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Parameter identification for solar cells and module using a Hybrid Firefly and Pattern Search Algorithms

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ABSTRACT

Accurate estimation the electrical equivalent circuit parameters of photovoltaic arrays of solar cells is needed to enhance the performance of solar energy systems. Thus this field has attracted the attention of various researchers. Since the current versus voltage *I-V* characteristics of photovoltaic is nonlinear, thus an optimization technique is necessary to adjust experimental data to the solar cell model. Some optimization algorithms have been used to estimate the electrical parameters of the model. However, more investigation is needed to improve estimation of the model. The Firefly algorithm is one of the recently proposed swarm intelligence based optimization algorithm that showed impressive performance in solving optimization problems. This algorithm is good for exploring solution if applied alone but need a local optimization method to improve exploitation. In this study, we combine pattern search as a local optimization method with firefly algorithm to improve this algorithm. The proposed algorithm is applied for parameter estimation of single and double diode solar cell models. To show the performance of this algorithm the results are compared, with the other optimization algorithms for parameters of photovoltaic. The results show that the proposed algorithm is a competitive algorithm to be considered in the modeling of solar cell systems.

1. Introduction

Renewable energy sources gaining the attention of many researchers because of increasing cost of fossil fuels and their probable depletion and other issues such as air pollution, global warming phenomenon. Solar energy is a powerful renewable energy source to be apply in many applications.

Recently, different approaches have been introduced for the extraction of optimal parameters for solar cells. Traditional methods and evolutionary methods can be considered as main types for the extraction of optimal parameters (Chan et al., 1986; Lun et al., 2013; Zhang et al., 2011). Different traditional methods to obtain the parameters were used including Newton–Raphson method (Easwarakhanthan et al., 1986; Phang et al., 1984), conductivity method (CM) (Chegaar et al., 2001) and the Levenberg–Marquardt (LM) algorithm (Ma et al., 2014). Solutions of these approaches are depended on the initial parameter values and easily trapped into local optima. Thus, traditional methods are not suitable to extract optimal parameters for solar cells. Thus, evolutionary algorithms are proposed to solve these issues that are based on global optimization population algorithms (Tamrakar and Gupta, 2015). Gervase et al. used Genetic Algorithm (GA) method for PV parameter extraction problem in 2001 (Jervase et al., 2001). Particle Swarm Optimization (PSO) approach is applied for PV parameter extraction problem by Ye et al., (2009) and Wei et al. (2011). Simulated Annealing (SA) and a pattern search heuristic algorithms are used for this purpose also (El-Naggar et al., 2012; AlHajri et al., 2012). Differential Evolution (DE) method is a simple powerful population-based stochastic search technique that is applied for PV parameter extraction in (Ishaque and Salam, 2011). Other algorithms, called artificial bee colony (ABC) and artificial bee swarm optimization (ABSO) that inspired foraging behavior of honey bee swarm were applied for PV parameter extraction problem by Askarzadeh and Rezazadeh (2013a), Oliva et al. (2014). Pattern search algorithm (PS) is also used in (Askarzadeh and Rezazadeh, 2013a) as a method. A harmony search (HS) and improved global HS (IGHS) optimization algorithm that inspired tuning music based on the available memory is used for the PV parameter extraction process. To find global optimum, main parameters, including pitch adjusting rate, bandwidth and harmony memory should be adjusted in this algorithm (Askarzadeh and Rezazadeh, 2012). Bird Mating Optimization (BMO) techniques, mimicking metaphorically the mating strategies of bird species were used for the PV parameter extraction process in (Askarzadeh and Rezazadeh,

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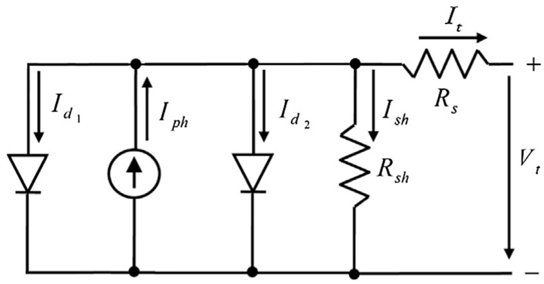

Fig. 1. Equivalent circuit of the double model with seven parameters.

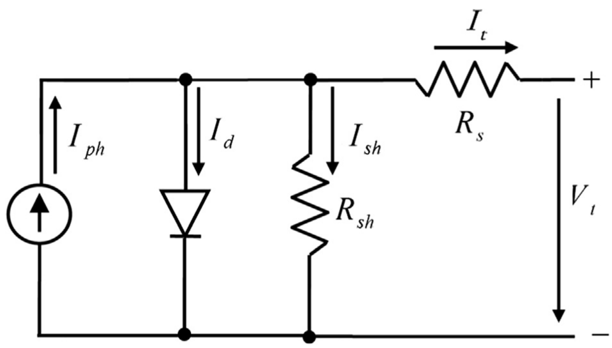

Fig. 2. Equivalent circuit of the single model with five parameters.

