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Parameter extraction of two diode solar PV model using Fireworks algorithm

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ABSTRACT

The double diode model for photovoltaic (PV) modules is currently less adopted than one-diode model because of the difficulty in the extraction of its seven unknown parameters I_{PV}, I_{01}, I_{02}, R_s, R_p, a_1 and a_2, which is a serious inverse problem. This paper proposes application of the Fireworks Algorithm (FWA) for the accurate identification of these unknown parameters in such a way to solve effectively this modeling problem. In particular, firstly, the FWA has been comprehensively tested with two different technologies of Mono-Crystalline (SM55 & SP70) and Multi-Crystalline (Kyocera200GT) PV modules. In addition, further statistical and error analysis for three different panels are exclusively carried out to validate the suitability of proposed methodology. The results of proposed algorithm are benchmarked with popular Genetic Algorithm and Particle Swarm Optimization (PSO) methods. Fitness convergence curves or FWA method for SM55, SP70 and Kyocera200GT produce very less objective function as 2.2498E−07, 2.85765E−08 and 4.0075E−08 respectively. This illustrates the wise and accurate validation of FWA method. Calculated curve-fit via FWA in agreement to datasheet curve strongly suggest the FWA can constitute the core of suitable optimization code for two diode PV parameter extraction.

1. Introduction

Energy scarcity motivated researchers around the globe to think for pollution free, and cost effective energy alternative. Presently 40.4% of world's energy demand is met by coal, however, its continuous depletion, hazardous effluent emission and limited stock availability turned world's attention towards renewable energy resources. Among the various types, Solar Photovoltaic (PV) is the most promising one, due to its significant advantages such as zero emission, zero noise and easy maintenance (Sudhakar Babu et al., 2015). Further it is an excellent choice for remote area electrification since extension of existing power grid can be too expensive.

One of the major hurdles faced by the PV researchers is solar PV cell modeling. This occur due to (i) non-linear current-voltage characteristic of PV (Mohammed Azharuddin et al., 2014), (ii) complex parameter identification and (iii) generating PV array characteristics under partial shaded condition is tedious. Therefore PV cell modeling is given higher importance. Moreover, an accurate solar PV cell model is always helpful in predicting the system performance precisely. Among many ways, the most common and the convenient form are via electrical equivalent circuit where two main modeling methods exist: (i) One-diode model and (ii) Two diode model. One diode model also called 5 parameter model (De Soto et al., 2006; Laudani et al., 2014a) require 5 unknown parameters and is widely accepted for its simplicity. However, the one diode model fails to include the recombination loss occur in the depletion region. Thus, for precise PV cell modeling two diode models is preferred. Though it requires 7 parameters to model, the complexity can be easily justified in view of high accuracy. In addition, it is true that, the closeness of the predicted PV characteristics depend on accuracy of cell model parameter values. However, the non-linearity present impose difficulty towards the extraction of model parameters that cannot be overtaken as done for one diode model by means of reduced forms (Laudani et al., 2014a, 2014b). Therefore, identification of double diode model parameters of PV module is a fundamental topic for researchers and various researchers worked on different methods to provide solution.

Owing to problem solving capability, many researchers followed optimization technique in literature for solar PV parameter extraction. Genetic Algorithm (GA) method is first proposed in

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(Jervase et al., 2001) for PV parameter extraction problem; however the results produced show relatively high percentage of errors. Alternatively authors in (Ye et al., 2009; Wei and Deyun, 2011) used Particle Swarm Optimization (PSO) method but similar to GA, this method also suffers from premature convergence problem. Avoiding the above problem Simulated Annealing (SA) method intended for extraction of solar PV parameters is implemented in (El-Naggar et al., 2012). Since the performance of SA is highly dependent on cooling schedule it is extremely difficult to obtain better results without proper tuning. In (AlHajri et al., 2012) a new pattern search heuristic algorithm is used. Even though obtained results are comparatively good, the method exhibit large complexity in exploration of search space. Authors Oliva et al. (2014) proposed Artificial Bee Colony (ABC) optimization technique. The bee behavior based on hunt for food is derived and implemented for solar PV parameter estimation. However, due to its slower convergence the algorithm is less chosen. Artificial Bee Swarm Optimization (ABSO) a class ABC method yields better convergence in comparison to the ABC however, it show sluggish performance when applied for PV parameter extraction (Askarzadeh and Rezazadeh, 2013). The method of tuning music based on the available memory is used for the PV parameter extraction process in (Askarzadeh and Rezazadeh, 2012). This harmony based optimization uses three important parameters, such as pitch adjusting rate, bandwidth and harmony memory to find global optimum. The selection of initial parameters and requirement of large memory space impose constraints on computational time. Bird Mating Optimization (BMO) technique, a recently devised metaheuristic algorithm, imitating metaphorically the mating strategies of bird species is proposed in (Alireza and Alireza, 2013). Though, BMO method seems to be simple, the complexity arises when perceptive different species are used. The authors in (Alireza and Alireza, 2013) implemented chaos optimization technique for PV parameter estimation; but this method suffers from parameter selection. In paper (Rajasekar et al., 2013), Bacterial Foraging Algorithm (BFA) is implemented for extracting solar PV characteristics from datasheet value but, high computational burden limits its usage. The Differential Evolution (DE) method is another heuristic algorithm adopt the characteristics of GA is applied for PV parameter extraction in (Ishaque et al., 2011b). The method show very good convergence however involvement of more parameters makes DE less preferred (Ishaque et al., 2011c).

To sum up, the methods implemented solar PV for parameter estimation have the following drawbacks: (1) large convergence time (2) prone to errors and (3) complexity. Therefore as an alternative method in this paper, a new optimization technique named FireWork Algorithm (FWA) is proposed for solving solar PV parameter extraction problem. FW algorithm (Tan and Zhu, 2010; Fireworks Algorithm, 2015) is relatively a new global optimization method inspired by the phenomenon of fireworks explosion, where fireworks and sparks are analogous to solutions to a given problem, and an explosion can be viewed as a search in the solution space around the firework. With proper balance between exploration and exploitation process, the FW algorithm finds better solution for the given optimization problem. Further numerical experiments on various set of benchmark functions showed that, the FWA method converge to a global optimum at a much faster rate than conventional algorithm (Fireworks Algorithm, 2015). To know the suitability of FWA for PV parameter extraction problem, numerical simulations are performed with FWA method and other optimized model parameter. To know the veracity, FireWork (FW) results are compared with timeworn GA and PSO method. In addition, a comprehensive analysis is made between methods employing two diode models. Moreover to demonstrate the superiority of FW method error between actual and simulated values is plotted.

The remaining section of the paper is organized as follows: Section 2 expounds the modeling of the solar PV. Section 3 describes the steps involved in application of FW method for PV parameters estimation problem. Discussions on results obtained are elaborated in Section 4. In addition, comparative studies of FW method with three different PV panels are analyzed in Section 5. Conclusions are presented at last.

2. Modeling of PV module

It is advisable to model a solar PV system before proceeding into the installation part of it; since it is helpful to better understand the behavior of solar panel under varying atmospheric conditions. Therefore for accuracy reasons two diode models is preferred. Moreover, actually it brings out the exact behavior of PV cell characteristics. It comprises of a current source I_{pv} in parallel with two diodes D_1 and D_2 connected to series (R_S) and shunt resistances (R_P). Diode D_1 indicates diffusion process while diode D_2 gives idea about the space charge region of the junction, series resistance R_s represents initial losses caused by current flow and contacts leads, and shunt resistance R_p stands for modeling the reverse saturation current. The schematic representation of two diode model is shown in Fig. 1.

Applying, Kirchhoff's Current rule (KCL) the PV cell terminal current for double diode model is given by

$$I = I_{pv} - I_{o1}\left[\exp\left(\frac{V+IR_s}{a_1V_{T1}}\right) - 1\right] - I_{o2}\left[\exp\left(\frac{V+IR_s}{a_2V_{T2}}\right) - 1\right] - \left(\frac{V+IR_s}{R_p}\right) \quad (1)$$

where

I_{pv} is the current generated by PV cell,
I_{01}, I_{02} are the leakage currents of diodes D_1 and D_2 respectively.
V_{T1}, V_{T2} are the thermal voltages of PV module and is given by $\left(\frac{N_s k_B T}{q}\right)$
N_s is the number of cells connected in series
q is the electron charge (1.602×10^{-19} C)
k_B is the Boltzmann constant 1.38×10^{-23} J/K
T is the temperature of p-n junction in Kelvin.
$a_1,\ a_2$ ideality factors of diodes D_1 and D_2 respectively.

