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A new hybrid bee pollinator flower pollination algorithm for solar PV parameter estimation

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ABSTRACT

The inaccurate I-V curve generation in solar PV modeling introduces less efficiency and on the other hand, accurate simulation of PV characteristics becomes a mandatory obligation before experimental validation. Although many optimization methods in literature have attempted to extract accurate PV parameters, all of these methods do not guarantee their convergence to the global optimum. Hence, the authors of this paper have proposed a new hybrid Bee pollinator Flower Pollination Algorithm (BPFPA) for the PV parameter extraction problem. The PV parameters for both single diode and double diode are extracted and tested under different environmental conditions. For brevity, the I_{01}, I_{02}, I_{pv} for double diode and $I_{0,}$ I_{pv} for single diode models are calculated analytically where the remaining parameters 'R_s, R_p, a_1, a_2' are optimized using BPFPA method. It is found that, the proposed Bee Pollinator method has all the scope to create exploration and exploitation in the control variable to yield a less RMSE value even under lower irradiated conditions. Further for performance validation, the parameters arrived via BPFPA method is compared with Genetic Algorithm (GA), Pattern Search (PS), Harmony Search (HS), Flower Pollination Algorithm (FPA) and Artificial Bee Swarm Optimization (ABSO). In addition, various outcomes of PV modeling and different parameters influencing the accurate PV modeling are critically analyzed.

1. Introduction

Increased environmental threat, ozone layer depletion and acid rain have alarmed the mankind to look for pollution free energy alternatives. Being known for its potential superiority among renewable energy resources; solar energy research has gained momentum in the recent past and proved to be one of the finest energy resource [1].

Understanding the necessity, researchers in the recent past have presented many scholarly research articles in the field of Solar PV system. Among which the PV parameter extraction, i.e., finding suitable PV parameter to derive accurate non-linear I-V characteristics that corresponds to a solar PV panel is given highest priority [2]. Since, it is a well known fact that modeling accuracy of any solar PV system directly depends on PV cell modeling accuracy, research on PV parameter extraction becomes inevitable [3].

The PV parameter extraction techniques have been categorized into two common approaches (1) analytical and (2) numerical extraction method. The earlier method utilizes data's given in the manufacturer's data sheet such as (i) open circuit voltage (V_{oc}), (ii) short circuit current (I_{sc}), (iii) maximum power voltage (V_{mp}) and (iv) maximum power current (I_{mp}) to model I-V Characteristics of any module [4,5]. However, the procedure adopted remain unsuitable to change in irradiation conditions. Further, it is evident that improper parameter identification lead to erroneous results [6–11]. Alternatively, the numerical extraction technique utilizes individual point on the actual I-V curve and hence exact reproduction of the I-V curve is made possible for all change in irradiation and temperature conditions. Whilst its popularity, the method consume all the data points in the I-V curve compounding to computational complexity. Therefore, many new/different optimization algorithms were evolved to generate better solutions for PV parameter extraction problems [13,18–25]. Some of the most profound works in the field of parameter estimation applying optimization techniques are: Genetic Algorithm (GA) [14–17], Simulated Annealing (SA) [18], Bacterial Foraging Algorithm (BFA) [19], Particle Swam Optimization (PSO) [20], Bird Mating (BM) [21,22], Pattern Search (PS) [23], Harmony Search (HS) [24],

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Artificial Bee Swam Optimization (ABSO) [25] and Flower Pollination algorithm [27]. Among which, GA method require wide search to select chromosomes from an initial population that makes the method computationally complex and less accurate [14]. Alternative to GA method, PSO methods computations are faster; but the hindrance on initial parameter selection and tuning impose burden in computation [20,21]. In case of pattern search algorithm, there is a probability that selected pattern may go wrong and hence solutions converge prematurely [23]. In case of SA method, proper care must be taken while matching temperature and cooling schedules [18].

Other methods with faster convergence and high accuracy that have been tried for PV parameter extraction BFA [19,34], BM [22], and ABSO [25]. In which, the ABSO method failed to converge during repeated succession; while, the Brood mechanism adapted in BM have procedural complexity and made it difficult for implementation [22]. Though BFA method show improved results, involvement of too many parameters that increase the computational burden and enlarged complexity. Similar problem can be seen in recent Lambert-*W* method [34] and the Fireworks Algorithm (FWA) [36]. Despite of their excellence in accuracy, they are really compound to code since laborious effort is needed to tune many numbers of parameters. One of the common phenomenon that occur with all the methods are they lack to create randomness in the control variable, once they convergence to near optimal solution. But FPA method proposed in [27] produces randomness via exploitation process and show good convergence and curve-fit. Albeit its accuracy to determine exact curve fit, fitness evaluation process in FPA method failed to examine the pollens continuously producing poor fitness value thereby leading to delayed convergence. Therefore, it is envisaged that its performance can further be enhanced via improving certain properties like quick convergence and accuracy. Hence, in this paper an attempt is made to improve qualities of FPA method via bee pollinator method [28]. Unlike its predecessor, this Bee Pollinated Flower Pollination Algorithm (BPFPA) method show wider search ability, avoids poor convergence and restricts poor solution quality via a unique crossover between original FPA and Honeybee search algorithm. More importantly, this method creates randomness to the control variable continuously producing poor solution via simplex method. In addition, mutation process in local search adds enlarged search ability to Bee Pollinator FPA method. Moreover the method suitability has already been tested for cluster analysis problem and proved to be superior via A-Nova test in [28]. Thus in this work, BPFPA method is tested to solve PV parameter extraction problem.

To showcase the effectiveness of BPFPA technique, the parameters & results of single diode and double diode model is compared with existing literature like GA [14], PS [23], HS [24], ABSO [25] and FPA [27] methods. Also, a comprehensive analysis based on various performance parameters for BPFPA are provided at the last. The remaining section of the paper is formatted as below.

In Section 2 modeling of single diode and two diode model is explained. In Section 3, the problem formulation of bringing minimal objective function is briefed. In Sections 4 and 5, original FPA followed by newly proposed Bee Pollinator FPA is discussed. In Section 6, simulation and results for the proposed algorithm is displayed.

2. Modeling of solar PV

The most popular modeling methods for solar PV modeling are one diode and two diode model [13,24,25,33,34]. It may be clear from the literature that one diode model is simple and less complex, but to improve the accuracy of the modeling, two diode models are preferred. The paper attempts to compute PV parameter for both the models and the results are comprehensively compared.

2.1. Single diode model

The equivalent circuit representation of a one diode model to determine PV characteristics is shown in Fig. 1. The circuit comprises of PV current (I_{pvn}), diode current (I_d), series resistance (R_s) and parallel resistance (R_p).

The output current of a PV cell can be calculated by applying KCL at node '*a*',

$$I_{PV} = I_{PV,n} - I_D - \frac{V_{PV} + I_{PV}Rs}{Rp} \tag{1}$$

The ideal diode current equation 'I_D' is given below, in which 'I_o' is the reverse saturation current. 'α' is the diode ideality factor and 'V_T' is the Thermal voltage.

$$I_D = I_O(e^{V_D/\alpha V_T} - 1) \tag{2}$$

The thermal voltage subjected to any temperature, is given by,

$$V_T = \frac{N_S KT}{q} \tag{3}$$

where 'N_s' is the number of cells connected in series, 'K' is the Boltzmann constant $1.3805 * 10^{-23}$, 'T' is the temperature at STC and 'q' is the charge of the electron $1.9 * 10^{-19}$ C.

Sub Eq. (2) in (1), the output current of a Single diode PV module is given as

$$I_{PV} = N_{pp}\left\{I_{PV,n} - I_O\left[\exp\left(\frac{V_{PV} + I_{PV}R_S}{V_t N_{ss}}\right) - 1\right]\right\} - \left(\frac{V_{PV} + I_{PV}R_S}{R_P}\right) \tag{4}$$

where 'N_{ss}'and 'N_{pp}'are the number of cells connected in series and parallel.

2.2. Two diode model

The two diode circuit model representing solar cell is shown in Fig. 2. The additional diode present in the equivalent circuit represents the loss occurring due to the recombination effect [12,35,36]. Alike single diode model the parameter involved is 'I_{pvn}' PV current, 'I_{D1}' and 'I_{D2}' are the diode currents and 'R_s', 'R_p' showing series and parallel resistances used to measure the losses.

Thus the output equation for two diode model is given by

$$I_{PV} = I_{PV,n} - I_{D1} - I_{D2} - \frac{V_{PV} + I_{PV}Rs}{Rp} \tag{5}$$

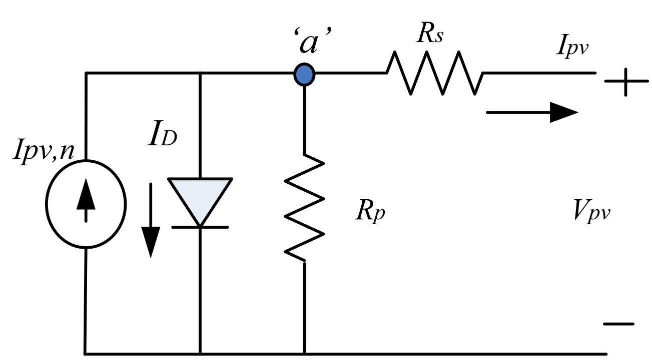

Fig. 1. Single diode model of solar PV.