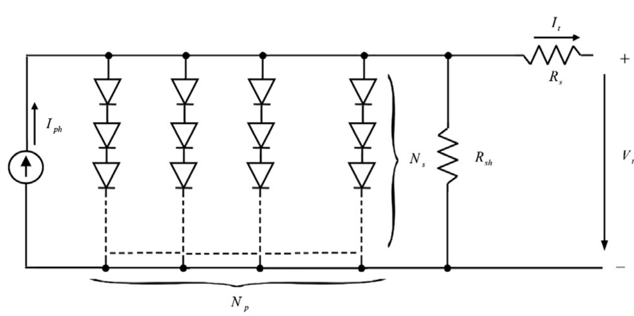

Fig. 3. Equivalent circuit of the single diode module with five parameters.

Table 1
Bounds of the solar cell models and PV modules parameters.

Parameter	Lower	Upper	Lower	Upper
$R_s(\Omega)$	0	0.5	0	2
$R_{sh}(\Omega)$	0	100	0	2000
$I_{ph}(A)$	0	1	0	10
$I_{sd}(\mu A)$, $I_{sd_1}(\mu A)$ and $I_{sd_2}(\mu A)$	0	1	0	50
n , n_1, and n_2	1	2	1	100

2013b). Rajasekar et al. (2013) implement Bacterial Foraging Algorithm (BFA) that is inspired by the pattern exhibited by bacterial foraging behaviors to enhance PV parameter extraction problem (Rajasekar et al., 2013). A simplified swarm optimization (SSO) and modified SSO (MSSO) introduced by Lin et al. (2017) to improve PV parameter extraction problem (Lin et al., 2017). In (Chen et al. 2016) a new optimization method called GOTLBO (generalized oppositional teaching learning based optimization) was used to extract the parameters of solar cell performance. Multi-verse optimization (MVO) has been used in (Ali et al., 2016) for curve fitting I-V characteristic in photovoltaic. Improved variants of Particle Swarm Optimization (PSO) including Quantum Particle Swarm Optimization (QPSO) by Muralidharan (2017), chaos particle swarm optimization algorithm (CPSO) by Wei et al. (2011), and PSO with enhanced leader, named as

Step 1: set parameters and initialize
  Generate the initial population of *n* Fireflies
  Define light absorption coefficient
Step 2: Main evolution loop
  For *k*=1:MaxGeneration
  Evaluate new solutions and update light intensity
  Rank the Fireflies and the current best solution.
    For *i*=1:*n*
      For *j*=1:*n*
      if $(I_i > I_j)$
        Calculate distance *r* between two butterflies
        Calculate attractiveness via $\exp[-\gamma r^2]$
        Move Firefly *i* towards *j* via (11).
      End *if*
      End for *j*
    End for *i*
  End for *k*

Fig. 4. Pseudo code of the Firefly Algorithm.

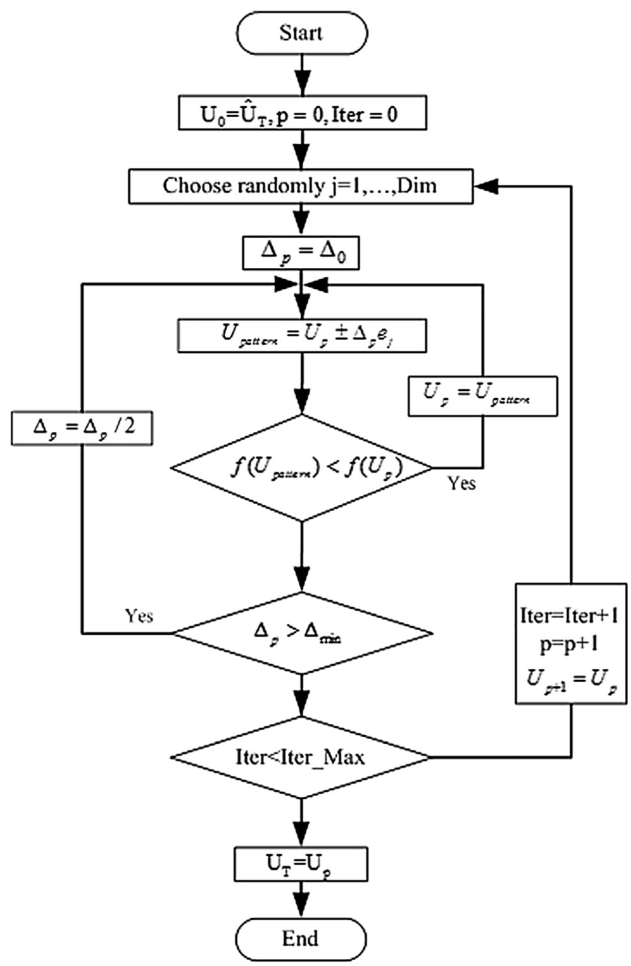

Fig. 5. Flowchart of pattern search algorithm.