The current generated by the PV cell (I_{pv}) depends on temperature and irradiation factor. Hence the PV current is calculated as

$$I_{pv} = (I_{scn} + k_i dT)\frac{G}{G_n} \quad (2)$$

where I_{scn} is the short circuit current at STC (Standard Test Conditions), k_i is the current temperature coefficient, G is the irradiation to which the panel is exposed, G_n is the irradiation of solar panel at

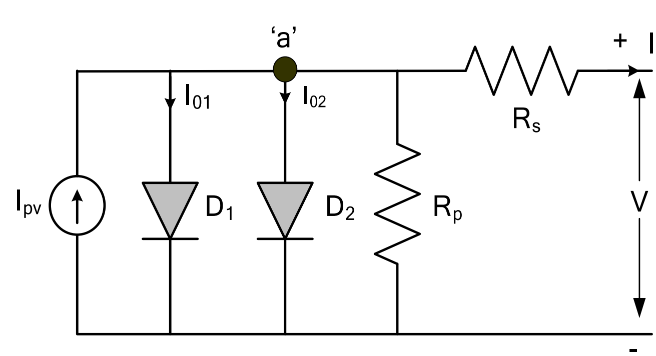

Fig. 1. Schematic of two diode model.

STC, i.e. 1000 W m^2 and $dT = T - T_n$ where T is the surface temperature of panel and T_n is the temperature at STC i.e., 25 °C. The value of $I_{01},\ I_{02}$ are considered to be equal to avoid computational complexity in iteration. Although the values are arrived via iteration, it is meaningful to validate the leakage current analytically to reduce the iteration time.

$$I_{01} = I_{02} = \frac{I_{PV}}{\exp[(V_{oc} + K_V dT/(a_1 + a_2 - 1)V_T] - 1} \tag{3}$$

where
k_v is the voltage temperature coefficient,
V_{oc} is the open circuit voltage

For precision the values of V_{oc} and V_{mp} are modified following guidelines given in (Rajasekar et al., 2013) and are calculated using the following:

$$V_{oc} = V_{ocn} + V_t \ln\left(\frac{G}{G_n}\right) + k_v dT + \alpha \log\left(\frac{G}{G_n}\right) \tag{4}$$

$$V_{mp} = V_{mpn} + V_t \ln\left(\frac{G}{G_n}\right) + k_v dT + \beta V_t \log\left(\frac{G}{G_n}\right) \tag{5}$$

where $\alpha,\ \beta$ are the panel coefficients that vary with temperature and irradiation values.

Proper definition of the objective function is very important for accurate extraction of parameter values which ensures that the model behaves exactly the same as the real PV panel. Therefore, the following section discusses about the formulation of objective function. Power obtained from PV panel is DC and is expressed as

$$P = VI \tag{6}$$

Differentiating the above equation with respect to voltage on both sides, we get

$$\frac{dP}{dV} = \frac{d(I * V)}{dV} + I \tag{7}$$

From the Power curve shown in Fig. 2 it can be inferred that, the derivative of power with respect to voltage at Maximum Power Point (MPP) is equal to zero. Applying this condition we get

$$\frac{dP}{dV} = V\frac{dI}{dV} + I = 0 \tag{8}$$

On rearranging the above equation results in a new objective function where it is a minimization function,

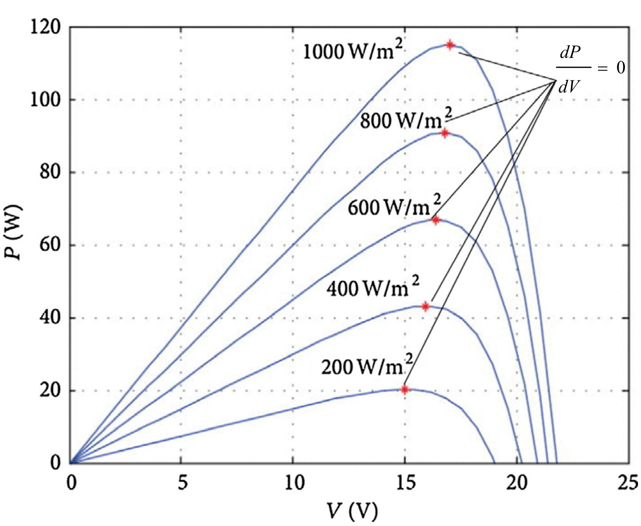

Fig. 2. P-V curve for different irradiations.

$$\min\left(\left|\frac{dP}{dV}\right|\right)_{mp} = \left|\frac{dI}{dV}\right|_{(V_{mp},\ I_{mp})} + \frac{I_{mp}}{V_{mp}} \tag{9}$$

The term $\left|\frac{dI}{dV}\right|_{(V_{mp},\ I_{mp})}$ can be obtained by differentiating the basic current equation of double diode model with respect to voltage and is given below,

$$\left|\frac{dI}{dV}\right|_{(V_{mp},\ I_{mp})} = \frac{I_{o1}\Gamma\exp\{\Gamma(V_{mp} + I_{mp}R_s)\} + I_{o2}\Gamma\exp\{\Gamma(V_{mp} + I_{mp}R_s)\} - G_p}{1 + I_{o1}\Gamma R_s\exp\{\Gamma(V_{mp} + I_{mp}R_s)\} + I_{o2}\Gamma R_s\exp\{\Gamma(V_{mp} + I_{mp}R_s)\} - G_p R_s} \tag{10}$$

where $G_P = \frac{1}{R_P}$ and $\Gamma = \frac{1}{aV_T}$

3. Optimization technique

Fireworks algorithm (FWA) developed by Tan Y and Zhu Y is a recent arrival in the field of optimization technique that falls under the class of global optimization algorithms. This stochastic optimization technique is capable of solving non-linear, complex numerical computation with high accuracy. Further various works on solving practical optimization problems with FWA method can be found in literature (Sangeetha et al., 2016; Srikanth Reddy et al., 2016; Zhang et al., 2016; Goswami and Chakraborty, 2015). In this method, number of fireworks (particles) is generated in the search space and a stochastic explosion process is initiated for each firework. On the completion of explosion process, a shower of sparks is generated around the local space of exploded firework. Both the fireworks as well as the newly generated sparks represent the potential solutions to the optimization problem. Since FWA algorithm makes use of Gaussian mutation operator it enhances the local search capability and creates randomness in control variable. Moreover the key feature of this algorithm is its ability to properly balance between exploration as well as exploitation process. This behavior is quite suitable for parameter estimation problem; since the method has to confine its search by exploration followed by exploitation process. The steps involved in Fireworks algorithm implementation for PV parameter estimation are detailed below:

Step1: Initialization of Fireworks: Specify iteration count as 1000 and Initialize twenty Fireworks $\{R_s,\ R_P,\ a_1,\ a_2\}$ at different locations of search space. Specify the boundary limits for $R_s,\ R_P,\ a_1\ \&\ a_2$ as $0.2 \leqslant R_s \leqslant 2,\ 200 \leqslant R_p \leqslant 500,\ 1 \leqslant a_1 \leqslant 2\ \&\ 1 \leqslant a_2 \leqslant 2$ where other parameters like $I_{01},\ I_{02}\ \&\ I_{PV}$ are calculated manually. The representation of sample 5 fireworks inside the search space is represented in Fig. 3(a).