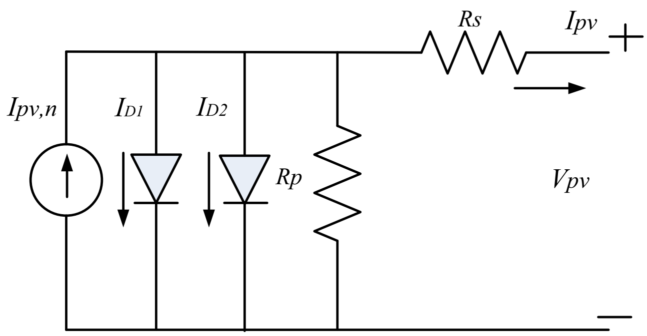

Fig. 2. Double diode model for solar PV.

The diode currents are given by

$$I_{D1} = I_{01}\left[\exp\left(\frac{V_{PV} + I_{PV}R_S}{a_1 V_t N_{ss}}\right) - 1\right],$$
$$I_{D2} = I_{O2}\left[\exp\left(\frac{V_{PV} + I_{PV}R_S}{a_2 V_t N_{ss}}\right) - 1\right] \quad (6)$$

where 'a_1' and 'a_2' are the diode ideality factors, 'I_{01}, I_{02}' are the reverse saturation currents and 'N_{ss}' and 'N_{pp}' are the number of cells connected in series and parallel.

After substitution of $I_{D1}\&I_{D2}$ the output current equation of a module can be given as

$$I_{PV} = N_{pp}\left\{I_{PV,n} - I_{01}\left[\exp\left(\frac{V_{PV} + I_{PV}R_S}{a_1 V_t N_{ss}}\right) - 1\right]\right.$$
$$\left. -I_{02}\left[\exp\left(\frac{V_{PV} + I_{PV}R_S}{a_2 V_t N_{ss}}\right) - 1\right]\right\} - \left(\frac{V_{PV} + I_{PV}R_S}{R_P}\right) \quad (7)$$

Thus, the above discussion comprehends that for one diode solar PV modeling 5 parameters (and) are required, whereas 7 parameters ($I_{o1}, I_{02}, I_{pv}, R_s, R_p, a_1$ and a_2) are required for double diode modeling. To avoid computational burden I_0 and $I_{pv,n}$ values are calculated analytically for both the models. The PV current can be calculated from Eq. (8)

$$I_{PV,n} = (I_{scn} + K_i \Delta T)\frac{G}{G_n} \quad (8)$$

where 'I_{scn}' is the nominal short circuit current, 'K_i' is the temperature current coefficient, 'G_n' is the nominal irradiance at Standard Test Conditions (STC) –(1000 W/m^2) and $\Delta T = T - T_n$, where 'T_n' is the nominal temperature at STC (25 °C). Generally the nominal values like I_{scn}, V_{ocn}, K_i, K_v and $P_{\max}$ will be given in the manufacturer's data sheet. The reverse saturation current for the single diode and double diode model can be calculated as follows.

For single diode model,

$$I_o = \frac{I_{PV}}{\exp[(V_{oc} + K_v \Delta T)/a/V_T] - 1} \quad (9)$$

For double diode model,

$$I_{o1} = \frac{I_{PV}}{\exp[(V_{oc} + K_v \Delta T)/a_1/V_T] - 1} \quad (10)$$

$$I_{o2} = \frac{I_{PV}}{\exp[(V_{oc} + K_v \Delta T)/a_2/V_T] - 1} \quad (11)$$

where 'a' is the diode ideality factor for a single diode model while '$a_1\&a_2$' are the ideality factors in double diode model, and 'K_v' is the short circuit voltage ratio.

3. Problem formulation

At the outset both two diode and one diode model require seven and five PV parameters for the PV cell modeling respectively. In both the cases, model parameters are need to be adjusted in such a way that I-V characteristic of the panel that corresponds to any atmospheric conditions are reproduced exactly. The proposed method follows numerical extraction procedure where the synthetic data's of I-V characteristics at different instances are matched at every point via single and double diode parameter extraction. Thus, the curve fitting values for single and double diode values are evaluated for every point in the I-V curve. The objective function is a minimization function where the computed parameter via optimization tries to minimize the error between the synthetic data and computed values. The fitness function equation in terms of voltage and current is given in Eqs. (12) and (13) for single and double diode models respectively. Further to evaluate the preciseness of curve fit accuracy Root Mean Square Error (*RMSE*) is utilized as presented in (14).

For single diode model,

$$f(V_t, I_t, x) = N_{pp}N_{pp}\left\{I_{PV,n} - I_O\left[\exp\left(\frac{V_{PV} + I_{PV}R_S}{V_t N_{ss}}\right) - 1\right]\right\}$$
$$- \left(\frac{V_{PV} + I_{PV}R_S}{R_P}\right) \quad (12)$$

For double diode model,

$$f(V_t, I_t, x) = N_{pp}\left\{I_{PV,n} - I_{01}\left[\exp\left(\frac{V_{PV} + I_{PV}R_S}{a_1 V_t N_{ss}}\right) - 1\right]\right.$$
$$\left. -I_{02}\left[\exp\left(\frac{V_{PV} + I_{PV}R_S}{a_2 V_t N_{ss}}\right) - 1\right]\right\} - \left(\frac{V_{PV} + I_{PV}R_S}{R_P}\right) \quad (13)$$

where '$I_{pv,n}$' and 'V_t' are computed based on the data provided on the manufacturers data sheet.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(f(V_t, I_t, x)^2} \quad (14)$$

where 'N' is the total number of points on the I-V curve.

4. Flower pollination algorithm

Flower Pollination Algorithm (FPA) is a nature inspired algorithm proposed by yang in the year 2012 [26]. The term Pollination refers to transfer of pollens characterized by two types of processes, biotic and abiotic process. Biotic process represents the pollination occurring between two different species of flowers (Cross Pollination) while an abiotic process happens between the species of the same type (Self Pollination). The characteristic of new flowers depends upon the number of parental flowers involved in pollination; 90% of the pollination is arrived via cross pollination and the rest through self pollination. The agents responsible to transfer pollens in self and cross pollination are bees, birds, and wind [27]. The following are the steps incorporated in FPA algorithm to find an optimal solution for a given objective function:

Step 1: Biotic and cross-pollination represent global pollination accompanied by Levy flights. Global pollination is characterized by Eq. (15)

$$x_i^{t+1} = x_i^t + \gamma L(\lambda)(gbest - x_i^t) \quad (15)$$

where '$L(\lambda)$' is the levy factor responsible for the transfer of pollens between different species of flowers. Where the scaling factor '$\gamma = 0.25$' is used to control the step size.

$$L(\lambda) = \frac{\lambda\Gamma(\lambda)\sin(\pi\lambda/2)}{\pi}\frac{1}{S^{1+\lambda}}(S >> S_0 > 0) \quad (16)$$

where '$\Gamma(\lambda)$' the standard gamma function and the distribution is applicable to a large step size which is greater than zero. In this work, BPFPA implemented for parameter estimation have used '$\lambda = 1.5$' to ensure optimal performance.

Step 2: Abiotic and self-pollination represents the local pollination and is characterized by the equation.

$$x_i^{t+1} = x_i^t + \varepsilon(x_k^t - x_j^t) \quad (17)$$

where 'x_k^t'and 'x_j^t'are the different pollens of same species. The ε (epsilon) represents the local search which is of uniform distribution $\varepsilon \in [0,1]$.

Step 3: The switching between global and local pollination is controlled by a probability switch $P \in [0,1]$ and its optimal value is found to be 0.8 in most of the cases [17, 18, and 19]. Further, it is noticeable that FPA involves less parameter for computation so; it is expected to have reduced computational time and less complexity.

5. Flower pollination algorithm with bee pollinator

Bee Pollinated Flower Pollination Algorithm (BPFPA) method is an extended adaptation of Flower Pollination Algorithm. It is an amalgamated approach of FPA with Artificial Bee colony (ABC) method. In BPFP method, Bees characteristic like discard pollen operator are effectively indulged with FPA method to enhance the randomness property of FPA method. In addition, replacing the local pollination of conventional FPA method with elite based mutation operation strengthens the search ability of BPFPA method. Aforementioned additions in BPFPA method improve the randomness in solutions.

5.1. Global pollination process

5.1.1. Discard pollen operator

In the Artificial Bee Colony method, bees are associated with a discard solution operator to generate diversity in the population. The *limit* is the control parameter that decides when a discard pollen operator need to be called. The necessity of discard solution operator arises due to the reason that, in FPA method every pollen after a few iterations lose its exploration ability, thereby it reduces the randomness in the control variable. Hence, to strengthen the exploration process, pollens having poor characteristics need to be replaced with pollens of characteristics, hence discard pollen operator in BPFPA method improves solution quality and it is implemented via simplex method. The steps followed in creating new pollen with the help of the simplex method for improving the exploration process is explained below:

Step 1: Calculate the fitness values of all the pollens. Among the total population, rank the pollens to their fitness. For instance the best pollen is denoted by $f(x_g)$, the second best is denoted by $f(x_b)$ and the pollen to be discarded is denoted by $f(x_s)$. The corresponding pollen is denoted by x_g, x_b.

Step 2: Find the midpoint x_c of the best two pollens.

$$x_c = \frac{x_g + x_b}{2} \quad (18)$$

Step 3: Do reflection operation using the given expression

$$x_r = x_c + \alpha(x_c - x_s) \quad (19)$$

where 'x_r' the reflecting is point and 'α' is the reflecting coefficient, which is set to be 1.

