE PERC 60M 310W monocrystalline PV module of parameter estimation problem to validate the robustness of proposed technique. Datasets for the first two cases are obtained from [47] which have been utilized by many researchers [8], [9], [49], [50]. The stopping criteria for parameter estimation problem is the maximum number of iterations which is taken as 10,000 with population size of 10. Initially switch probability was set to 1 and then decreased exponentially till 0. Step size was initially set as 1 and then decreased exponentially according to the number of iterations. p_{max} and p_{min} are the maximum and minimum values of basic probabilistic value. Their values are chosen as $p_{max} = 1$ and $p_{min} = 0$. Reliability and efficiency of the proposed technique have been validated for 30 runs and compared with many other approaches from literature.

TABLE 4. Wilcoxon signed rank test results.

Functions	Algorithms				
	GWO	GOA	SSA	FPA	ALO
F1	0	0	0	0	0
F2	1	0	0	0	0
F3	0	0	0	0	0
F4	0	0	0	0	0
F5	0	0	1	0	0
F6	1	0	0	0	0
F7	0	0	0	0	0

A. RESULTS OF BENCHMARK FUNCTIONS

The performance of proposed improved variant of FPA is compared with Greywolf Optimizer (GWO) [51], Grasshopper Optimization Algorithm (GOA) [52], Salp Swarm Algorithm (SSA) [53], Ant Lion Optimizer (ALO) [54] and Flower Pollination Algorithm (FPA) [55] for selected benchmarks. Control parameters setting for each algorithm is taken from [51]–[55]. All the algorithms are performed on Haier Information technology with following experimental environment:

Processor: Intel(R) Core (TM) m3-7Y30 CPU @ 1.00GHz 1.61GHz

RAM: 8.00 GB

Operating System: Windows 10, 64-bit

MATLAB: R2015a

To do a fair comparison between algorithms population size and maximum iteration is set to 25 and 1000, respectively for all the algorithms according to [55]. Statistical results in terms of mean and standard deviation for each algorithm is obtained for 30 independent runs and are presented in Table 5. This table depicts that proposed methodology is better than other algorithms in terms of mean value for F1, F3, F4, F5 and

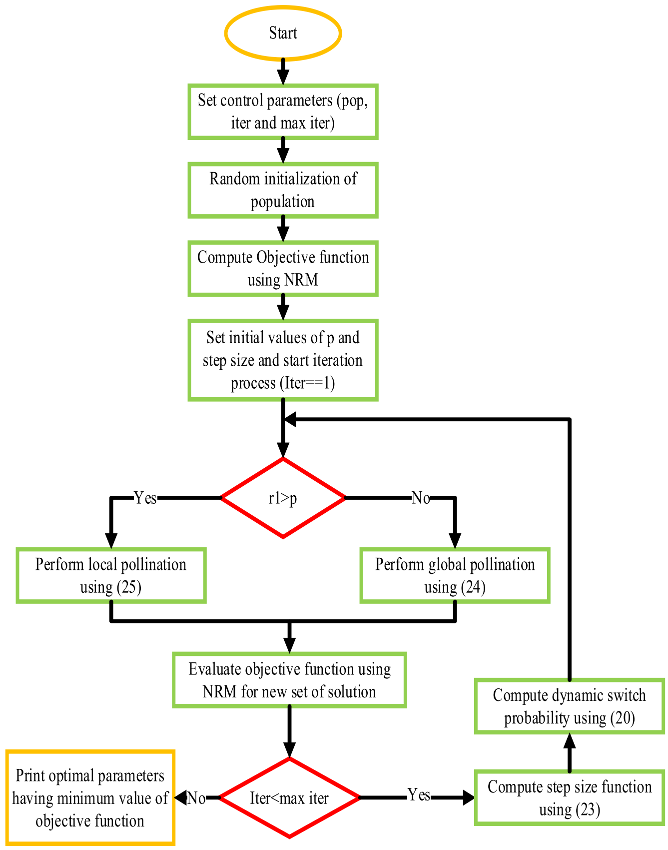

FIGURE 4. Flowchart of proposed methodology.

TABLE 5. Statistical results for benchmark functions of proposed FPA and comparison with other algorithms.

Functions		Algorithms					
		GWO	GOA	SSA	ALO	FPA	IFPA
F1	Mean	0.045894	8.42×10^{-7}	4.52×10^{-9}	3.49×10^{-9}	6.62×10^{-21}	9.82×10^{-23}
	Std	5.69×10^{-4}	2.03×10^{-6}	1.16×10^{-9}	1.23×10^{-9}	2.25×10^{-20}	3.51×10^{-22}
F2	Mean	3.91×10^{-62}	2.50×10^{-3}	3.11×10^{-5}	1.12×10^{-4}	6.40×10^{-11}	1.18×10^{-14}
	Std	6.03×10^{-62}	3.85×10^{-3}	0.000115	3.05×10^{-4}	1.83×10^{-10}	2.17×10^{-14}
F3	Mean	2.65×10^{-12}	0.255832	1.24×10^{-10}	1.58×10^{-5}	1.61×10^{-20}	4.44×10^{-25}
	Std	1.13×10^{-11}	0.375291	8.19×10^{-11}	2.40×10^{-5}	4.29×10^{-20}	2.33×10^{-24}
F4	Mean	5.29×10^{-13}	0.028373	6.81×10^{-6}	2.20×10^{-4}	1.68×10^{-10}	2.41×10^{-13}
	Std	3.23×10^{-11}	0.041208	2.68×10^{-6}	2.37×10^{-4}	4.38×10^{-10}	4.86×10^{-13}
F5	Mean	0.787895	6.40×10^{-1}	6.036079	3.581851	2.20×10^{-6}	1.09×10^{-7}
	Std	0.554028	0.909587	3.001217	1.664882	1.10×10^{-5}	2.30×10^{-6}
F6	Mean	1.66×10^{-14}	2.52×10^{-4}	4.71×10^{-6}	2.44×10^{-5}	5.66×10^{-10}	8.53×10^{-13}
	Std	3.45×10^{-15}	2.47×10^{-4}	1.22×10^{-6}	5.32×10^{-6}	9.76×10^{-10}	1.69×10^{-12}
F7	Mean	9.15×10^{-3}	0.309429	0.17319	0.227438	1.27×10^{-3}	3.58×10^{-4}
	Std	1.76×10^{-2}	0.149917	0.13346	0.106395	1.83×10^{-3}	7.80×10^{-4}