Step 2: Spark and Amplitude Evaluation: For every individual set of $R_s,\ R_P,\ a_1\ \&\ a_2$ perform spark evaluation to know the quality of Firework based on Eq. (11). To understand the goodness of sparks generated, perform amplitude evaluation. The firework performing spark and amplitude evaluation is represented in Fig. 3(b). If the amplitude of sparks is less, then it is an indication that firework reached the position closer to global optimal region and vice versa if the amplitude is high (i.e.) Firework is far away from optimal location. Therefore, Good and bad explosion are identified with the number of sparks generated and amplitude in the search space. For instance, highly populated sparks with less amplitude around the Firework indicate good explosion and less dense indicate bad explosion. In present case objective function having lesser error and larger error indicates good and bad explosion respectively. For the given objective function $f(x)$ the Fireworks $x_1, x_2, x_3 \ldots x_n$ undergo spark evaluation based on the following equation.

$$S_i = m \cdot \frac{y_{\max} - f(x_i) + \xi}{\sum_{i=1}^{n}(y_{\max} - f(x_i) + \xi)} \tag{11}$$

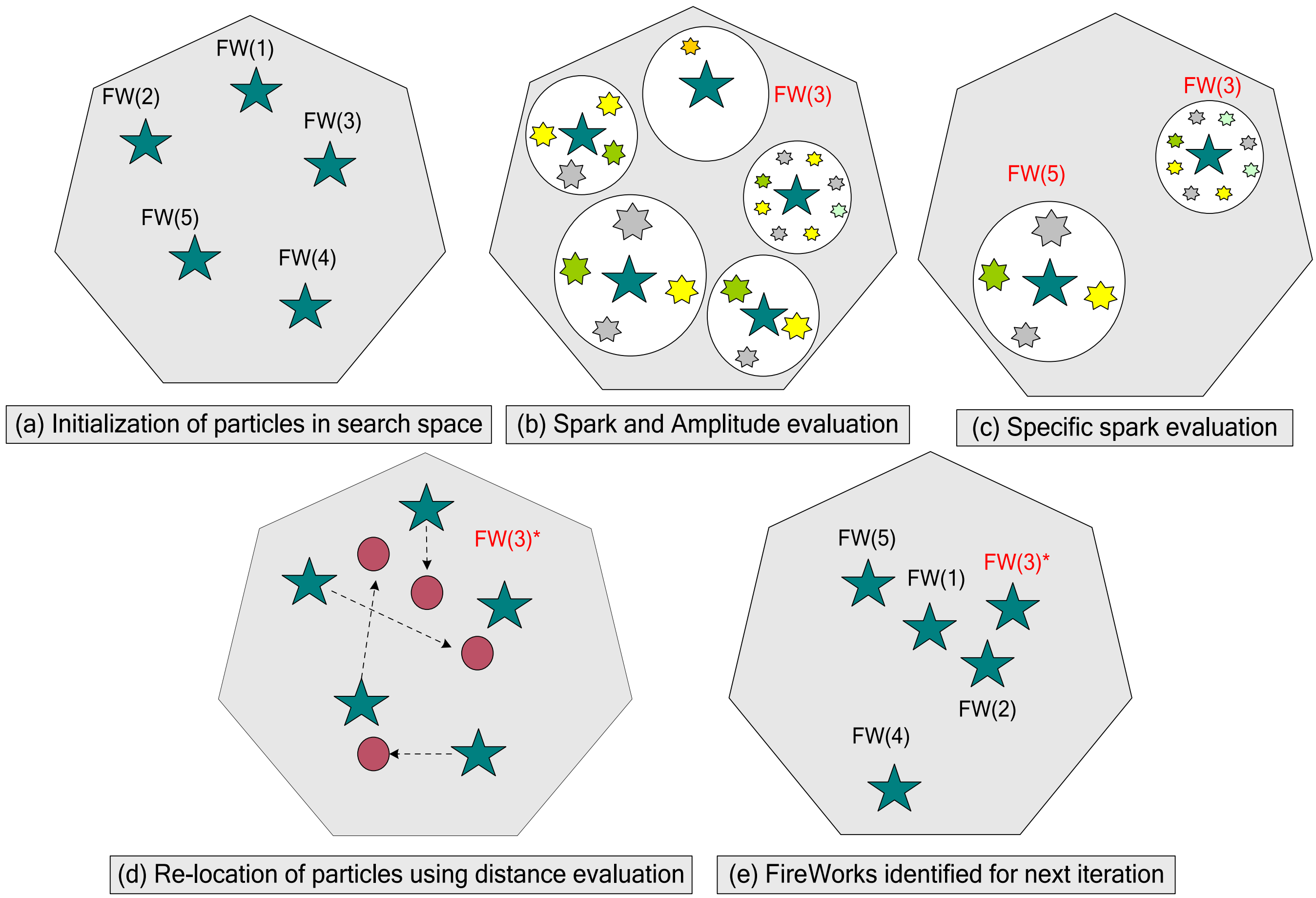

Fig. 3. Movement of firework in search space for one dimensional problem.

where 'm' is the control parameter responsible for number of sparks generated, 'y_{max}' is the maximum objective function, 'i' corresponds to iteration number and 'ξ' is the constant used here to avoid zero division error. To restrict the spark evaluation within limits, constraints are introduced in spark evaluation as follows.

$$S_i = \begin{cases} round(a.m) & S_i < a.m \\ round(b.m) \quad \text{if} & S_i > b.m, \; a < b < 1 \\ round(S_i) & otherwise. \end{cases} \tag{12}$$

where 'a' and 'b' are constants used for spark evaluation. In order to exemplify the spark evaluation, the amplitude evaluation in contrast to spark evaluation is carried out (i.e.). For good explosion the firework amplitude is smaller and for a bad explosion the amplitude explosion is higher.

$$A_i = \hat{A}_m \cdot \frac{f(x_i) - y_{max} + \xi}{\sum_{i=1}^{n}(f(x_i) - y_{max}) + \xi} \tag{13}$$

where 'A_m' is the minimum explosion amplitude and 'y_{max}' is the minimum objective function for $(i = 1, 2, 3 \ldots n)$.

Step 3: Identification of Location for Fireworks: Since the target function of parameter estimation is a minimization function, each firework is made to undergo a dimensionality test to effectively locate the Firework nearest to least objective function. Map the location of spark for inside the search space using the following equation.

$$x_j^k = x_k^{min} + |x_j^k| \% (x_k^{max} - x_k^{min}) \tag{14}$$

Step 4: Specific Spark Evaluation: To improve diversity in Fireworks, specific spark evaluation is carried out at random manner using Gaussian distribution.

$$g = gaussain(1, 1) \tag{15}$$

$$\hat{x}_j^k = x_j^k \cdot g \tag{16}$$

This additional process emphasizes to identify the strength of sparks indicating optimal location of Firework. To differentiate the spark evaluation to specific spark evaluation; in a group of five fireworks two firework undergoing specific spark evaluation is shown in Fig. 3(c).

Step 5: Identification of Global Location: Reserve the best Firework ($Gbest$, (x^*)) with least objective function for further iterations and remaining (n−1) Fireworks undergo distance evaluation to find their new locations in subsequent iteration as shown in Fig. 3(d). The distance between Fireworks is calculated as follows.

$$W(x_i) = \sum_{j \in K} d(x_i, x_k) = \sum_{j \in K} \|x_i - x_k\| \tag{17}$$

where 'K' corresponds to current locations of individual sparks where, the probability of Firework corresponding to different location is defined in the following.

$$Q(x_i) = \frac{W(x_i)}{\sum_{j \in K} W(x_i)} \tag{18}$$

The distance calculation may involve Euclidean distance, angular distance or Manhattan distance to calculate distance of Firework for next iteration. Fireworks new position after the 1st iteration is represented in Fig. 3(e). Two important steps that suit Firework to be a choice for non-linear problems are (i) Spark evaluations in first stage followed by specific spark evaluation create necessary randomness for the successful implementation of Firework method over existing methods. Surprisingly this reason has given overwhelming results on achieving lesser objective function value. (ii) Further the method predominantly avoids premature convergence via Gaussian distribution. The above factors influence the use of FW method parameter extraction problem. The flowchart for FWA implemented parameter estimation is shown in Fig. 4.