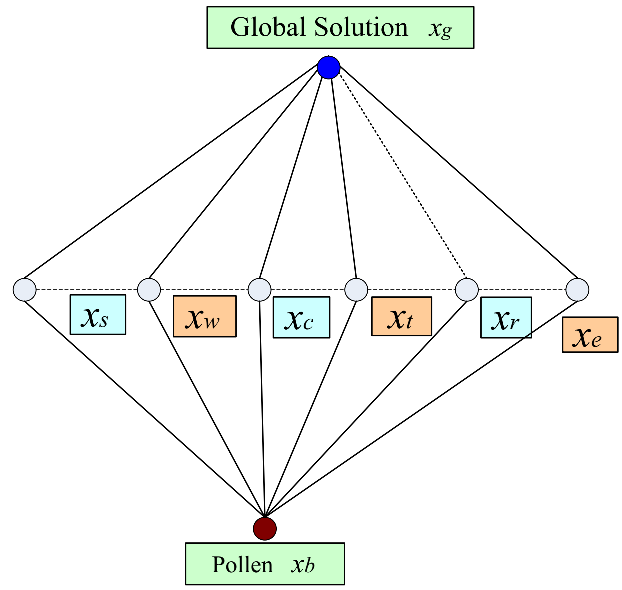

Fig. 3. Representation of simplex method.

Step 4: If the fitness value of x_r being less than x_g, $(f(x_r) < f(x_g))$, extension operation is carried out based on the expression (20)

$$x_e = x_c + \gamma(x_r - x_c) \quad (20)$$

where 'γ' the extension coefficient is set as 2 and x_e is the extension point. If $(f(x_e) < f(x_g))$, then replace x_s with x_r.

Step 5: If the fitness of x_r greater than x_s (i.e.) $(f(x_r) > f(x_s))$ then, do the compression operation using (21).

$$x_t = x_c + \beta(x_s - x_c) \quad (21)$$

where 'β' the compression coefficient is set to be 0.5 and x_t is the extension point of x_s. If $(f(x_t) < f(x_s))$, then replace x_s with x_t.

Step 6: If $f(x_s) > f(x_r) > f(x_g)$, then do shrink operation using (22)

$$x_w = x_c - \beta(x_s - x_c) \quad (22)$$

where 'β' the shrink coefficient set to be 0.5 and x_w is the shrink point.

If $f(x_w) < f(x_s)$, then x_w replaces x_s else x_r is used to substitute x_s.

The randomness created via simplex method helps to avoid the major complication of getting trapped in local peaks and in another way, it will improve the convergence of the algorithm towards the best solution. To understand the process of creating randomness in control variables via discard pollen operator, it is assumed that a pollen continuously producing poor fitness have arrived to the simplex method to update its position. Based on the global fitness value, earlier pollen with poor fitness is updated using following operations compression, shrinking and extension to obtain its position nearer to global fitness value as shown in Fig. 3. Hence this method of improving solution quality assures all the particles to converge for global region. Further, at regular intervals the simplex method is kept activated to introduce continuous randomness to the control variable. This method ensures a wide scope and does a fair job in improving accuracy.

5.2. Elite based mutation operation

As a replacement for local search process in FPA method, BPFPA method performs exploitation using elite based mutation process. The mutation process makes satisfactory utilization of parental pollens for exploiting the solution superiority. This helps BPFPA method to find best fitness value in the local search process. The equation used in exploitation process is shown in (23).

$$X_{i,G+1} = X_i + \alpha(X_{best} - X_{i,G}) + \beta(X_{P,G} - X_{q,G}) \tag{23}$$

where 'X_{best}' the pollen with minimal fitness value is, '$X_{P,G}$&$X_{q,G}$' are the random pollens in population, $p,q \in (0,1)$ and 'β,α' $\in (0,1)$ are the constants that obey uniform distribution. The pseudo code for the bee pollinator FPA is given below.

5.3. Application of bee pollinated FPA for PV parameter estimation

This section explains the procedure and the steps involved in the implementation of Bee Pollinated FPA method applied to PV parameter estimation problem.

1. ***Initialization of variables:*** Define maximum number of iterations as *N-iter*, *limit* factor, constants α, β, scaling factor γ, probability switch '*P*' and define the constraints of single and double diode model as follows: For single diode model: $0 < R_S < 2$, $50 < R_P < 900$ & $0.5 < a < 2$. For double diode model: $0.1 < a_1 < 2$, $1.2 < a_1 < 4$ respectively. It is noteworthy to mention that I_o&I_{PV} for single diode and I_{o1}, I_{02}&I_{PV} for a double diode model is calculated analytically.
2. ***Generation of initial control variables:*** Place/initialize 20 pollens/control variables at different locations within the search space to perform random search for optimal solutions.
3. ***Fitness function evaluation:*** Evaluate the initial solutions and obtain the fitness values via objective function. Identify the best position of control variable producing minimum fitness and assign it as best particle for initial iteration.
4. ***Pollination process:*** Based on the probability switch perform either global and local pollination based on the following.

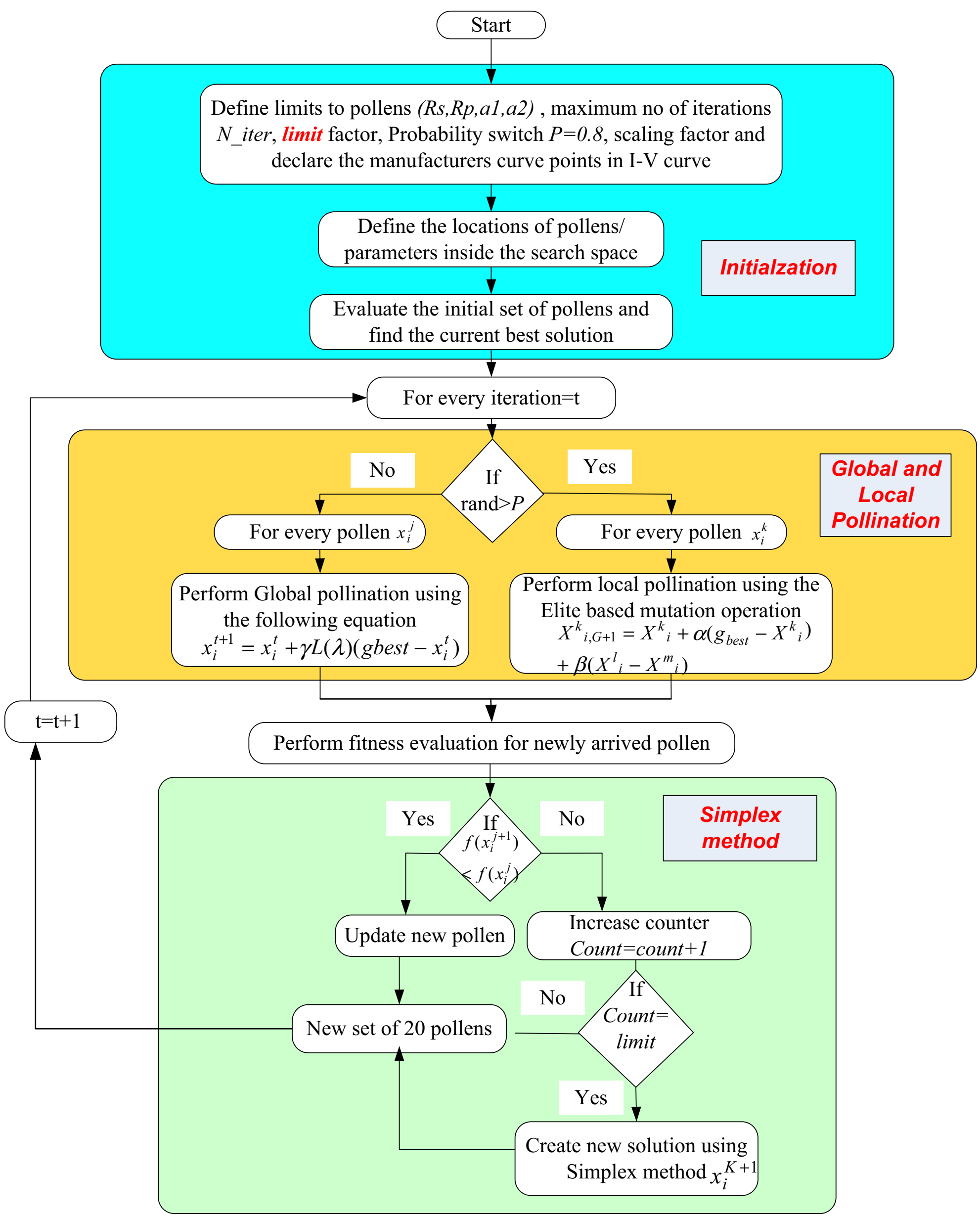

Fig. 4. Flowchart for Bee pollinator FPA method.

Table 1
Comparison of BPFP performance with other algorithms - single diode model-PV cell.

Parameters	BPFPA	FPA	ABSO	CPSO	PS	SA	GA
R_S (Ω)	**0.0366**	0.03654	0.03659	0.0354	0.0313	0.0345	0.0299
R_P (Ω)	**57.7151**	52.8771	52.2903	59.012	64.1026	43.1034	42.3729
I_{PV} (A)	**0.7600**	0.76077	0.76080	0.7607	0.7617	0.7620	0.7619
I_o (μA)	**0.3106**	0.310677	0.30623	0.4000	0.9980	0.4798	0.8087
a	**1.4774**	1.47707	1.47583	1.5033	1.6000	1.5172	1.5751
RMSE	**7.27E−4**	7.730E−4	9.91E−4	0.00139	0.01494	0.01900	0.01908

Table 2
Comparison of BPFPA performance with other algorithms - double diode model-PV cell.