F7 which is 9.82×10^{-23}, 4.44×10^{-25}, 2.41×10^{-13}, 1.09×10^{-7} and 3.58×10^{-4}, respectively and worse values for F2 and F6. Similarly, standard deviation of proposed FPA is better for F1, F3, F4, F5 and F7 which is 3.51×10^{-22}, 2.33×10^{-24}, 4.86×10^{-13}, 2.30×10^{-6} and 7.80×10^{-4}, respectively and worse value for F2 and F6. Moreover, it can be observed form Table 5 that proposed FPA outclass conventional FPA in all considered benchmark functions. Convergence curves for the best run of all the algorithms is shown in Fig. 5 for F1, F4 and F6. Convergence behavior shows that proposed methodology converges faster for some functions rather than other algorithms. Furthermore, to evaluate performance of proposed FPA Wilcoxon signed rank test is also performed on obtained results for benchmarks to find a significant difference between the behavior of proposed technique and other algorithms. This test is based on three hypothesis which includes 0 for better performance, 1 for worst performance and 2 for equal performance of proposed

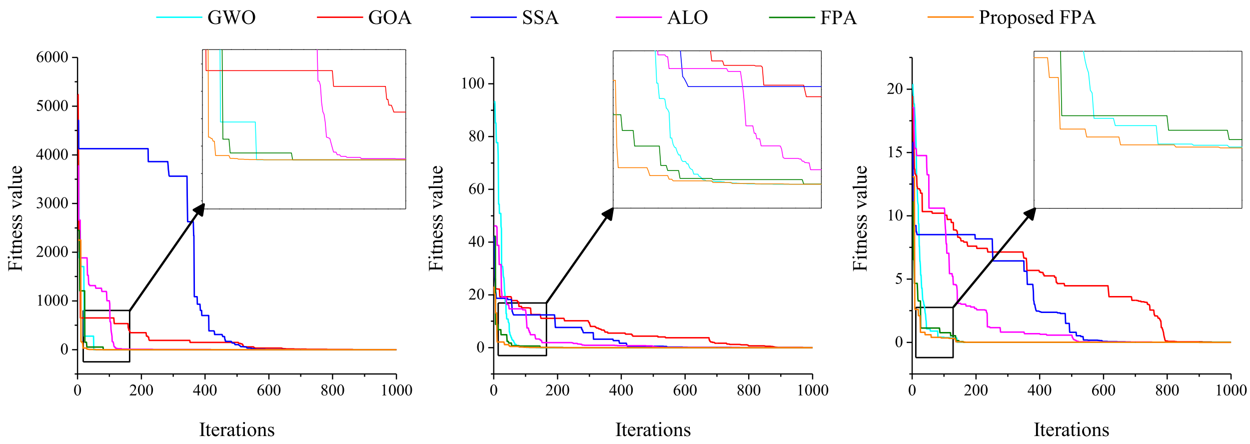

FIGURE 5. Convergence curves for F1, F4 and F6 benchmark functions.

methodology compared with other algorithms. Wilcoxon test results are presented in Table 5. Analysis of Table 4 and Table 5 proves that proposed methodology has faster convergence rate, more accuracy and high stability.

B. RESULTS FOR PV CASE STUDY 1

The results of RTC France silicon solar cell for parameter estimation problem using proposed technique at 33°C, under 1000W/m^2 irradiance level have been presented and discussed here.

1) SDM

The best parameters obtained for single diode PV cell are presented in Table 6 and comparison results of minimum, mean and maximum RMSE values and standard deviation with other techniques available in literature are presented in Table 7 which are Generalized Opposition-based learning mechanism FPA with NM (GOFPANM), Guaranteed Convergence Particle Swarm Optimization (GCPSO), Double Exponential Dynamic Inertia Weight Particle Swarm Optimization (DEDIWPSO), Artificial Bee Colony (ABC), Enhanced Leader PSO (ELPSO), Hybridized Interior Search Algorithm (HISA), Improved Cuckoo Search Algorithm (ImCSA), Opposition based Sine Cosine Approach with local search (ISCA), Hybridization of Grey Wolf Optimizer with Cuckoo Search algorithm (GWOCS), Cuckoo Search Algorithm (CS), Teaching Learning Based Optimization algorithm (TLBO), Metaphor-less algorithms called Rao-2 and Rao-3 (R-II,R-III), Memetic adaptive differential evolution (MADE) and Self adaptive ensemble based DE (SEDE). RMSE is highly sensitive to obtained optimal parameters. Minimum, mean and maximum RMSE obtained using proposed approach is 7.7300626 $\times 10^{-04}$ and standard deviation obtained by proposed technique is 3.46961 $\times 10^{-17}$.

Minimum, mean and maximum number of iterations required to obtain optimal parameters are also presented in Table 6. Individual Absolute Error (IAE) which is computed for each voltage and current pair using (26) is presented in Fig. 9. IAE is the performance measurement index that indicates how approximate is the estimated current to the measured current. The results presented proved the efficiency

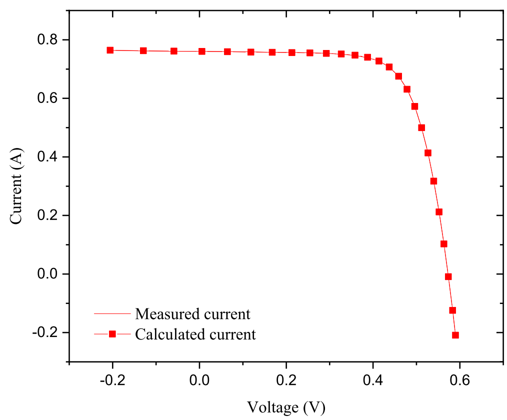

FIGURE 6. Measured and calculated I-V curves for single diode model of PV cell.