4. Results and discussions

In order to test the effectiveness of Fireworks based solar PV parameter extraction three panels such as KC200GT, SM55, SP70 of various make with entirely different characteristics having different materials Multi crystalline, mono crystalline are considered

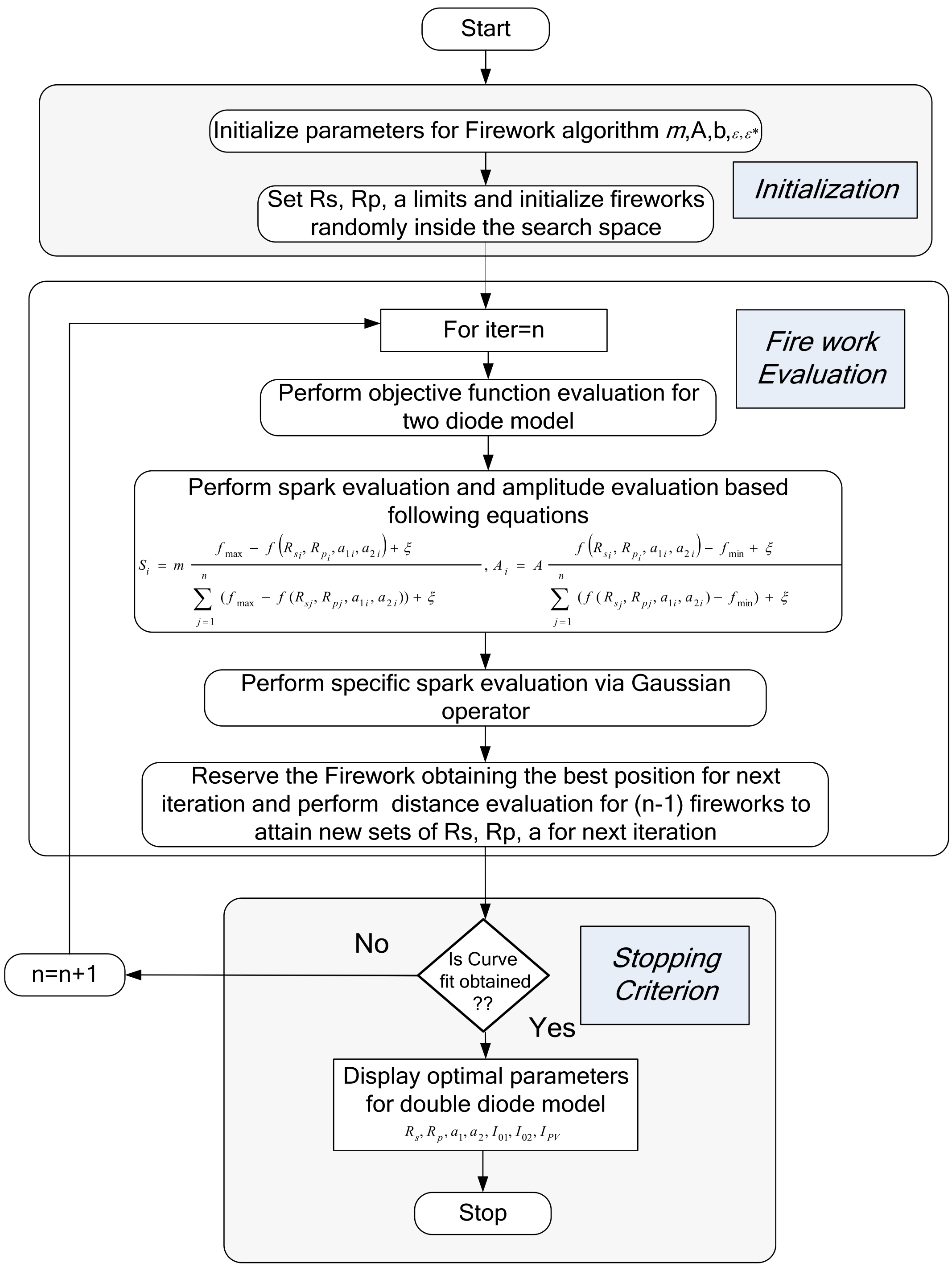

Fig. 4. Flowchart for FWA implemented for parameter estimation.

for the study. The usage of different panel types and its current market share is presented in Fig. 5. Since the efficiency and market share of multi crystalline and mono crystalline type panels are comparatively high, the authors validated their method only with aforementioned type panels.

To provide thorough evaluation, data corresponding to the above mentioned panels are taken from manufacturer's datasheet and I-V curves are matched with the simulation results obtained using FWA method. Further, to know the quality of the curve fit between FWA values to the experimental data, statistical analysis is carried out by measuring Individual Absolute Error (IAE) and Relative Error (RE) values. The IAE and RE values are calculated by using the mentioned formula.

$$\text{Individual Absolute Error (IAE)} = |I_{measured} - I_{estimated}| \quad (19)$$

$$\text{Relative Error (RE)} = \frac{I_{measured} - I_{calculated}}{I_{measured}} \quad (20)$$

To implement FW steps for parameter estimation, a dedicated software program is developed in MATLAB Two diode model parameter values obtained via FWA method is first substituted in the built-in simulation model and numerical simulations are performed for three panels under study. Simulations are carried out using 2.4 GHz INTEL i3 processor personal computer with 2.0 GB RAM and results are compared with GA and PSO method. Further to achieve better performance FWA parameters are tuned and their values are $n = 20,\ m = 50,\ a = 0.8,\ b = 0.8,\ \hat{A} = 40,\ \hat{m} = 20$.

The computed parameter values that correspond to 1000 W/m^2 irradiation are provided in Table 1. To investigate the closeness of the parameter values, the identified parameters are compared with some of the published results available in literature (Ishaque et al., 2011a, 2011b, 2011c).

From the comparison, it is evident that except $R_P,\ I_{01},\ I_{02}$ other parameters are in very close agreement with the parameters available in existing literature for the same panels under study. The deviation in $R_P,\ I_{01},\ I_{02}$ values could be attributed due to the following: (i). Ideally, to achieve high Fill Factor (FF) panels are designed to have high Rp (Solanki, 2015). Further high Rp value ensures shifts the I-V curve towards the MPP without much change in V_{oc} & I_{sc} values. On comparison, I-V curves of FWA method with the results presented in (Ishaque et al., 2011a, 2011c) it is clear that the curve plotted with (Ishaque et al., 2011a) deviates around MPP due to low R_P value. Also, R_s & R_P value is arrived via mathematical relation while, remaining five parameters are calculated analytically which is not an accurate validation moreover, RMSE value arrived in (Ishaque et al., 2011b) was high and the algorithm was struck to local convergence. But, in this work $a_1,\ a_2,\ R_s$ & R_P are computed via optimization procedure resulted in better convergence with very less RMSE. In order to demonstrate the variation that occur in I-V characteristics due to the difference in R_P values, the authors have simulated the double diode model with FW identified parameter and literature values. For understanding, the authors have represented the FW results as 'proposed', literature model as 'Kashif model' and datasheet values as 'datasheet' in Fig. 6. From the figure it is seen that the results with existing literature produce deviation in I-V characteristics and consequently accuracy is comprised. On the other hand, FW model is highly accurate and matches with larger area in I-V curve with very less error. (ii). For simplicity, the values of I_{01} and I_{02} are computed analytically but the diode ideality factor '$a_1,\ a_2$' influencing I_{01} and I_{02} are arrived via iteration in FW method whereas, all these values in

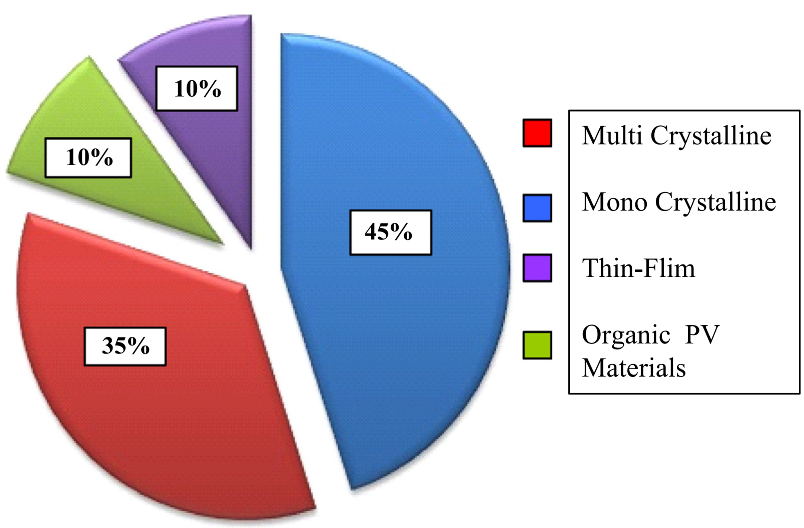

Fig. 5. Usage of different types of solar panels.

Table 1
Extracted model parameter values employing FWA, GA, PSO for different panels.