Parameters	BPFPA	FPA	ABSO	HS	PS	SA
R_S (Ω)	**0.0364**	0.0363	0.03657	0.03545	0.032	0.034
R_P (Ω)	**59.624**	52.347	54.6219	46.8269	81.3008	43.10
I_{PV} (A)	**0.7600**	0.76079	0.76078	0.76176	0.7002	0.762
I_{o1} (μA)	**0.3211**	0.3008	0.26713	0.12545	0.9889	0.476
I_{o2} (μA)	**0.04528**	0.16615	0.38191	0.2547	0.0001	0.01
a_1	**1.4793**	1.4747	1.46512	1.49439	1.6	1.517
a_2	**2.000**	2.000	1.98152	1.49989	1.981	2
RMSE	**7.23E−4**	7.84E−4	9.83E−4	0.00126	0.0158	0.016

Global Pollination: Global pollination is performed using the following equation $x_i^{t+1} = x_i^t + \gamma L(\lambda)(gbest - x_i^t)$. 80% of pollens perform exploration via global pollination.

Local Pollination via Elite based mutation: Local pollination is performed using the following equation $X_{i,G+1} = X_i + \alpha(X_{best} - X_{i,G}) + \beta(X_{P,G} - X_{q,G})$.

Discard pollen operator: In this process, all the pollens undergoing global and local pollination will crosscheck their fitness value with previous iteration fitness value. The ***counter*** feature in BPFPA method gets incremented whenever the fitness value of corresponding pollen fails to update its position towards a global optimum. Further, when the pollens counter reaches the ***limit*** in subsequent iterations, it is an indication that the pollen continuously fail to produce randomness to the control variable. Hence in such situations the unimproved pollen is allowed to undergo to simplex evaluation procedure to introduce randomness to the control variables.

5. ***Stopping Criterion:*** Repeat steps 3&4 for ***N-iter***(1000) iterations and obtain the pollen/PV parameters producing exact I-V curve matching datasheet to produce minimal Root Mean Square Error (RMSE) value.

The major issue faced by optimization algorithm is that the methods converge to local minima due to premature convergence [29,30,15,31]. Even the method like FPA has the ability to reach the global optimum has this problem. To avoid local convergence randomness in control variable should be always present to jump out of local minima. Notably, in BPFPA method the ***limit*** factor in global and local search process is the state of intelligence that drives the unimproved pollen to global optimal regions via simplex method. This feature in BPFPA method is considered to be a preponderant benefit in an optimization method which leads to the attainment of quick convergence. For understanding the application of the BPFPA method to PV parameter estimation problem is presented in flowchart Fig. 4.

6. Results and discussions

Since two different modeling approaches are followed in the literature, the authors have performed a stringent mathematical analysis to identify the accuracy either of the modeling method. Performance evaluation via analytical tools such as Relative Error (RE), Individual Absolute Error (IAE), curve fit accuracy and convergence to global optimum is made to know the quality of modeling. Focusing on above four important factors that decide the precision in solar PV modeling is exclusively analyzed. Experimentation is carried out under various operating conditions for different methods. For fairness of comparison 26 instances from the I-V curve is extracted and curve fitted with Bee pollinator FPA single and double diode model results. The proposed algorithm is set to an initial population size of 20 (pollens), probability switch of 0.8 and stopping criterion of 1000 iterations. The algorithm is executed on the MATLAB R2014a platform with the system description of 4 GB RAM and i3 processor.

6.1. Comparison between single diode and double diode model

To state the usefulness of BPFPA method, the method extracted single diode and double diode PV model parameters of RTC France are compared in Tables 1 and 2. respectively. The comparison include some of the recent work with low RMSE. Various methods taken for comparison are: Flower Pollination Algorithm (FPA), Simulated Annealing (SA), Pattern Search (PS), Genetic Algorithm (GA), Particle Swam Optimization (PSO) and Artificial Bee Swarm Optimization (ABSO) methods.

From Tables 1 and 2, it is obvious that BPFPA method records the lowest RMSE value (7.27e−4, 7.23 E−4) among the various methods considered for comparison. Further the method parameter values fall in line with values of FPA, ABSO having low RMSE value. It is noteworthy to state that significant improvement in RMSE value can be seen with BPFPA method. This could be attributed due to the significant difference in 'R_P' value. Among the computed RMSE value, double diode model produces lowest error to ensure the accuracy of the model.

Validation between actual and computed values can be effectively judged based on the error analysis. Hence, the relative error between actual and computed values for both modeling methods at each instance of RTC France I-V curve is calculated using (24) and the statistical data is presented in Table 3.

$$RE = \frac{I_{t(measured)} - I_{t(Calculated)}}{I_{t(measured)}} \tag{24}$$

Table 3
Comparison of actual and experimental values for single and double diode model.

S. no	V_t-measured (V)	I_t-measured (A)	Single diode model		Double diode model	
			I_t-calculated (A)	Relative error	I_t-calculated (A)	Relative error
1.	**−0.2057**	**0.764**	0.763907	0.000121	0.763926	9.65E−05
2.	**−0.1291**	**0.762**	0.761754	0.000322	0.761725	0.000361
3.	**−0.0588**	**0.7605**	0.760537	−4.90E−05	0.76053	−3.90E−05
4.	**0.0057**	**0.7605**	0.75942	0.001421	0.759433	0.001403
5.	**0.0646**	**0.76**	0.758397	0.002109	0.75843	0.002066
6.	**0.1185**	**0.759**	0.757454	0.002037	0.757503	0.001972
7.	**0.1678**	**0.757**	0.756567	0.000573	0.75663	0.000489
8.	**0.2132**	**0.757**	0.755677	0.001747	0.755752	0.001649
9.	**0.2545**	**0.7555**	0.75468	0.001085	0.754759	0.000981
10.	**0.2924**	**0.754**	0.753315	0.000908	0.75339	0.000809
11.	**0.3269**	**0.7505**	0.7511	−0.0008	0.751157	−0.00088
12.	**0.3585**	**0.7465**	0.747129	−0.00084	0.747152	−0.00087
13.	**0.3873**	**0.7385**	0.739955	−0.00197	0.739926	−0.00193
14.	**0.4137**	**0.728**	0.727342	0.000904	0.727246	0.001036
15.	**0.4373**	**0.7065**	0.706984	−0.00069	0.706821	−0.00045
16.	**0.459**	**0.6755**	0.675403	0.000144	0.675186	0.000464
17.	**0.4784**	**0.632**	0.631047	0.001508	0.630809	0.001885
18.	**0.496**	**0.573**	0.572274	0.001266	0.57205	0.001658
19.	**0.5119**	**0.499**	0.499696	−0.00139	0.49951	−0.00102
20.	**0.5265**	**0.413**	0.413706	−0.00171	0.413565	−0.00137
21.	**0.5398**	**0.3165**	0.317454	−0.00302	0.317341	−0.00266
22.	**0.5521**	**0.212**	0.212388	−0.00183	0.212268	−0.00126
23.	**0.5633**	**0.1035**	0.10309	0.003957	0.102919	0.005609
24.	**0.5736**	**−0.01**	−0.00876	0.124102	−0.00903	0.097227
25.	**0.5833**	**−0.123**	−0.12373	−0.00596	−0.12415	−0.00932
26.	**0.59**	**−0.21**	−0.20841	0.007587	−0.20895	0.004979

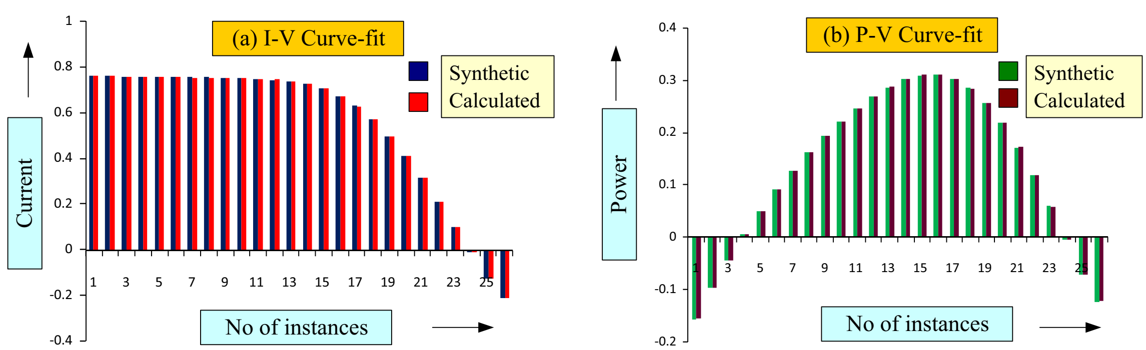

Fig. 5. Curve fit I-V and P-V curve for single diode model.

Further synthetic data representing actual values are also included in the table for clarity. From the tabulated values, it can be concluded that double diode model has least error which proves the accuracy of the method. To confirm the relative error analysis, curve fit is made between synthetic and calculated values for single and double diode model and is presented in Figs. 5 and 6. respectively. The curve plotted with double diode PV parameter closely resemble the actual curve with very small marginal error.