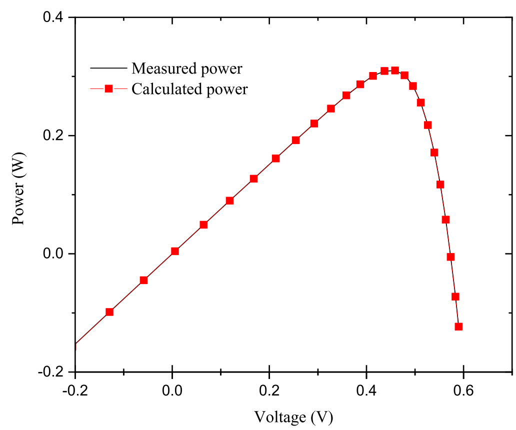

FIGURE 7. Measured and calculated P-V curves for single diode model of PV cell.

TABLE 6. Optimal results using proposed approach for single diode model of PV cell.

Best obtained solutions				Computational cost			
Optimal parameters		RMSE		Iterations		Time (s)	
I_{ph} (A)	0.76078796	Minimum	7.730062×10^{-4}	Minimum	2770	Minimum	70
I_{rs} (μA)	$3.10684576 \times 10^{-1}$	Mean	7.730062×10^{-4}	Mean	7049	Mean	90
R_p (Ω)	52.88978941	Maximum	7.730062×10^{-4}	Maximum	9591	Maximum	105
R_s (Ω)	0.03654694	Std	3.469605×10^{-17}				
n	1.47558946						

TABLE 7. Comparison of proposed approach with techniques in literature for single diode PV cell.

Optimization Algorithms	Minimum	Mean	Maximum	Std
Proposed approach	7.730062×10^{-4}	7.730062×10^{-4}	7.730062×10^{-4}	3.469605×10^{-17}
GOFPANM [29]	9.860219×10^{-4}	9.860219×10^{-4}	9.860219×10^{-4}	5.591415×10^{-15}
GCPSO [8]	7.730063×10^{-4}	7.730063×10^{-4}	7.730063×10^{-4}	4.405583×10^{-11}
DEDIWPSO [9]	7.730062×10^{-4}	7.730062×10^{-4}	7.730062×10^{-4}	5.18668×10^{-15}
ABC [56]	1.41740×10^{-3}	9.88148×10^{-4}	1.12125×10^{-3}	1.19818×10^{-4}
ELPSO[57]	7.7301×10^{-4}	7.7314×10^{-4}	7.7455×10^{-4}	3.4508×10^{-7}
HISA[58]	7.7300627×10^{-4}	7.7300627×10^{-4}	7.7300624×10^{-4}	2.44862×10^{-11}
ImCSA[59]	9.860219×10^{-4}	9.860219×10^{-4}	9.860219×10^{-4}	2.987589×10^{-12}
ISCA[50]	7.34231×10^{-4}	7.23043×10^{-4}	7.45921×10^{-4}	1.30287×10^{-6}
GWOCS[49]	9.8607×10^{-4}	9.8874×10^{-4}	9.9095×10^{-4}	2.4696×10^{-6}
CS [60]	2.01185×10^{-3}	7.60819×10^{-3}	6.09130×10^{-2}	1.10512×10^{-2}
TLBO[61]	9.87332×10^{-4}	1.04761×10^{-3}	1.23579×10^{-3}	6.58940×10^{-5}
R-II[62]	9.86022×10^{-4}	1.93871×10^{-3}	2.32485×10^{-1}	0.74907×10^{-3}
R-III[62]	9.86022×10^{-4}	2.02330×10^{-3}	2.42768×10^{-1}	0.95863×10^{-3}
MADE [63]	9.8602×10^{-4}	9.8602×10^{-4}	9.8602×10^{-4}	2.74×10^{-15}
SEDE[64]	9.86022×10^{-4}	9.86022×10^{-4}	9.86022×10^{-4}	4.20×10^{-17}

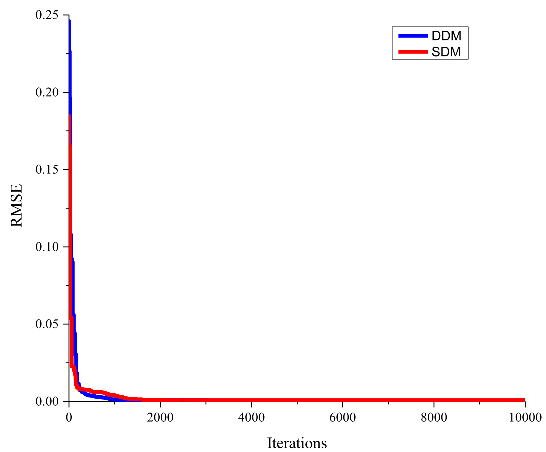

FIGURE 8. Convergence curve for single and double diode model of PV cell.

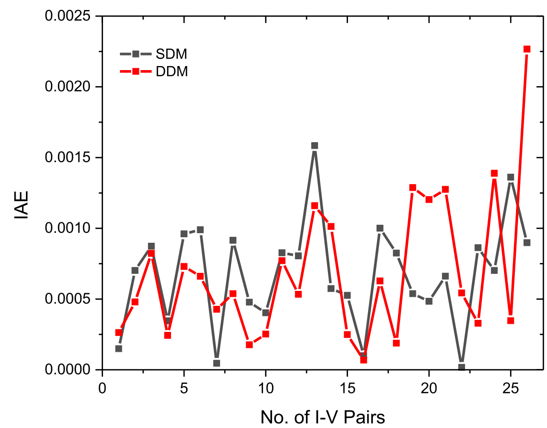

FIGURE 9. IAE values for single and double diode model of PV cell.

and accuracy of proposed approach than other techniques available in literature.

$$IAE = |I_{measured} - I_{estimated}| \tag{26}$$

Fig. 6 shows I-V curve of measured and estimated currents and Fig. 7 shows P-V characteristic curve of measured and estimated power. These curves show how closely these estimated curves follow the measured curves representing the efficiency of proposed approach. The convergence curve presented in Fig. 8 shows the behavior of proposed approach to obtain optimal results.

2) DDM

The best parameters obtained for double diode model of PV cell are given in Table 8 and comparison results of minimum, mean and maximum RMSE values and standard deviation with other techniques available in literature are presented in Table 9 which are Generalized Opposition-based learning mechanism FPA with NM (GOFPANM), Artificial Bee Colony (ABC), Enhanced Leader PSO (ELPSO), Improved Cuckoo Search Algorithm (ImCSA), Opposition based Sine Cosine Approach with local search (ISCA), Hybridization of Grey Wolf Optimizer with Cuckoo Search algorithm (GWOCS), Cuckoo Search (CS), Teaching Learning Based Optimization algorithm (TLBO), Teaching Learning Based

TABLE 8. Optimal results using proposed approach for double diode model of PV cell.