enhanced leader PSO (ELPSO) by Jordehi (2018) were also used for parameter extraction of solar cells. Tong and Pora (2016) proposed a simple algorithm, which is called a loop of search process called (LSP) and uses the prior knowledge of load points an intrinsic property of solar cells to parameter extraction of solar cells. Mughal et al. (2017)

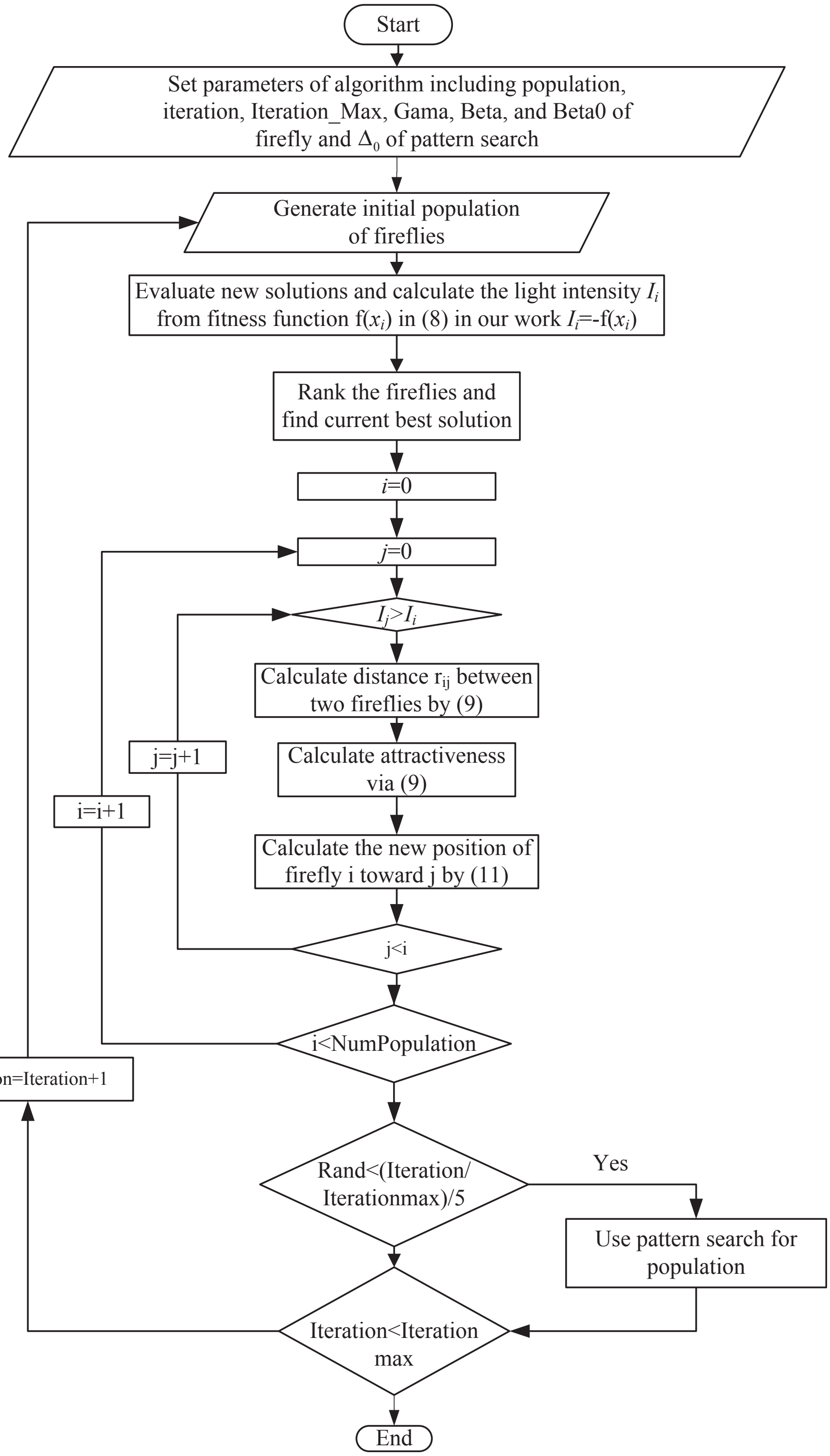

Fig. 6. Flowchart of proposed HFAPS algorithm.

used hybrid particle swarm optimization and simulated annealing (HPSOSA) to extract solar cell parameters. A new hybrid Bee pollinator Flower Pollination Algorithm (BPFPA) for the PV parameter extraction problem introduced by Ram et al. (2017).