To know the reason behind BPFPA method performance, an extended analysis based on Individual Absolute Error (IAE) for the 26 instances of I-V curve is plotted. To perform a fair comparative study, the computed data of Mutative-scale Parallel Chaos Optimization Algorithm (MPCOA) [32] and Bird Mating Optimizer (BMO) method [21,22] are utilized and their respective IAE values are plotted against the BPFPA method in Fig. 7. The formula used for calculating Individual Absolute Error (*IAE*) is given below:

$$IAE = |I_{measured} - I_{calculated}| \tag{25}$$

On comparison, for all the 26 instances in an I-V curve, Bee Pollinator FPA method produces very low Individual Absolute Error (IAE) for both modeling methods (single and double diode). Experimental results corresponding to MPCOA and BMO introduce significant IAE. The reason for the poor performance is discussed in the following. In MPCOA method, a chaotic sequence depending on initial solutions is followed. Further velocity updation in MPCOA method makes the control variable to jump to the global solutions. Although explorations in control variables create randomness, the absence of exploitation in MPCOA make less diversity and produces higher relative error. In case of Bird Mating Optimizer Method (BMO) distinct patterns are used to update the position of control variables. Since effective exploration is carried out with a different brood mechanism; successful accomplishment of accurate I-V characteristics is obtained. However, the BMO fails to produce randomness after its convergence to optimal region. Moreover, it is not assured that all the control variables will converge to the global optimum. Hence, both the methods discussed above lacks to create diversity in solutions that attributes to high IAE value in comparison with BPFPA method. With the credibility of dual step involving exploration and exploitation, BPFPA method has emerged as one of the viable tools to achieve greater accuracy.

Usually a high accurate, large step optimization technique gets penalized in the form of slow convergence. Since BPFPA method is

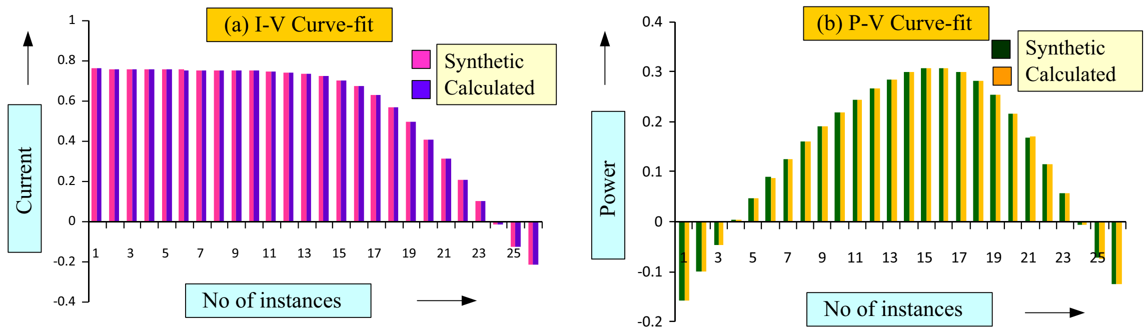

Fig. 6. Curve fit I-V and P-V curve for double diode model.

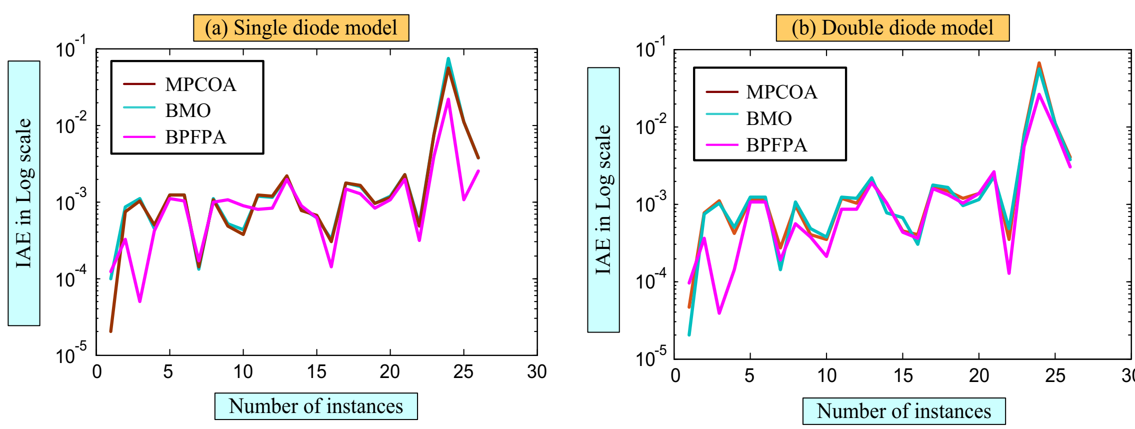

Fig. 7. Individual Absolute Error plots for single and double diode methods.

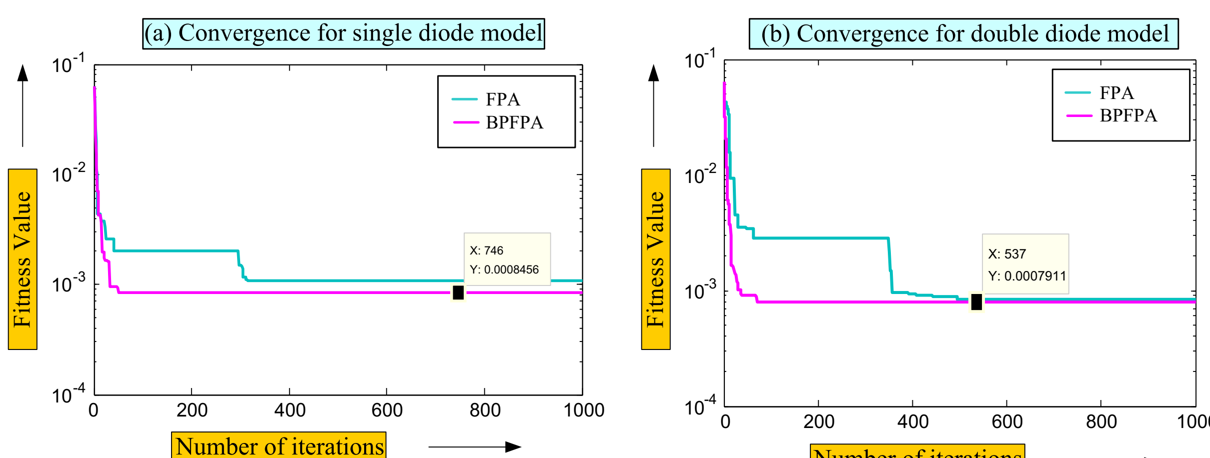

Fig. 8. Convergence characteristics of single and double diode model for FPA and BPFPA method.

an extended version of the FPA method with an additional step, a detailed analysis based on convergence characteristics is mandatory before any conclusions are derived. For comparison, FPA and BPFPA methods are judicially chosen and executed to attain their convergence characteristics shown in Fig. 8. From the convergence characteristics plotted in Fig. 8. it is perceived that, there exists a convergence delay in FPA method. On the other hand, a strong convergence is observed in BPFPA that enable the method to converge in less than 60 iterations. The reason behind faster convergence is that diversity in population that occurred in all the pollens of the population. Further both exploration and exploitation search process has the counter to limit/monitor the control variable producing poor fitness value. If the *limit* factor reach threshold, then the control variable with deprived fitness will undergo assertive simplex evaluation to create randomness. This process in BPFPA method creates randomness to assert more arbitrariness inside

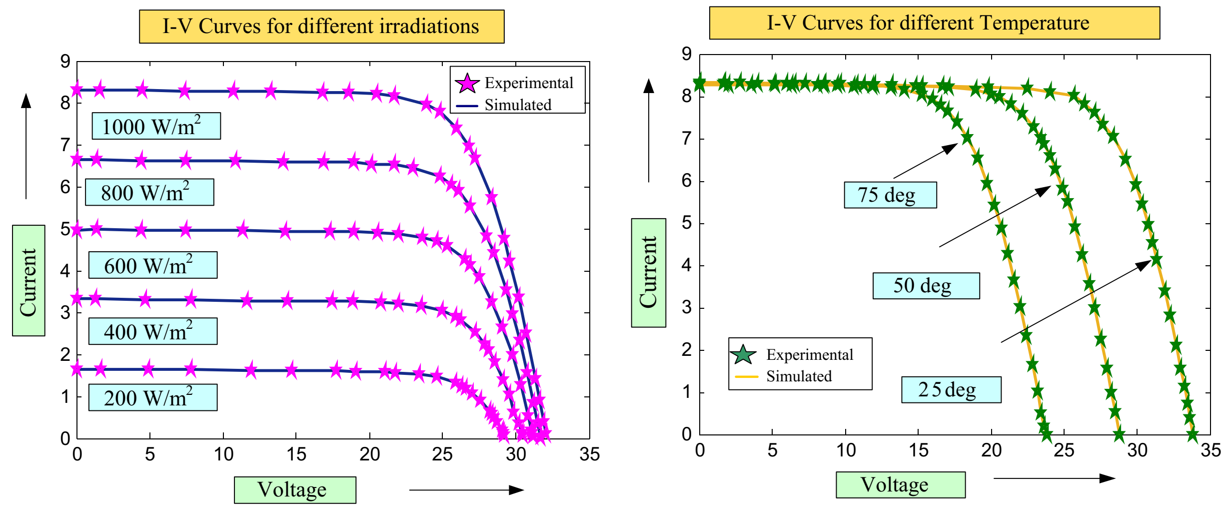

Fig. 9. I-V Curve of Kyocera KG200GT for different irradiance and temperature conditions.