Best obtained solutions				Computational cost			
Optimal parameters		RMSE		Iterations		Time (s)	
I_{ph} (A)	0.76082939	Minimum	7.182046×10^{-4}	Minimum	9802	Minimum	190
I_{rs1} (μA)	$1.35304510 \times 10^{-1}$	Mean	7.244521×10^{-4}	Mean	9966	Mean	195
I_{rs2} (μA)	8.03246444	Maximum	7.458571×10^{-4}	Maximum	10000	Maximum	200
R_p (Ω)	60.94109728	Std	8.825451×10^{-06}				
R_s (Ω)	0.03795510						
n_1	1.40219750						
n_2	2.49999999						

TABLE 9. Comparison of proposed approach with techniques in literature for double diode PV cell.

Optimization Algorithms	Minimum	Mean	Maximum	Std
Proposed approach	7.182046×10^{-4}	7.244521×10^{-4}	7.458571×10^{-4}	8.825451×10^{-6}
GOFPANM [29]	9.824849×10^{-4}	9.954827×10^{-4}	1.340531×10^{-3}	6.518742×10^{-5}
ABC [56]	9.89560×10^{-4}	1.05765×10^{-3}	1.28482×10^{-3}	6.18669×10^{-5}
ELPSO[57]	7.4240×10^{-4}	7.5904×10^{-4}	7.9208×10^{-4}	9.4291×10^{-6}
ImCSA[59]	9.8249×10^{-4}	9.8258×10^{-4}	9.8396×10^{-4}	2.8197×10^{-7}
ISCA[50]	9.8342×10^{-4}	9.83800×10^{-4}	9.86863×10^{-4}	1.65397×10^{-6}
GWOCS[49]	9.8334×10^{-4}	9.9411×10^{-4}	1.0017×10^{-3}	9.5937×10^{-6}
CS [60]	2.44398×10^{-3}	7.90243×10^{-3}	4.37199×10^{-2}	8.06719×10^{-3}
TLBO [61]	1.00692×10^{-3}	1.15977×10^{-3}	1.52057×10^{-3}	1.86022×10^{-5}
TLABC [24]	9.84145×10^{-4}	1.05553×10^{-3}	1.50482×10^{-3}	1.55034×10^{-4}
R-II[62]	9.82485×10^{-4}	1.99799×10^{-3}	1.82783×10^{-1}	0.80439×10^{-3}
R-III[62]	9.83508×10^{-4}	2.21797×10^{-3}	2.31045×10^{-1}	1.00129×10^{-3}
MADE[63]	9.8261×10^{-4}	9.8608×10^{-4}	9.8786×10^{-4}	8.02×10^{-5}
SEDE[64]	9.824848×10^{-4}	9.82893×10^{-4}	9.86022×10^{-4}	9.17×10^{-7}

ABC algorithm (TLABC), Metaphor-less algorithms called Rao-2 and Rao-3 (R-II,R-III), Memetic adaptive differential evolution (MADE) and Self adaptive ensemble based DE (SEDE). Minimum, mean and maximum RMSE obtained using proposed approach is 7.18204×10^{-4}, 7.24452×10^{-4} and 7.45857×10^{-4} respectively and standard deviation obtained by proposed technique is 8.82545×10^{-06}. Minimum, mean and maximum number of iterations required to obtain optimal parameters are also presented in Table 8. The higher values of iterations show that double diode model is more complex and need more iterations than single diode model to obtain optimal parameters.

Individual Absolute Error (IAE) which is computed for each voltage and current pair using (26) is presented in Fig. 9. The results presented proved the efficiency and accuracy of proposed approach than other techniques available in literature. Fig. 10 shows I-V characteristic curve of measured and estimated currents and Fig. 11 shows P-V curve of measured and estimated power. These curves show how closely these estimated curves follow the measured curves representing the efficiency of proposed approach. The convergence curve presented in Fig. 8 shows the behavior of proposed approach to obtain optimal results.

C. RESULTS FOR PV CASE STUDY 2

The results of Photo-watt PWP-201 module for parameter estimation problem using proposed technique at temperature of 45°C, under 1000W/m^2 irradiance have been presented and discussed here.

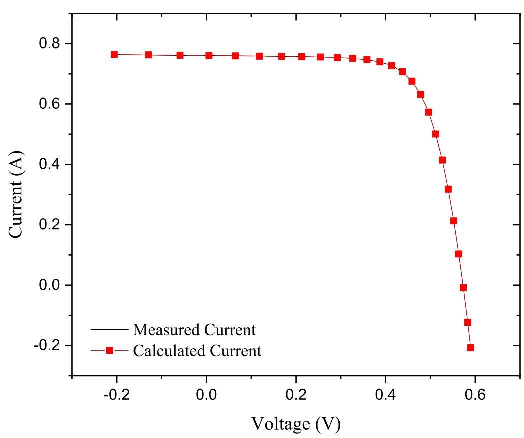

FIGURE 10. Measured and calculated I-V curves for double diode model of PV cell.

1) SDM

The best parameters obtained for single diode PV model are presented in Table 10 and comparison results of minimum, mean and maximum RMSE values and standard deviation with other techniques available in literature are presented in Table 11 which are Generalized Opposition-based learning mechanism FPA with NM (GOFPANM), Guaranteed Convergence Particle Swarm Optimization (GCPSO), Double Exponential Dynamic Inertia Weight Particle Swarm Optimization (DEDIWPSO), Grey Wolf Optimizer (GWO), Improved Cuckoo Search Algo-

TABLE 10. Optimal results using proposed approach for single diode model of PV module.

Best obtained solutions				Computational cost			
Optimal parameters		RMSE		Iterations		Time (s)	
I_{ph} (A)	1.03235759	Minimum	2.039992× 10^{-3}	Minimum	2266	Minimum	60
I_{rs} (µA)	2.49659581	Mean	2.039992× 10^{-3}	Mean	7410	Mean	90
R_p (Ω)	748.32299513	Maximum	2.039992× 10^{-3}	Maximum	9849	Maximum	100
R_s (Ω)	1.24054732	Std	1.220433 × 10^{-17}				
n	1.31713189						

TABLE 11. Comparison of proposed approach with techniques in literature for single diode PV module.