Parameters	SM55		KC200GT		SP70	
	FWA	Ishaque et al. (2011b)	FWA	Ishaque et al. (2011a)	FWA	Ishaque et al. (2011c)
I_{01} (A)	**2.35E−08**	2.232E−10	**1.11E−08**	4.218e−10	**1.87E−10**	4.206E−10
I_{02} (A)	**2.35E−08**	2.232E−10	**1.11E−08**	4.218e−10	**1.87E−10**	4.206E−10
R_s (Ω)	**0.54741**	0.47	**0.303**	0.32	**0.502444**	0.51
R_p (Ω)	**410.55**	144.3	**343.10**	160.5	**264.9071**	91
a_1	**1**	1.0	**1**	1	**1**	1.5
a_2	**1.2**	1.2	**1.2**	1.2	**1.2**	1.5
I_{PV}	**3.45**	3.45	**8.21**	8.21	**4.7**	4.7

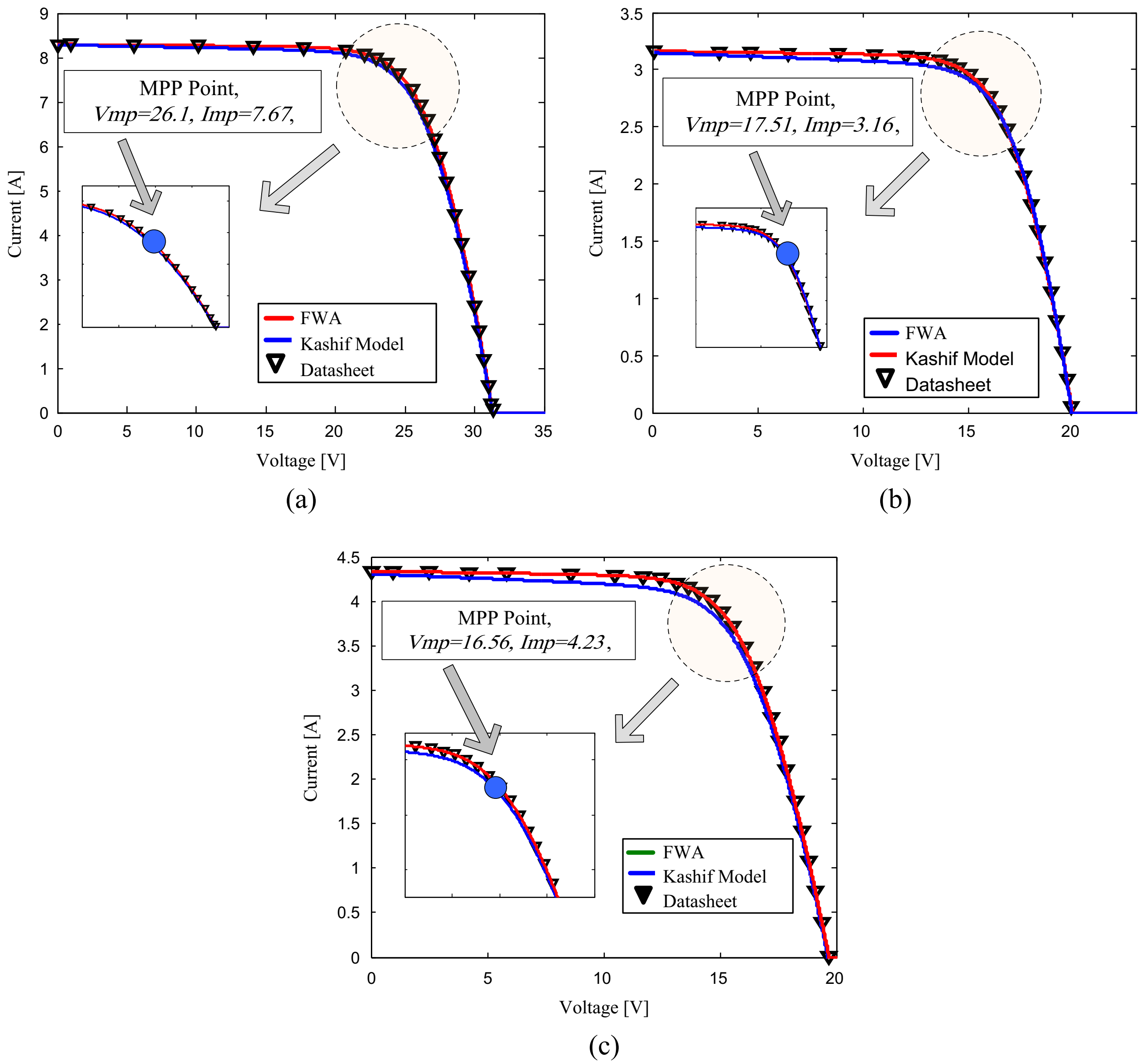

Fig. 6. Comparison of I-V characteristics between datasheet, Kashif model and FWA method for (a) Kyocera KC200GT panel, (b) SM55 panel and (c) SP70 panel.

(Ishaque et al., 2011c) are arrived analytically. However the differences that exist between methods of less significant in terms of PV cell modeling. This illustrates the viability of proposed method to double diode parameter estimation.

In order to check the quality of curve fit with the experimental data GA, PSO, FWA results are analyzed via statistical tools (i.e.) IAE and RE. The computed error values for SM55, Kyocera 200GT and SP70 panel that corresponds to GA, PSO and FWA methods are presented in Table 2–4 respectively. Further for brevity, experimental voltage (V_t) and (I_t) current values are presented along with simulated/calculated (I_{cal}) one.

From the tabulated values, it can be inferred that, when each point on I-V curve exactly match it attribute to lower IAE and RE values. For understanding, the significance of FWA is highlighted in bold. Further, the value of Individual Absolute Error values is the lowest for all the cases with FWA method. On the other hand, GA and PSO method introduce larger error between measured and calculated values; additionally these methods on an average produce individual absolute error of 0.34995 and 0.207503 respectively. In case of FWA method a close accuracy of 0.014065 is maintained. The error value is an indication that the I-V curves are expected to have in poor curve fit. The reason for large error in GA, PSO can be due to the fact that both methods do not involve any exploitation in control variables.

To further substantiate the performance of FWA method, the convergence characteristics are plotted for KC200GT, SM55 and SP70 panels along with GA and PSO method. The convergence curve indicates that FW method converges to the optimal value of 2.24 e−7, 4.0075 e−8 and 2.87e−8 for KC200GT, SM55 and SP70 panels respectively. Further, it is an indication that precise closeness is maintained between simulated and experimental data. It is been envisaged that GA method has involved large parameters and complex computation procedure in PV parameter estimation. Moreover, the GA method has failed to create randomness between iterations. While in case of PSO method, the velocity updation between particles is highly dependent to the initialization of parameters. Although it is an acceptable truth that PSO is one of the exceptional tools to solve non-linear problems however the

Table 2
Computation of IAE and RE of FWA, GA and PSO methods for Kyocera kc200gt (Multi crystalline) PV module.