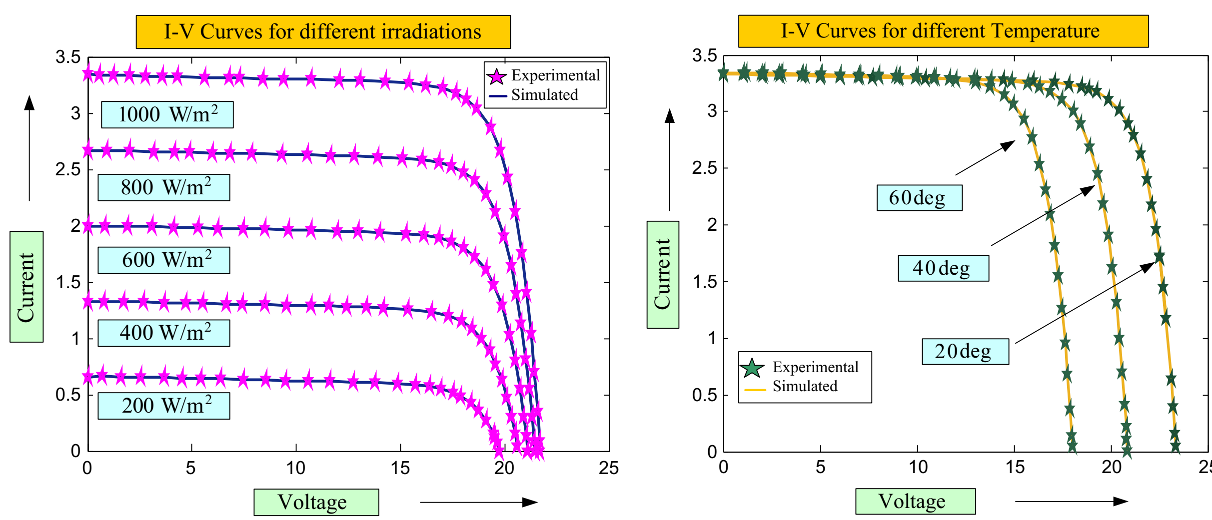

Fig. 10. I-V Curve of SM55 for different irradiance and temperature conditions.

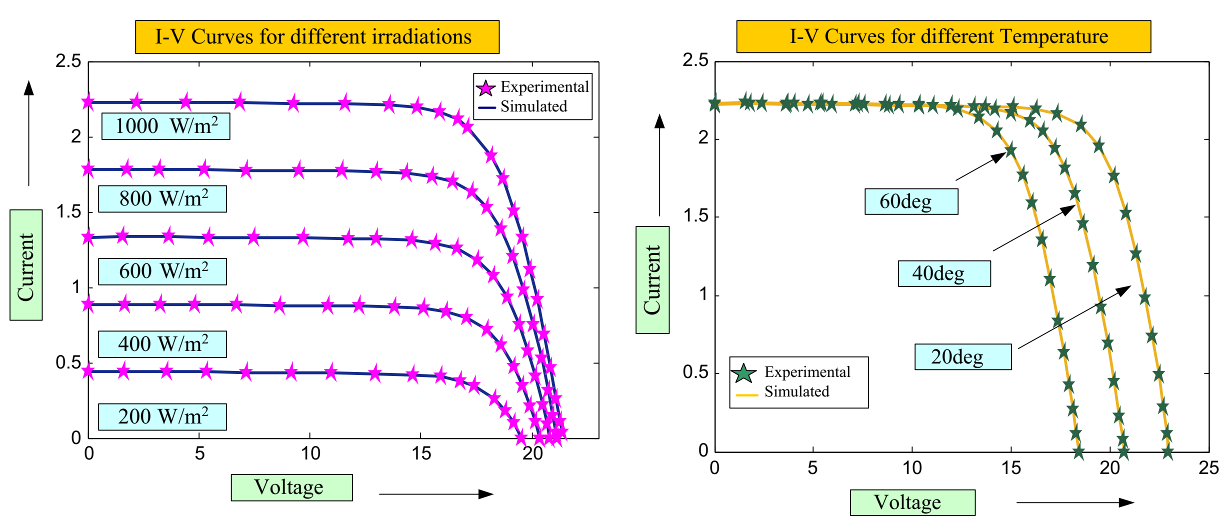

Fig. 11. I-V Curve of Shell S36 panel for different irradiance and temperature conditions.

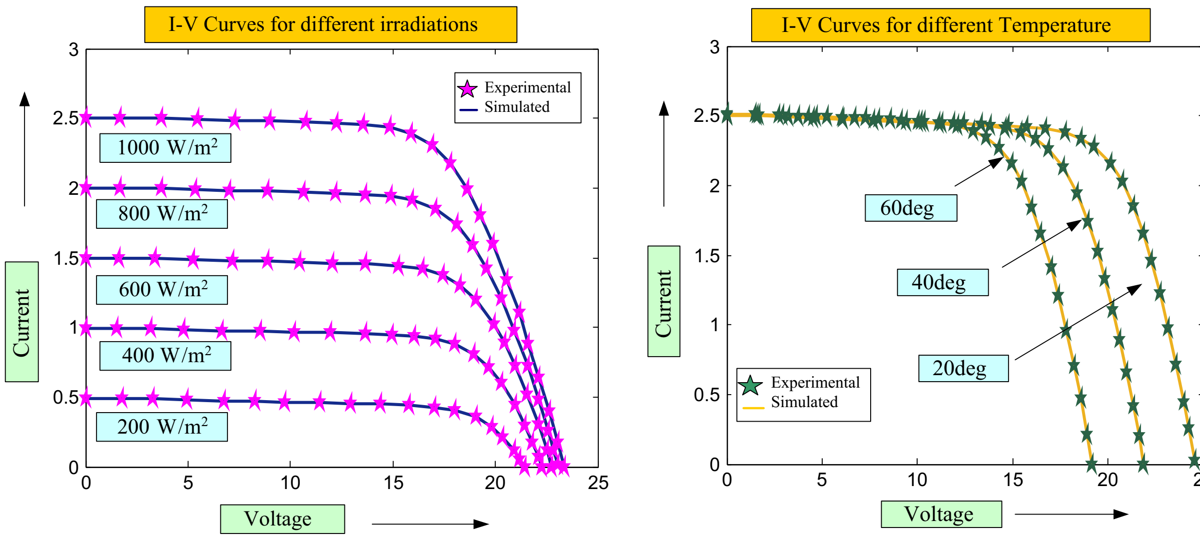

Fig. 12. I-V Curve of Shell ST40 panel for different irradiance and temperature conditions.

Table 4
PV parameters of the double diode model at different irradiation arrived via BPFPA method.

Model parameter	Kyocera KC200GT		SM55		S36		ST40	
	Kashif method	BPFPA method	Kashif method	BPFPA method	Kashif method	BPFPA method	Kashif method	BPFPA method
G = 1000 W/m²								
a_1	1	1.802	1	1.29875	1	1.5	1	1.495
a_2	1.3	2.98	1.3	2.2048	1.3	3.13	1.3	3.256
I_{01} (A)	4.218E−10	0.638E−8	2.232E−10	0.13345E−7	4.206E−10	0.1604E−7	1.13E−9	0.1596E−7
I_{02} (A)	4.218E−10	25.695E−8	2.232E−10	0.3997E−7	4.206E−10	1.1489E−8	1.13E−9	1.563E−8
R_S (Ω)	0.32	0.339	0.47	0.31358	0.5	0.0258	1.6	1.102
R_P (Ω)	160.5	400.12	144.3	400.658	91	458.36	263.3	332.54
RMSE/fitness	2.23E−2	2.2E−4	2.4E−2	4.58E−4	2.62E−2	5.87E−4	2.5E−2	3.65E−4
G = 800 W/m²								
a_1	1	1.741	1	1.289	1	1.489	1	1.425
a_2	1.3	2.655	1.3	2.9685	1.3	3.210	1.3	3.458
I_{01} (A)	4.218E−10	0.452E−8	2.232E−10	0.1408E−7	4.206E−10	1.156E−7	1.13E−9	0.15036E−7
I_{02} (A)	4.218E−10	38.74E−8	2.232E−10	0.65985E−6	4.206E−10	1.524E−8	1.13E−9	1.485E−8
R_S (Ω)	0.32	0.341	0.47	0.425	0.5	0.0215	1.6	1.196
R_P (Ω)	160.5	389.77	144.3	415.352	91	492.32	263.3	344.56
RMSE/fitness	2.23E−2	4.12E−4	2.4E−2	1.58E−4	2.62E−2	8.57E−4	2.5E−2	5.59E−4
G = 600 W/m²								
a_1	1	1.769	1	1.2563	1	1.455	1	1.402
a_2	1.3	2.663	1.3	2.6942	1.3	3.254	1.3	3.445
I_{01} (A)	4.218 E−10	0.492E−8	2.232E−10	0.1359E−7	4.206E−10	0.1402E−7	1.13E−9	0.1148E−7
I_{02} (A)	4.218E−10	47.653E−8	2.232E−10	0.5568E−7	4.206E−10	1.506E−8	1.13E−9	1.4658E−8
R_S (Ω)	0.32	0.314	0.47	0.3533	0.5	0.0205	1.6	1.125
R_P (Ω)	160.5	374.51	144.3	420.665	91	485.52	263.3	329.56
RMSE/fitness	2.23E−2	3.48E−4	2.4E−2	3.65E−4	2.62E−2	6.98E−4	2.5E−2	7.85E−4
G = 400 W/m²								
a_1	1	1.753	1	1.325	1	1.48	1	1.487
a_2	1.3	2.982	1.3	2.365	1.3	3.21	1.3	3.502
I_{01} (A)	4.218E−10	0.458E−8	2.232E−10	0.1986E−7	4.206E−10	0.155E−7	1.13E−9	0.1558E−7
I_{02} (A)	4.218E−10	28.653E−8	2.232E−10	0.45560E−7	4.206E−10	1.499E−8	1.13E−9	1.5887E−8
R_S (Ω)	0.32	0.32	0.47	0.366	0.5	0.0265	1.6	1.129
R_P (Ω)	160.5	396.47	144.3	418.36	91	492.6	263.3	336.52
RMSE/fitness	2.23E−2	2.47E−4	2.4E−2	1.26E−4	2.62E−2	9.9E−4	2.5E−2	2.53E−4
G = 200 W/m²								
a_1	1	1.966	1	1.454	1	1.463	1	1.448
a_2	1.3	2.741	1.3	2.854	1.3	3.365	1.3	3.352
I_{01} (A)	4.218E−10	0.853E−8	2.232E−10	0.2563E−7	4.206E−10	0.1435E−7	1.13E−9	0.1398E−8
I_{02} (A)	4.218E−10	39.653E−8	2.232E−10	0.5986E−7	4.206E−10	1.598E−8	1.13E−9	1.5885E−7
R_S (Ω)	0.32	0.287	0.47	0.3569	0.5	0.0245	1.6	1.115
R_P (Ω)	160.5	387.36	144.3	440.56	91	490.56	263.3	322.58
RMSE/fitness	2.23E−2	3.12E−4	2.5E−2	6.85E−4	2.62E−2	5.88E−4	2.5E−2	5.25E−4