Optimization Algorithms	Minimum	Mean	Maximum	Std
Proposed approach	2.039992× 10^{-3}	2.039992× 10^{-3}	2.039992× 10^{-3}	1.220433 × 10^{-17}
GCPSO [8]	2.046536 × 10^{-3}	2.046536 × 10^{-3}	2.046536 × 10^{-3}	1.105194 × 10^{-10}
TLBO [61]	2.425× 10^{-3}	2.438× 10^{-3}	2.5475× 10^{-3}	2.4336× 10^{-5}
GOFPANM [29]	2.425075× 10^{-3}	2.425075× 10^{-3}	2.425075× 10^{-3}	2.918886× 10^{-16}
DEDIWPSO[9]	2.039992 × 10^{-3}	2.039992 × 10^{-3}	2.039992 × 10^{-3}	2.995289 × 10^{-15}
TLABC [24]	2.4251× 10^{-3}	2.4264× 10^{-3}	2.446× 10^{-3}	3.9956× 10^{-6}
GWO [49]	2.1903 × 10^{-3}	3.9111 × 10^{-3}	6.9661 × 10^{-3}	1.2608 × 10^{-3}
ImCSA [59]	2.425075× 10^{-3}	2.425075× 10^{-3}	2.425091× 10^{-3}	2.915426× 10^{-3}
GWOCS[49]	2.4251× 10^{-3}	2.4261× 10^{-3}	2.4275× 10^{-3}	1.1967× 10^{-6}
R-II[62]	2.81094× 10^{-3}	3.35173× 10^{-3}	1.07989× 10^{-1}	0.62531× 10^{-2}
R-III[62]	2.81094× 10^{-3}	3.29498× 10^{-3}	4.25525× 10^{-1}	0.98385× 10^{-2}
MADE[63]	2.4250× 10^{-3}	2.4251× 10^{-3}	2.4251× 10^{-3}	3.07× 10^{-17}
SEDE[64]	2.42507× 10^{-3}	2.42507× 10^{-3}	2.42507× 10^{-3}	3.14× 10^{-17}

TABLE 12. Optimal results using proposed approach for double diode model of PV module.

Best obtained solutions				Computational cost			
Optimal parameters		RMSE		Iterations		Time (s)	
I_{ph} (A)	1.03235759	Minimum	2.039992× 10^{-3}	Minimum	5558	Minimum	70
I_{rs1} (µA)	1.02600744 × 10^{-06}	Mean	2.039992× 10^{-3}	Mean	8333	Mean	80
I_{rs2} (µA)	2.49659484	Maximum	2.039992× 10^{-3}	Maximum	10000	Maximum	195
R_p (Ω)	748.32298752	Std	2.118171× 10^{-12}				
R_s (Ω)	1.24054732						
n_1	1.31713189						
n_2	1.31713101						

TABLE 13. Comparison of proposed approach with techniques in literature for double diode PV module.

Optimization Algorithms	Minimum	Mean	Maximum	Std
Proposed approach	2.039992× 10^{-3}	2.039992× 10^{-3}	2.039992× 10^{-3}	2.118171× 10^{-12}
GWO [49]	2.2138 × 10^{-3}	3.5558 × 10^{-3}	5.1250 × 10^{-3}	1.0786 × 10^{-3}
TVACPSO [65]	2.0530 × 10^{-3}	2.0583 × 10^{-3}	2.1125 × 10^{-3}	1.3101 × 10^{-7}
GCPSO [8]	2.046535× 10^{-3}	2.046535× 10^{-3}	2.046535× 10^{-3}	1.673103× 10^{-10}
CPSO [23]	2.053× 10^{-3}	2.064× 10^{-3}	2.100× 10^{-3}	1.342× 10^{-3}

rithm (ImCSA), TLBO, TLABC, Hybridization of Grey Wolf Optimizer with Cuckoo Search algorithm (GWOCS), Metaphor-less algorithms called Rao-2 and Rao-3 (R-II,R-III), Memetic adaptive differential evolution (MADE) and Self adaptive ensemble based DE (SEDE).

Minimum, mean and maximum RMSE obtained using proposed approach is 2.039992 × $\mathbf{10^{-3}}$ and standard deviation obtained by proposed technique is 1.22043 × $\mathbf{10^{-17}}$. Minimum, mean and maximum number of iterations required to obtain optimal parameters are also presented in Table 10. Individual Absolute Error (IAE) which is computed for each voltage and current pair using (26) is presented in Fig. 15. The results presented proved the efficiency and accuracy of proposed approach than other techniques available in literature. Fig. 12 shows I-V characteristic curve of measured and estimated currents and Fig. 13 shows P-V curve of measured and estimated power. These curves show how closely these estimated curves follow the measured curves representing the efficiency of proposed approach. The convergence curve

TABLE 14. Characteristic points of EAGLE PERC 60M monocrystalline module.

Characteristic points	
Maximum power P_{max}	310 Wp
Maximum power voltage V_{mp}	33 V
Maximum power current I_{mp}	9.40 A
Open circuit voltage V_{oc}	40.5 V
Short circuit current I_{sc}	9.92 A

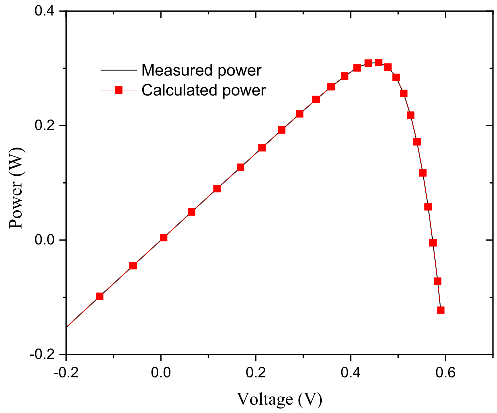

FIGURE 11. Measured and calculated P-V curves for double diode model of PV cell.