Measurement	EXP		FWA			GA			PSO		
	Vt	It	Ical	IAE	RE	I cal	IAE	RE	Ical	IAE	RE
1	0.0000	8.1983	**8.2066**	**0.0082**	**0.0010**	8.2161	0.0095	0.0012	8.2131	0.0147	0.0008
2	0.5438	8.1770	**8.2066**	**0.0296**	**0.0036**	8.2161	0.0095	0.0012	8.2131	0.0361	0.0008
3	2.0268	8.1556	**8.1947**	**0.0392**	**0.0048**	8.2161	0.0214	0.0026	8.2131	0.0575	0.0022
4	3.0155	8.1556	**8.1829**	**0.0273**	**0.0033**	8.1968	0.0139	0.0017	8.2020	0.0464	0.0023
5	4.0042	8.1449	**8.1711**	**0.0262**	**0.0032**	8.1968	0.0257	0.0031	8.1909	0.0460	0.0024
6	5.2401	8.1342	**8.1592**	**0.0250**	**0.0031**	8.1871	0.0279	0.0034	8.1909	0.0567	0.0039
7	7.0198	8.1235	**8.1474**	**0.0239**	**0.0029**	8.1774	0.0300	0.0037	8.1687	0.0452	0.0026
8	8.1073	8.1128	**8.1237**	**0.0108**	**0.0013**	8.1774	0.0537	0.0066	8.1687	0.0559	0.0055
9	12.0127	8.0915	**8.1000**	**0.0085**	**0.0011**	8.1484	0.0484	0.0059	8.1466	0.0551	0.0057
10	13.9901	8.0594	**8.0763**	**0.0169**	**0.0021**	8.1387	0.0624	0.0077	8.1355	0.0761	0.0073
11	16.0169	8.0487	**8.0526**	**0.0039**	**0.0005**	8.1194	0.0667	0.0082	8.1244	0.0757	0.0088
12	17.5000	8.0273	**8.0290**	**0.0016**	**0.0002**	8.1194	0.0904	0.0111	8.1133	0.0860	0.0104
13	18.0438	8.0166	**8.0290**	**0.0123**	**0.0015**	8.1097	0.0807	0.0100	8.1022	0.0856	0.0090
14	19.0325	7.9959	**7.9653**	**0.0306**	**0.0038**	8.1000	0.1347	0.0166	8.1022	0.1063	0.0169
15	21.0099	7.8356	**7.8596**	**0.0240**	**0.0031**	8.0807	0.2211	0.0274	8.1022	0.2666	0.0299
16	22.0480	7.5632	**7.5816**	**0.0184**	**0.0024**	8.0807	0.4991	0.0618	7.9865	0.4233	0.0507
17	24.2232	7.1124	**7.1326**	**0.0202**	**0.0028**	8.0516	0.9191	0.1141	7.6583	0.5459	0.0686
18	26.0523	6.5866	**6.4988**	**0.0878**	**0.0135**	7.8871	1.3883	0.1760	7.3256	0.7391	0.1129
19	26.9915	6.0557	**6.0860**	**0.0303**	**0.0050**	7.6065	1.5205	0.1999	6.6895	0.6338	0.0902
20	28.5240	5.3658	**5.3990**	**0.0331**	**0.0061**	6.6097	1.2107	0.1832	5.6598	0.2940	0.0461
21	29.0184	4.3217	**4.3985**	**0.0769**	**0.0175**	6.1452	1.7466	0.2842	4.9856	0.6640	0.1178
22	30.0565	3.6527	**3.6359**	**0.0168**	**0.0046**	4.9258	1.2899	0.2619	3.8956	0.2429	0.0667
23	31.2924	2.5352	**2.5599**	**0.0247**	**0.0096**	3.0523	0.4924	0.1613	2.9568	0.4216	0.1342
24	32.0339	1.3756	**1.3895**	**0.0139**	**0.0100**	1.6469	0.2574	0.1563	1.9865	0.6109	0.3005
25	32.9237	0.1496	**0.1492**	**0.0004**	**0.0029**	0.1533	0.0041	0.0267	0.8956	0.7460	0.8334

Table 3
Computation of IAE and RE of FWA, GA and PSO methods for SM55 (Mono crystalline) PV module.

Measurement	EXP		FWA			GA			PSO		
	Vt	It	Ical	IAE	RE	I cal	IAE	RE	Ical	IAE	RE
1	0	3.4367	**3.4514**	**0.0147**	**0.0043**	3.4541	0.0027	0.0008	3.4617	0.0250	0.0030
2	1	3.4367	**3.4457**	**0.0090**	**0.0026**	3.4541	0.0084	0.0024	3.4530	0.0163	0.0021
3	2	3.4367	**3.4457**	**0.0090**	**0.0026**	3.4450	0.0008	0.0002	3.4486	0.0119	0.0008
4	3	3.4367	**3.4400**	**0.0033**	**0.0010**	3.4450	0.0050	0.0014	3.4442	0.0075	0.0012
5	5	3.4315	**3.4343**	**0.0028**	**0.0008**	3.4312	0.0031	0.0009	3.4398	0.0083	0.0016
6	6	3.4264	**3.4286**	**0.0022**	**0.0006**	3.4266	0.0020	0.0006	3.4355	0.0091	0.0020
7	6.8	3.4264	**3.4229**	**0.0035**	**0.0010**	3.4220	0.0008	0.0002	3.4355	0.0091	0.0037
8	7	3.4264	**3.4229**	**0.0035**	**0.0010**	3.4220	0.0008	0.0002	3.4355	0.0091	0.0037
9	9	3.4264	**3.4171**	**0.0092**	**0.0027**	3.4083	0.0089	0.0026	3.4267	0.0003	0.0028
10	12	3.4160	**3.4114**	**0.0046**	**0.0013**	3.3899	0.0215	0.0063	3.4092	0.0068	0.0007
11	13.5	3.4057	**3.4000**	**0.0057**	**0.0017**	3.3670	0.0330	0.0098	3.3917	0.0140	0.0025
12	14	3.3954	**3.4000**	**0.0046**	**0.0014**	3.3532	0.0468	0.0140	3.3786	0.0168	0.0063
13	14.4	3.3954	**3.3943**	**0.0011**	**0.0003**	3.3440	0.0502	0.0150	3.3698	0.0256	0.0073
14	15.4	3.3649	**3.3657**	**0.0008**	**0.0002**	3.3165	0.0492	0.0148	3.3392	0.0257	0.0079
15	16	3.2157	**3.2166**	**0.0009**	**0.0003**	3.2798	0.0633	0.0193	3.3392	0.1235	0.0367
16	16.3	3.0874	**3.0815**	**0.0059**	**0.0019**	3.2523	0.1708	0.0525	3.3129	0.2255	0.0698
17	17	2.8856	**2.8789**	**0.0067**	**0.0023**	3.1609	0.2820	0.0892	3.2867	0.4010	0.1241
18	17.5	2.5564	**2.5652**	**0.0088**	**0.0034**	3.0615	0.4963	0.1621	2.9875	0.4311	0.1414
19	17.6	2.1863	**2.1965**	**0.0102**	**0.0046**	3.0406	0.8441	0.2776	2.6580	0.4717	0.1736
20	18.3	1.8256	**1.8298**	**0.0042**	**0.0023**	2.8118	0.9820	0.3492	2.3652	0.5396	0.2264
21	19.8	1.4365	**1.4165**	**0.0200**	**0.0141**	1.9317	0.5152	0.2667	1.8965	0.4600	0.2531
22	20	0.9898	**0.9865**	**0.0033**	**0.0033**	1.7294	0.7429	0.4296	1.3680	0.3782	0.2789
23	20.9	0.6103	**0.6235**	**0.0132**	**0.0212**	0.8677	0.2442	0.2814	0.9987	0.3884	0.3757
24	21	0.2364	**0.2351**	**0.0013**	**0.0055**	0.7448	0.5097	0.6843	0.4560	0.2196	0.4844
25	21.7	0.0000	**0.0010**	**0.0010**	**1.0000**	0.0010	0.0000	0.0000	0.3125	0.3125	0.9968

improper particle updation made the PSO to end at local convergence. Further, the FWA method handles two stages of computation to create diversity in particles. Hence the scope for convergence to minimal error is always present in the Firework updation. This reason has made the FWA to converge faster with lesser iterations compared to GA and PSO method. The convergence characteristics for Kyocera200GT, SM55 and SP70 panels for PSO, GA and FWA methods are represented in Fig. 7 (a), (b) and (c) respectively. The key reason behind the slower convergence is: GA method uses more steps with large population size while PSO method require more tuning to converge at optimal value. From the figure it is seen that on an average GA and PSO method take 3.611 s and 1.71 s respectively to arrive at optimal solutions. With simple steps and fewer parameters to tune FWA method converged to low objective function within 0.7596 s.

Table 4
Computation of IAE and RE values of FWA, GA and PSO methods for SP70 (Mono crystalline) PV module.