Table 5
PV parameters of double diode model at different temperature arrived via BPFPA method.

Model parameter	Kyocera KC200GT		SM55		SP70		ST40	
	Kashif method	BPFPA method	Kashif method	BPFPA method	Kashif method	BPFPA method	Kashif method	BPFPA method
Temperature	T = 75 °C		T = 60 °C		T = 60 °C		T = 60 °C	
a_1	1	1.842	1	1.325	1	1.412	1	1.408
a_2	1.3	2.785	1.3	2.355	1.3	3.442	1.3	3.485
I_{01} (A)	4.218E−10	0.7524E−8	2.232E−10	0.1956E−7	4.206E−10	0.1309E−7	1.13E−9	0.1209E−7
I_{02} (A)	4.218E−10	40.653E−8	2.232E−10	0.4261E−7	4.206E−10	1.458E−8	1.13E−9 A	1.5498E−8
R_S (Ω)	0.32	0.298	0.47	0.366	0.5	0.0256	1.6	1.162
R_P (Ω)	160.5	389.5	144.3	411.36	91	483.35	263.3	329.65
RMSE/fitness	2.23E−2	2.11E−4	2.5E−2	2.36E−4	2.62E−2	5.58E−4	2.5E−2	5.74E−4
Temperature	T = 50 °C		T = 40 °C		T = 40 °C		T = 40 °C	
a_1	1	2.004	1	1.252	1	1.401	1	1.491
a_2	1.3	2.698	1.3	2.356	1.3	3.152	1.3	3.256
I_{01} (A)	4.218E−10	1.096E−8	2.232E−10	0.1878E−7	4.206E−10	0.119E−7	1.13E−9	0.1588E−7
I_{02} (A)	4.218E−10	38.653E−8	2.232E−10	0.4336E−7	4.206E−10	1.515E−8	1.13E−9	1.4898E−8
R_S (Ω)	0.32	0.256	0.47	0.3365	0.5	0.0225	1.6	1.109
R_P (Ω)	160.5	369.54	144.3	425.63	91	454.25	263.3	350.25
RMSE/fitness	2.23E−2	3.014E−4	2.4E−2	2.52E−4	2.62E−2	8.96E−4	2.5E−2	5.85E−4
Temperature	T = 25 °C		T = 20 °C		T = 20 °C		T = 20 °C	
a_1	1	1.838	1	1.312	1	1.322	1	1.453
a_2	1.3	2.866	1.3	2.454	1.3	3.266	1.3	3.365
I_{01} (A)	4.218E−10	0.7742E−8	2.232E−10	0.1925E−7	4.206E−10	1.203E−9	1.13E−9	0.14002E−7
I_{02} (A)	4.218E−10	43.653E−8	2.232E−10	0.4658E−7	4.206E−10	1.508E−8	1.13E−9	1.6022E−8
R_S (Ω)	0.32	0.31	0.47	0.329	0.5	0.0283	1.6	311.63
R_P (Ω)	160.5	359.65	144.3	428.96	91	475.9	263.3	1.136
RMSE/fitness	2.23E−2	3.70E−4	2.4E−2	5.25E−4	2.62E−2	9.85E−4	2.5E−2	6.5E−4

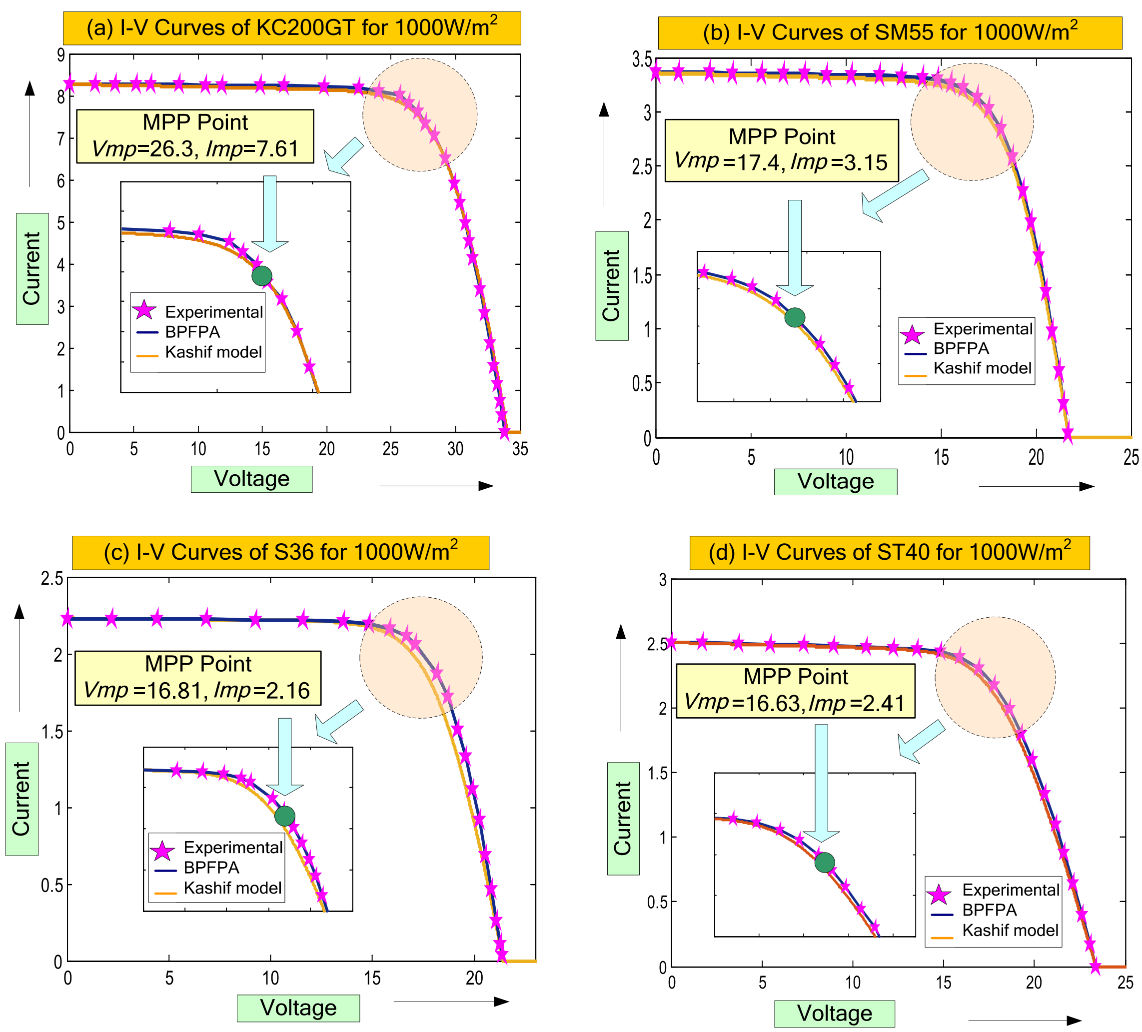

Fig. 13. Comparison of BPFPA method with existing literature for different PV technologies.

Table 6
Comparison of MPP data between BPFPA method, datasheet and Kashif model for 1000 W/m^2.

Panel	V_{mp} (V)			I_{mp} (A)			P_{mp} (W)		
	Experimental	Kashif	BPFPA	Experimental	Kashif	BPFPA	Experimental	Kashif	BPFPA
Kyocera KC200GT	26.30	26.15	26.31	7.61	7.59	7.59	**200.14**	**198.4**	**199.75**
SM55	17.40	17.38	17.39	3.15	3.13	3.15	**54.81**	**54.40**	**54.78**
S36	16.81	16.71	16.80	2.16	2.13	2.16	**36.31**	**35.59**	**36.29**
ST40	16.63	16.58	16.63	2.41	2.38	2.40	**40.08**	**39.46**	**39.91**

Table 7
Mapping between outcomes and parameters influencing expected outcomes.