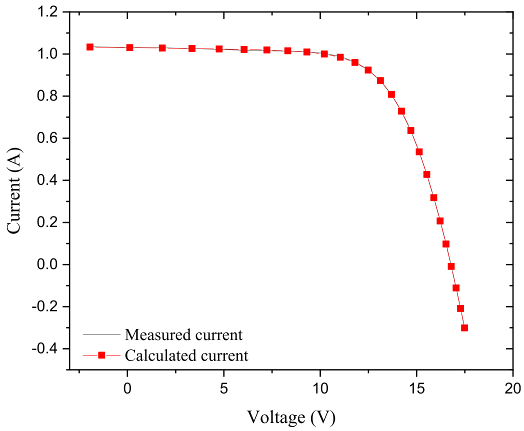

FIGURE 12. Measured and calculated I-V curves for single diode model of PV module.

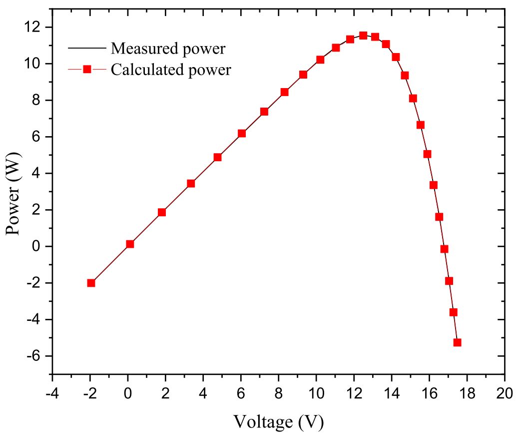

FIGURE 13. Measured and calculated P-V curves for single diode model of PV module.

presented in Fig. 14 shows the behavior of proposed approach to obtain optimal results.

2) DDM

The best parameters obtained for double diode PV model are presented in Table 12 and comparison results of minimum,

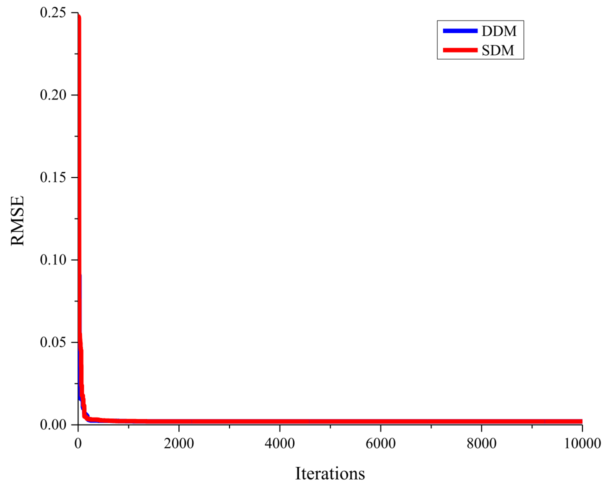

FIGURE 14. Convergence curve for single and double diode model of PV module.

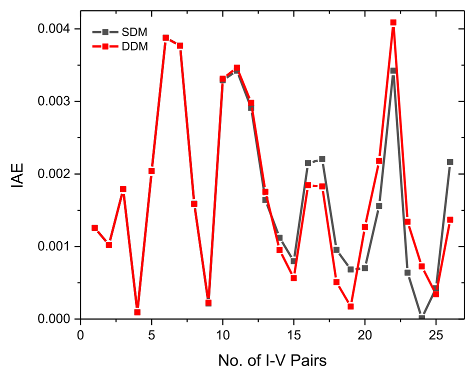

FIGURE 15. IAE values for single and double diode model of PV module.

mean and maximum RMSE values and standard deviation with other techniques available in literature are presented in Table 13 which are GCPSO, Time Varying Acceleration Coefficients PSO (TVACPSO), Constant PSO (CPSO) and GWO. Minimum, mean and maximum RMSE obtained using proposed approach is 2.039992×10^{-3} and standard deviation obtained by proposed technique is 2.11817×10^{-12}. Minimum, mean and maximum number of iterations required to obtain optimal parameters are also presented in Table 12. The higher values of iterations show that double diode model is more complex and need more iterations than single diode model to obtain optimal parameters. Individual Absolute Error (IAE) which is computed for each voltage and current pair using (26) is presented in Fig. 15. The results presented proved the efficiency and accuracy of proposed approach than other techniques available in literature. Fig. 16 shows I-V curve of measured and estimated currents and Fig. 17 shows P-V curve of measured and estimated power. These curves show how closely these estimated curves follow the measured curves representing the efficiency of proposed approach. The

TABLE 15. Optimal results for single diode model of EAGLE PERC 60M monocrystalline module.

Optimal Parameters	1000W/m^2 at 47°C	800W/m^2 at 44°C	600W/m^2 at 42°C	400W/m^2 at 36°C	200W/m^2 at 27°C
I_{ph} (A)	10.20008303	8.20728001	6.14071494	4.08220851	2.04204341
I_{rs} (μA)	2.93711725× 10^{-03}	1.15797596× 10^{-03}	3.79738282× 10^{-06}	1.00× 10^{-06}	2.0297635 × 10^{-05}
R_p (Ω)	337.51444005	257.57197951	174.25900055	232.47869649	341.28955721
R_s (Ω)	0.15605950	0.18617287	0.26677554	0.32076795	0.25510245
n	1.07425052	1.04576246	0.84148893	0.81853803	0.94101820
RMSE	0.062678	0.085799	0.045519	0.051972	0.027972
Std	4.984491× 10^{-16}	2.918889× 10^{-16}	1.290889× 10^{-03}	8.752293× 10^{-04}	1.018879× 10^{-04}

TABLE 16. Statistical results for single diode model of EAGLE PERC 60M monocrystalline module.