Measurement	EXP		FWA			GA			PSO		
	Vt	It	I cal	IAE	RE	I cal	IAE	RE	Ical	IAE	RE
1	0	4.67821	**4.68843**	**0.0102**	**0.0022**	4.7095	0.0210	0.0045	4.6914	0.0132	0.0006
2	0.4	4.6791	**4.68843**	**0.0093**	**0.0020**	4.7095	0.0210	0.0045	4.6914	0.0123	0.0006
3	1	4.6791	**4.68843**	**0.0093**	**0.0020**	4.7095	0.0210	0.0045	4.6914	0.0123	0.0006
4	2.1	4.67463	**4.68843**	**0.0138**	**0.0029**	4.7018	0.0134	0.0028	4.6914	0.0167	0.0006
5	2.5	4.67463	**4.68101**	**0.0064**	**0.0014**	4.6942	0.0132	0.0028	4.6914	0.0167	0.0022
6	3.1	4.67015	**4.67359**	**0.0034**	**0.0007**	4.6942	0.0206	0.0044	4.6836	0.0135	0.0021
7	3.5	4.67015	**4.67359**	**0.0034**	**0.0007**	4.6942	0.0206	0.0044	4.6836	0.0135	0.0021
8	4	4.67015	**4.67359**	**0.0034**	**0.0007**	4.6872	0.0136	0.0029	4.6836	0.0135	0.0021
9	4.5	4.67003	**4.67045**	**0.0004**	**0.0001**	4.6865	0.0161	0.0034	4.6759	0.0059	0.0012
10	5	4.67003	**4.67045**	**0.0004**	**0.0001**	4.6789	0.0084	0.0018	4.6759	0.0059	0.0012
11	5.5	4.66935	**4.67359**	**0.0042**	**0.0009**	4.6789	0.0053	0.0011	4.6759	0.0066	0.0005
12	6.6	4.66935	**4.67025**	**0.0009**	**0.0002**	4.6588	0.0115	0.0025	4.6759	0.0066	0.0012
13	7.4	4.66567	**4.66361**	**0.0021**	**0.0004**	4.6588	0.0049	0.0010	4.6682	0.0025	0.0010
14	8	4.66567	**4.65875**	**0.0069**	**0.0015**	4.6636	0.0049	0.0010	4.6682	0.0025	0.0020
15	8.5	4.5632	**4.5689**	**0.0057**	**0.0012**	4.6588	0.0899	0.0193	4.6682	0.1050	0.0213
16	9.4	4.4462	**4.4358**	**0.0104**	**0.0023**	4.6521	0.2163	0.0465	4.6605	0.2143	0.0482
17	10.6	4.2256	**4.1968**	**0.0288**	**0.0069**	4.6483	0.4515	0.0971	4.6605	0.4349	0.0995
18	11	3.76598	**3.75624**	**0.0097**	**0.0026**	4.6407	0.8844	0.1906	4.3568	0.5908	0.1378
19	12	3.3652	**3.3894**	**0.0242**	**0.0071**	4.6330	1.2436	0.2684	3.8956	0.5304	0.1299
20	12.8	3.0652	**3.08952**	**0.0243**	**0.0079**	4.6254	1.5359	0.3321	3.5689	0.5037	0.1343
21	13.6	2.6362	**2.6532**	**0.0170**	**0.0064**	4.6177	1.9645	0.4254	2.9999	0.3637	0.1156
22	14.8	1.8856	**1.8652**	**0.0204**	**0.0109**	4.5566	2.6914	0.5907	2.3658	0.4802	0.2116
23	19	1.3895	**1.3489**	**0.0406**	**0.0301**	2.8700	1.5211	0.5300	1.8957	0.5062	0.2884
24	20.9	0.7562	**0.7325**	**0.0237**	**0.0324**	0.6708	0.0617	0.0919	1.3635	0.6073	0.4628
25	21.4	0.049254	**0.0653**	**0.0160**	**0.2457**	0.0120	0.0533	4.4417	0.5658	0.5165	0.8846

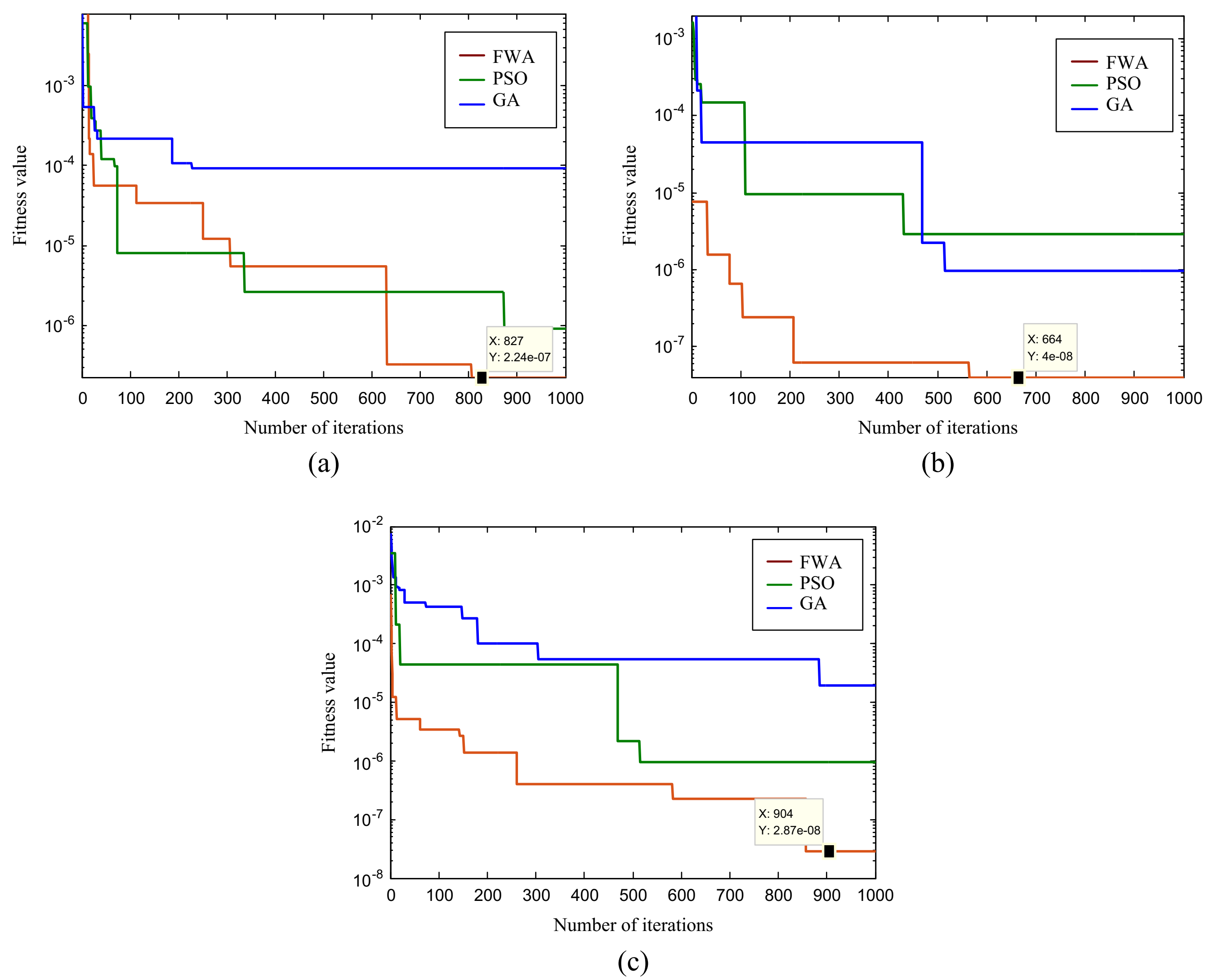

Fig. 7. Convergence curve for GA, PSO and FWA methods for (a) Kyocera KC200GT, (b) SM55, (c) SP70 PV panels.

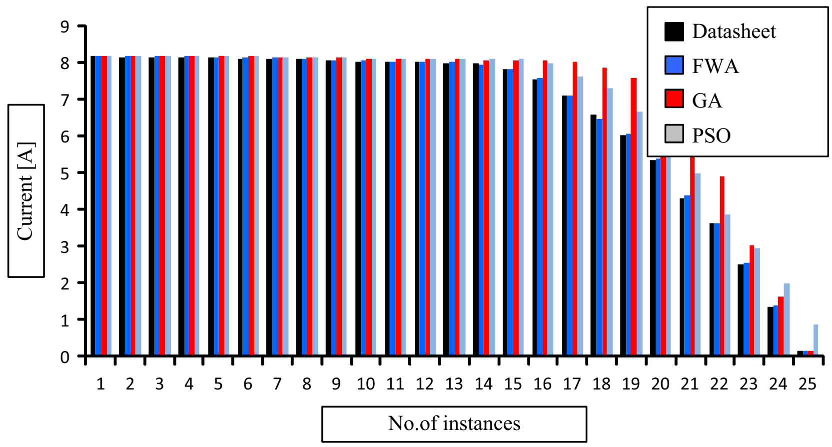

Fig. 8. Comparison of I-V characteristics between actual and obtained data of FWA, GA and PSO method for KyoceraKC200GT (Multi-crystalline).