Outcomes/parameters	Relative error		Parameter dependency		Convergence to local minimum		Convergence consistency		Viability of optimization method	
	L	H	L	H	L	H	L	H	L	H
Curve fit	✓		✓		✓			✓		✓
PV parameter precision	✓		✓		✓			✓		✓
Fill factor	✓		✓		✓			✓		✓
RMSE error	✓		✓		✓			✓		✓

Table 8
Performance comparison of BPFPA with other algorithms.

S. no	Parameter	GA [14]	PSO [20]	BMO [21]	FPA [27]	BFA [35]	FWA [36]	BPFPA
1.	No of parameters required	4	6	4	2	5	7	3
2.	Accuracy	Less	Moderate	High	High	High	High	High
3.	Convergence Speed	Less	High	Moderate	Moderate	High	High	High
4.	RMSE Error	High	Moderate	Moderate	Less	Moderate	Moderate	Less
5.	Exploration in control variable	✓	✓	✓	✓	✓	✓	✓
6.	Exploitation in control variable	–	–	–	✓	–	✓	✓

search space that improves the search ability of the method. It is noteworthy to mention that, this process of establishing randomness is continuously followed by BPFPA method to keep alive the algorithm for achieving better accuracy. Although two stage process helps the FPA method to a converge reasonable fitness value, the absence of Bee Pollinator restricts its accuracy. At this point, it is important to mention that the BPFPA method produce high degree of accuracy when implemented with double diode model.

6.2. Validation of different PV technologies via double diode PV model

Since BPFPA method proved to be efficient with double diode model; the method accuracy is tested for PV modules of different make and type. four different PV technologies matching to manufacturer's I-V curves are tested. The computed I-V curves along with synthetic data for different PV make are presented in Figs. 9–12.

Generally, the reproduction of actual I-V curves at lower irradiation profile is a challenging task where most of the modeling methods fail since, the parameters differ with change in different irradiations and temperature values. With most desirable advantage of dual stage search, BPFPA method has ensured its optimal parameters that suits to all types of irradiation conditions. To prove the accuracy of optimal parameters I-V characteristics that corresponds to KC200GT, SM55, S36 and SP70 panels are plotted along with the actual values in Figs. 9–12. A close agreement between actual nd computed can be seen with all the I-V curves.

6.3. Accuracy in parameter extraction

In order to further envisage the accuracy of double diode PV modeling with BPFPA method, the different PV parameters arrived under different irradiation and temperature conditions that corresponds to different make and type are tabulated in Tables 4 and 5. For wise validation the authors have compared the results presented in [12]. Since all the PV technologies tested in this research are closely interrelated with the literature [12], the authors have only tabulated values from [12] for understanding. With a closer examination on parameter values of BPFPA and Kashif method, one can see significant different in parameter values for every irradiation and temperature. The Kashif method utilized the same parameter for all the irradiation and temperature cases. This result is practically void since R_s, R_p, a values cannot be maintained the same for different irradiation and temperature due to the fact that series resistance attributing to metallic contacts, semiconductor leads and parallel resistance representing recombination losses vary with temperature and irradiance values. Hence it is highly uncertain for a PV panel to maintain the same values of R_s and R_p values for different environmental conditions. Moreover, Kashif method produce high RMSE value compared to BPFPA, the factors behind high RMSE values are: (i) except series and parallel resistance (R_s, R_p) all other parameter values are arrived analytically, (ii) the value of $a_1 \& a_2$ are assumed to be same, (iii) R_s and R_p values are not maintained at minimum and maximum values respectively. Therefore the above reasons have made the method [12] to arrive at imprecise results.

Further investigation in Tables 4 and 5, it is noticed that there is significant change in ideality factors because, the choice of ideality factors are arrived analytically in [12] whereas these values in BPFPA method are arrived via optimization procedure. It is important to note that assuming similar ideality factor for both the diodes in double diode model is not correct since the leakage losses in both the diodes practically differ.

6.4. Validation of proposed methodology with existing literature based on maximum power values

In order to show the curve fit between the proposed methodology and Kashif method I-V curves are plotted between the methods for different PV technologies at 1000 W/m^2 and it is shown in Fig. 13. From the figure, I-V curve representing Kashif model deviate from actual values around MPP is clearly seen. To know the amount of deviation; MPP values having P_{mp}, I_{mp} & V_{mp} that corresponds to Kashif model and proposed model is compared in Table 6. The tabulated values confirms that the power at MPP deviates with Kashif model.

7. Comparative study

Generally PV parameters decide the accuracy of PV characteristics. To estimate the influence of PV parameter on I-V characteristics accuracy; mapping between the parameters and outcomes are carried out. The influence of parameters on outcomes is weighed in the scale of 'Low-L' to 'High-H'. The parameters and outcomes that have been accounted for the study are (i) accurate curve fit, (ii) PV parameters precision, (iii) Fill Factor and (iv) RMSE error & (i) Individual Absolute Error, (ii) Relative Error, (iii) parameter dependency, (iv) convergence to local optimum, (v) convergence consistency and (vi) viability of optimization method respectively. The mapping can be understood in the following way: for the given parameter if its corresponding outcome is 'Low-L' then the influence of parameter on outcomes is low and vice versa. Thus, any method can be gauged with respect to performance parameters and it can be analyzed. For instance, if the reliability of optimization technique is high, then the outcome will be a good curve fit, high precision, high Fill Factor and low RMSE. Thus mapping between the outcomes and PV parameters explicitly indicate the quality of any optimization technique. This illustration can be understood as shown in Table 7.

To evaluate the performance of BPFPA method, a qualitative comparison is compiled based on outcomes discussed earlier. Further, this comparison becomes a viable tool to determine the choice of an algorithm. To provide this comparison, the popular methods in parameter estimation techniques like Genetic Algorithm [14], Particle Swarm optimization [20], Bird mating optimizer [21] and other recent nature inspired methods like Flower Pollination Algorithm [27], Bacterial Foraging Algorithm [35] & Fireworks Algorithm (FWA) [36] are unanimously chosen to validate bee pollinated FPA method. The quality of the proposed method is evaluated based on following criteria's: (1) no of parameters required, (2) accuracy, (3) convergence speed (4) RMSE Error, (5) exploration in the control variable and (6) exploitation in the control variable. This evaluation is presented in Table 8.

In general tuning of parameters in any of the method adds complexity and increases the data manipulation. In that case BPFPA method has fewer parameters next to FPA. Whilst the other methods like FWA, BFA, PSO has a higher parameter which indirectly illustrates their complexity. In addition parameter tuning increases the computational time and reduces the time for convergence. FWA method though, has higher recommendation in parameter estimation; the execution speed is comparatively slower when compared to BPFPA method.

With respect to accuracy and convergence, the recent nature inspired methods like FWA, FPA, and BPFPA are more reliable since all the methods have the inherent quality of creating randomness in solutions. The exploration and exploitation in the control variable pay more attention since it is vital to evaluate the algorithm performance. Specifically, this ensures the negligence of premature convergence where BPFPA has the strongest influence to converge for global solutions since randomness is ensured by exclusive discard pollen operator. Although FWA and FPA method have exploration and exploitation ability, the FWA involve too much complexity to eliminate the unimproved solution and on the other hand FPA just randomly explores any of the pollens in the population. But BPFPA method has the inherent ability to accurately eliminate the particle/pollen that posse's poor fitness and hence to converge for global optimal solutions. This feature is found absent in all the methods compared in Table 8.

From Table 8, it is inferred that BPFPA method stands tall in all the parameters and out beaten other algorithms that exist in the literature. Three important observations which made BPFPA to be a suitable method when compared to other optimization methods are (i) the novel quality to create exploration and continuous exploitation in the control variables (ii) Achieving faster convergence at initial stages of computation (iii) Inherent simplicity and reduced execution time.

8. Conclusion

A new hybrid Bee Pollinator FPA is proposed for the PV parameter extraction problem. Though, it is a hybrid method of combing ABC and FPA, it is very less complex and easy to comprehend. The global search process of FPA along with simplex method has improved the solution quality to superior rate and thus the convergence of global optimum location via exploitation is assured via proposed method. This innovation incorporated to FPA by utilizing Bee behaviors have made the convergence at initial stages of computation is notable merit in the proposed method. It is worth to mention that, this BPFPA has faster execution speed in evaluation with other algorithms. Considering the performance and robustness, the potential in BPFPA is highly valued.

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Appendix A

S. no	Parameter	Kyocera KC200GT	Shell SM55	Shell S36	Shell ST40
1	Maximum power, [P_{mpp}]	200 W	55 W	36 W	40 W
2	Maximum power voltage [V_{mpp}]	26.3 V	17.4 V	16.5 V	16.6 V
3	Maximum power current [I_{mpp}]	7.61 A	3.15 A	2.16 A	2.41 A
4	Open circuit voltage [V_{oc}]	32.9 V	21.7 V	21.4 V	23.3 V
5	Short circuit current [I_{sc}]	8.29 A	3.45 A	2.30 A	2.68 A
6	Current temperature coefficient [K_i]	$(3.18 * 10^{-3})$ A/°C	$(3.18 * 10^{-3})$ A/°C	$(1.00 * 10^{-3})$ A/°C	$(0.35 * 10^{-3})$ A/°C
7	Voltage temperature coefficient [K_V]	$-1.23 * 10^{-1}$ V/°C	$-1.23 * 10^{-1}$ V/°C	$-0.76 * 10^{-1}$ V/°C	$-100 *$ mV/°C

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