Experimental curves	RMSE			Iterations		
	Maximum	Minimum	Mean	Maximum	Minimum	Mean
1000W/m^2 at 47°C	0.062678	0.062678	0.062678	9948	5818	8452
800W/m^2 at 44°C	0.085799	0.085799	0.085799	9999	7476	9128
600W/m^2 at 42°C	0.045519	0.052633	0.045811	10000	6097	9864
400W/m^2 at 36°C	0.056703	0.051972	0.052467	10000	8458	9920
200W/m^2 at 27°C	0.028374	0.027972	0.027999	10000	3347	9683

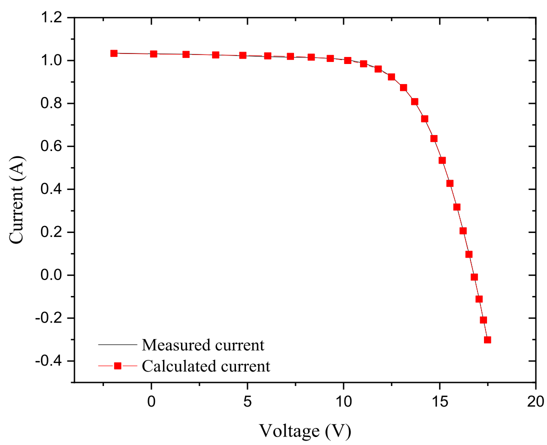

FIGURE 16. Measured and calculated I-V curves for double diode model of PV module.

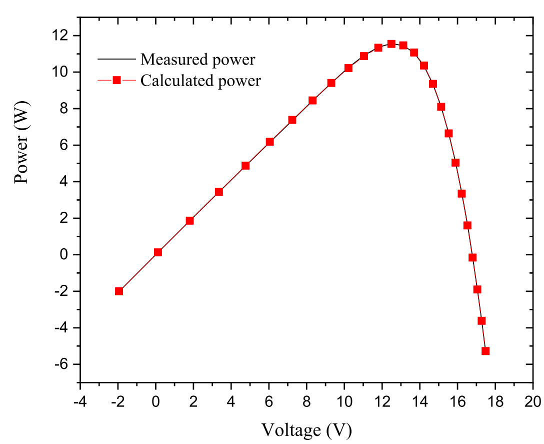

FIGURE 17. Measured and calculated P-V curves for double diode model of PV module.

convergence curve presented in Fig. 15 shows the behavior of proposed approach to obtain optimal results.

D. RESULTS FOR PV CASE STUDY 3

The proposed approach is evaluated under real and variable environmental conditions of temperature and irradiance for obtained data from EAGLE PERC 60M, 310W monocrystalline PV module. The 26 pairs of I-V curve data are used to obtain optimal parameters of single and double diode models. The module has 60 monocrystalline cells connected in series. The characteristic points of module are given in Table 14. The variable temperature and irradiance levels considered for this practical system are 1000W/m^2 at 47°C, 800 W/m^2 at 44°C, 600 W/m^2 at 42 °C, 400 W/m^2 at 36 °C and 200 W/m^2 at 27 °C.

1) SDM

The results for 30 independent runs were obtained for single diode model of EAGLE PERC 60M 310 W monocrystalline module using proposed approach. The best obtained parameters, RMSE and standard deviation at different environmental conditions are presented in Table 15. Minimum, mean and maximum RMSE values along with number of iterations required for convergence are given in Table 16. The I-V and P-V curves for the measured and estimated currents and powers at different environmental conditions are depicted in Fig. 18 (b) and 19 (b) respectively. Convergence curves for different levels of temperature and irradiance are given in Fig. 20. Individual Absolute Error (IAE) which is computed for each voltage and current pair using (26) is presented in Fig. 21.

2) DDM

The results for 30 independent runs were obtained for double diode model of EAGLE PERC 60M 310 W monocrystalline module using proposed approach. The best obtained parameters, RMSE and standard deviation at different environmental conditions are presented in Table 17. Minimum, mean and maximum RMSE values along with number of iterations required for convergence are given in Table 18. The higher

TABLE 17. Optimal results for double diode model of EAGLE PERC 60M monocrystalline module.

Optimal Parameters	1000W/m^2 at 47°C	800W/m^2 at 44°C	600W/m^2 at 42°C	400W/m^2 at 36°C	200W/m^2 at 27°C
I_{ph} (A)	10.20008304	8.20728002	6.14071524	4.08220852	2.04199596
I_{rs1} (μA)	4.29707367× 10^{-06}	2.40919651× 10^{-06}	1.00× 10^{-06}	1.00000013× 10^{-06}	2.11294595× 10^{-05}
I_{rs2} (μA)	2.93281945× 10^{-03}	1.15556717× 10^{-03}	3.79634152× 10^{-06}	1.00× 10^{-06}	1.00× 10^{-06}
R_p (Ω)	337.51430646	257.57192796	174.25228127	232.47866908	342.08278523
R_s (Ω)	0.15605950	0.18617286	0.26677909	0.32076795	0.25284098
n_1	1.07424869	1.04576138	2.49999999	2.49999990	0.94249697
n_2	1.07425051	1.04576211	0.84148893	0.81853803	2.49999999
RMSE	0.062678	0.085799	0.045519	0.051972	0.028063
Std	4.581367× 10^{-04}	2.928078× 10^{-04}	5.179674× 10^{-03}	1.523540× 10^{-03}	5.728559× 10^{-04}

TABLE 18. Statistical results for double diode model of EAGLE PERC 60M monocrystalline module.

Experimental curves	RMSE			Iterations		
	Maximum	Minimum	Mean	Maximum	Minimum	Mean
1000W/m^2at 47°C	0.064368	0.062678	0.062862	9999	7564	9626
800W/m^2 at 44°C	0.087029	0.085799	0.085899	10000	6859	9714
600W/m^2 at 42°C	0.071413	0.045519	0.048228	10000	8990	9931
400W/m^2 at 36°C	0.057100	0.051972	0.053084	10000	6352	9779
200W/m^2 at 27°C	0.029824	0.028063	0.028387	10000	8784	9905

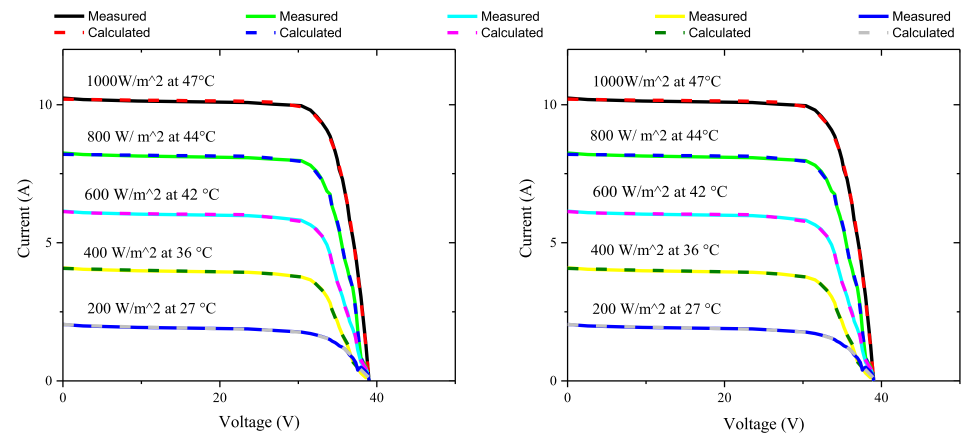

FIGURE 18. Measured and calculated I-V curves for (a) double and (b) single diode model of practical system.