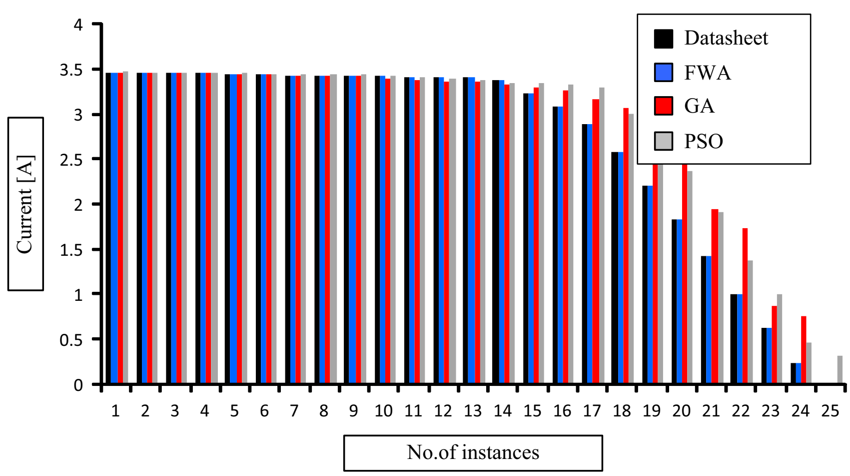

Fig. 9. Comparison of I-V characteristics between actual and obtained data of FWA, GA and PSO method for SM55 (Mono crystalline).

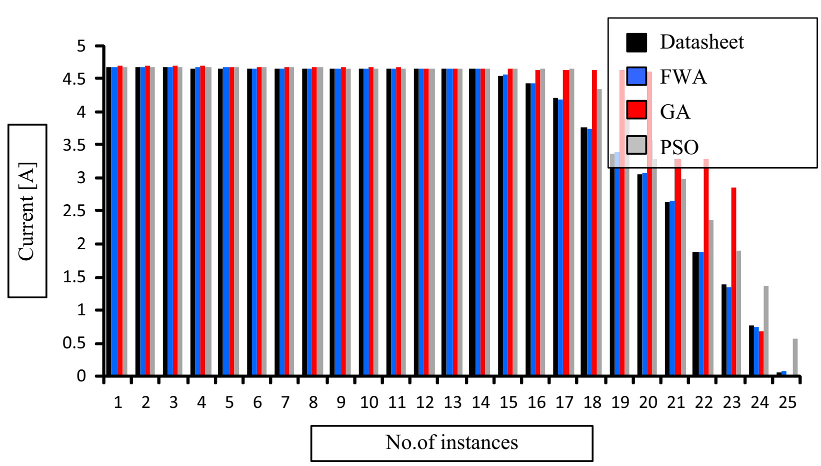

Fig. 10. Comparison of I-V characteristics between actual and obtained data of FWA, GA and PSO method for SP70 (Mono crystalline).

To confine with to date results the final convergence value is compared with recent Flower Pollination Algorithm proposed by Alam et al. (2015). Alike to FWA method, Flower Pollination algorithm perform dual stage search to arrive optimal PV parameter value. In this method, the probability to create randomness via local search is very less. Since the probability switch in FPA method allows only 10–20% of initial population to undergo local pollination hence only pollens are restricted to search locally. As a consequence FPA method has higher error value on parameter estimation. In FWA method, the Firework undergoing spark evaluation will also undergo specific spark evaluation to identify the optimal regions for global convergence. This feature is absent in

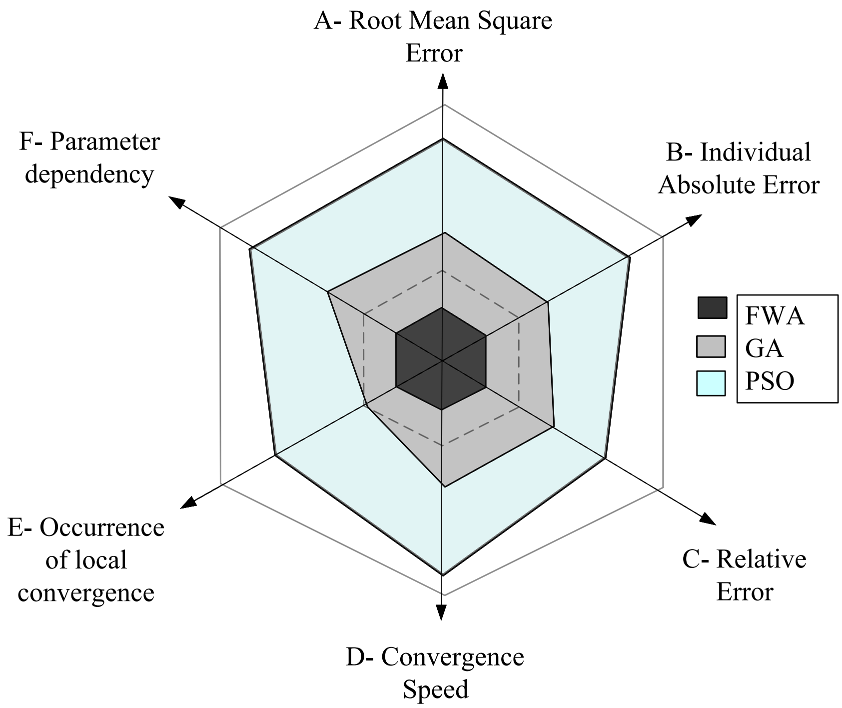

Fig. 11. Wheel chart based performance comparison of FWA, GA &PSO methods.

Table 5
Qualitative comparison of different methods employed in PV parameter estimation.

S. no	Parameter/method	Genetic Algorithm	Particle Swarm Optimization	Harmony search	Bird Mating Optimizer	Fire Works Algorithm
1	Convergence speed	Less	Moderate	Moderate	Moderate	High
2	Accuracy in curve fit	Less	Less	High	High	High
3	Parameter dependency	High	High	Moderate	Moderate	Less
4	Occurrence of local convergence	High	High	High	High	Less
5	Randomness in control variables	Less	Less	Moderate	Moderate	High
6	Step involved	Moderate	Moderate	Moderate	Moderate	Less

recently proposed methods like FPA and Differential Evolution methods.

In order to test the curve fit accuracy of GA, PSO and FWA methods, I-V curve for PV modules Kyocera200GT, SM55 and SP70 is plotted in Figs. 8, 9 and 10 respectively. To plot the characteristics, the actual current value at 25 instances from manufacturer data sheet is utilized and verified with the simulated data's. From the figure it is observed that, FWA method has closer resemblance with actual values and attribute to exact reproduction of I-V curve whereas, PSO and GA methods induce higher percentage of error when compared to FWA method. Notably, the slope of the I-V characteristics highly deviated due to the improper optimization in PV parameters.

5. Comparative study

To further emphasize the importance of FWA method a quantitative comparison is made with GA and PSO methods on six different parameters: (a) Root Mean Square Error, (b) Individual Absolute Error (c) Relative Error, (d) Convergence speed, (e) Occurrence of local convergence and (f) Parameter dependency. Wheel chart portraying the performance of the methods based on the above performance criteria is presented in Fig. 11. The chart can be understood in the following way, the method occupying lower radius in the circle indicate that it deliver optimal performance and is more suitable for PV parameter estimation while, the method with higher radii show high complexity and protrude to high relative error in I-V characteristics. Thus from Fig. 11, it can be summarized that FWA method is the best alternatives for existing methods.

In addition to quantitative comparison, a qualitative comparison is also made between methods available in literature and presented in Table 5. Further it is an essential assessment to know the validity of any optimization method. The detailed summary given in Table 5 indicates that FWA method takes fewer steps produce high curve fit accuracy in shorter time. As most valued benefit, the randomness in control variable in FWA method is always present as a notable merit. Further, converging to lower RMSE at the initial stage of computation is the key success of FWA method.

6. Conclusion

In this paper a new Fireworks algorithm for solar PV parameter estimation is proposed and the following conclusions are arrived.

(i) It is seen that the exploration and exploitation ability in Fireworks algorithm have a strong impact in reducing the probabilities of premature convergence.
(ii) To reduce computational complexity only four parameters (a_1, a_2, R_s, R_P) are obtained iteration wise and the other values are calculated manually.
(iii) The generated code via FWA method applied to KC200GT, SM55 and SP70 panels produces near accurate I-V characteristics in agreement to panel data sheet.

(iv) Convergences of panels Kyocera KC200GT, SM55 and SP70 via FWA starting at lower value have influenced FWA to attain faster convergence at 0.75 s while GA and PSO methods took 3.6 s and 1.7 s respectively.
(v) Performance comparison of FWA with GA and PSO methods, the Fireworks algorithm has acquired superior performance with accurate curve fit in P-V characteristics.

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