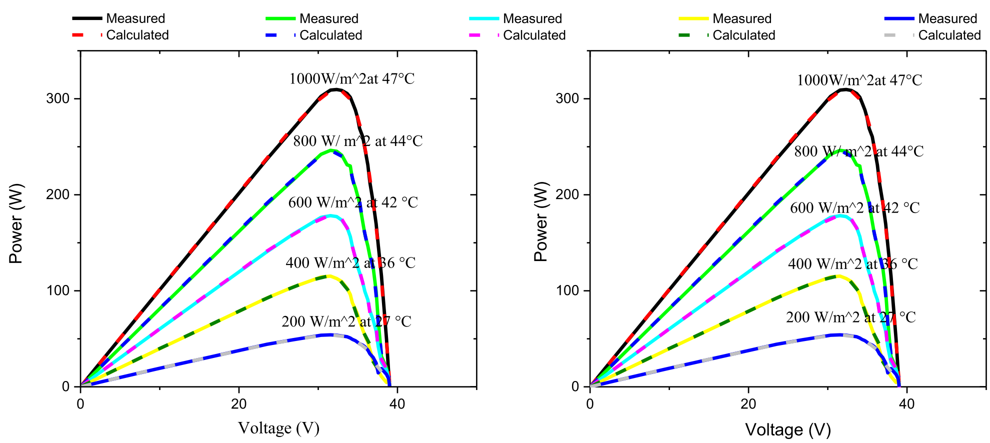

FIGURE 19. Measured and calculated P-V curves for (a) double and (b) single diode model of practical system.

values of iterations show that double diode model is more complex and need more iterations than single diode model to obtain optimal parameters. The I-V and P-V curves for the measured and estimated currents and powers at different environmental conditions are depicted in Fig. 18(a) and 19(a) respectively. Individual Absolute Error (IAE) which

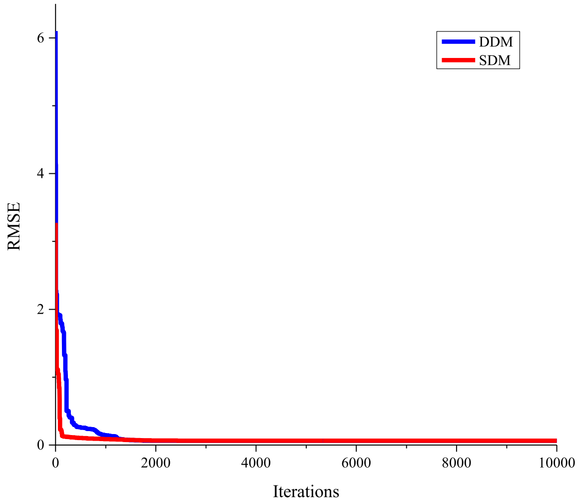

FIGURE 20. Convergence curve for single and double diode model of EAGLE PERC 60M monocrystalline module.

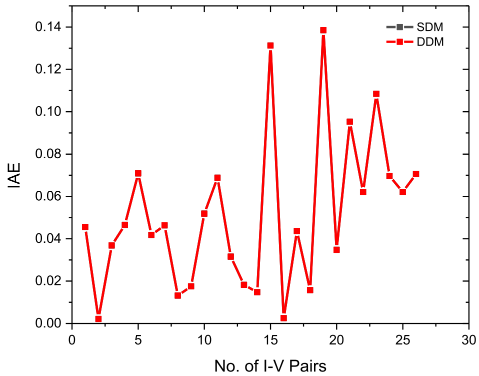

FIGURE 21. IAE values for single and double diode model of EAGLE PERC 60M monocrystalline module.

is computed for each voltage and current pair using (26) is presented in Fig. 21. Convergence curves for different levels of temperature and irradiance are given in Fig. 20.

VI. CONCLUSION

This paper presents a new variant of FPA to estimate PV model parameters accurately and efficiently. A double exponential dynamic switch probability is one of the improvements proposed in this paper to avoid premature convergence and local optima stagnation. It creates a balance between local and global pollination process. Second improvement is the dynamic step size function to improve convergence rate of FPA by improving search capabilities of search agents. Selected seven benchmark functions and three case studies are implemented in this paper to validate the efficiency of proposed approach which includes RTC France silicon PV cell, Photo-watt PWP-201 module and a practical system (EAGLE PERC 60M 310W monocrystalline module) under five different temperature and irradiance levels. The proposed methodology gives optimal values of all performance metrices for benchmark functions and RMSE in correspondence with the best obtained parameters of single and double diode PV models. Statistical and experimental results conclude the superiority of proposed technique as:

- Wilcoxon signed rank test proves the better performance of proposed approach as compared to other algorithms.
- The comparison of obtained results indicates that the proposed approach is a better option for multi modal problems like parameter estimation of PV models.
- Standard deviation proves the capability of proposed approach to reach the global optimum for maximum number of runs.
- Small number of iterations required to obtain optimal results for single diode models than double diode models but single diode models provide less accurate results than double diode model.
- Comparison of statistical results obtained from proposed approach with other techniques of literature proves its efficiency.
- Implementation of proposed approach for practical system illustrates its accuracy and reliability even under real environmental conditions.
- Convergence curves depicts fast convergence rate obtained using proposed approach while avoiding premature convergence and local optima stagnation.

Although the proposed method overcomes the shortcomings of conventional FPA, it may not be suitable for all optimization problems. Thus, the potential of proposed method may be assessed by implementing it in further optimization studies.

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