However, these algorithms suffer from premature convergence problem. Pattern search (PS) has been used widely in various scientific and engineering fields. However, it is successful in local search and suffers from premature convergence to local optimum (Torczon, 1997). Firefly Algorithm is a recently proposed meta-heuristic optimization technique, developed by Yang (2010b), which has been successfully used to solve mixed variable and constrained engineering problems (Gandomi et al., 2011). This algorithm does not show good performance at exploitation step. In this study we introduced hybrid firefly algorithm and pattern search algorithm to improve PV parameter extraction problem.

The rest of the paper is organized as follow: The Photovoltaic modeling and problem formulation by the objective function is described in Section 2. In Section 3 FA, PS and HFAPS algorithms are

Table 2
The results of parameters extraction for the SD model by various methods.

Approaches	Parameters					
Algorithm	$I_{ph}(A)$	$I_{sd}(\mu A)$	$R_s(\Omega)$	n	$R_{sh}(\Omega)$	RMSE
MVO	0.7616	0.32094	0.0365	1.5252	59.5884	0.1268
BFA	0.7602	0.8000	0.0325	1.6951	50.8691	0.029
GA	0.7619	0.8087	0.0299	1.5751	42.3729	0.01908
SA	0.7620	0.4798	0.0345	1.5172	43.1034	0.01900
LSP	0.7610	0.3635	0.03660	1.4935	62.574	1.5051E − 3
PS	0.7617	0.9980	0.0313	1.6000	64.1026	0.01494
NRM	0.7608	0.3223	0.0364	1.4837	53.7634	0.010072
HPSOSA	0.7608	0.3107	0.0365	1.4753	52.8898	0.0071
CPSO	0.7607	0.4000	0.0354	1.5033	59.012	0.00139
QPSO	0.7606	0.273	0.037	1.46	51.18	0.0010
PSO	0.7607	0.4000	0.0354	1.5033	59.0120	0.0013
CM	0.7608	0.4039	0.0364	1.5039	49.5050	2.8573E-03
BPFPA	0.76	0.3106	0.0366	1.4774	57.7151	1.2535E-03
HS	0.7607	0.30495	0.03663	1.47538	53.5946	9.9510E-04
IGHS	0.76077	0.34351	0.03613	1.48740	53.2845	9.9306E-04
ABSO	0.76080	0.30623	0.03659	1.47583	52.2903	9.9124E-04
GGHS	0.76092	0.32620	0.03631	1.48217	53.0647	9.9097E-4
GOTLBO	0.760780	0.331552	0.036265	1.483820	54.115426	9.87442E-04
SSO	0.760803	0.321044	0.036392	1.480468	53.152466	9.8640E-04
ABC	0.7608	0.3251	0.0364	1.4817	53.6433	9.862E-04
BMO	0.76077	0.32479	0.03636	1.48173	53.87	9.8608E-04
MSSO	0.760777	0.323564	0.036370	1.481244	53.742465	9.8607E-04
FA	0.760872	0.258459	0.037247	1.45907	48.3069	0.0010729
Proposed HFAPS	0.760777	0.322622	0.0363819	1.48106	53.6784	9.8602E-04

Table 3
The results of parameters extraction for the DD model by various methods.

Approaches	Parameters							
Algorithm	$I_{ph}(A)$	$I_{sd_1}(\mu A)$	$R_s(\Omega)$	n_1	$I_{sd_2}(\mu A)$	n_2	$R_{sh}(\Omega)$	RMSE
GA	0.7608	0.0001	0.0364	1.3355	0.0001	1.481	53.7185	3.6040E-01
PSO	0.7623	0.4767	0.0325	1.5172	0.01	2	43.1034	1.6600E-02
SA	0.7623	0.4767	0.0345	1.5172	0.0100	2.0000	43.1034	1.664E-02
PS	0.7602	0.9889	0.0320	1.6000	0.0001	1.1920	81.3008	1.518E-02
ELPSO	0.760808	1.000	0.037551	1.835767	9.92E-02	1.386091	55.920471	7.467E-03
BPFPA	0.76	0.3211	0.0364	1.4793	0.04528	2	59.624	5.687E-03
HS	0.76176	0.12545	0.03545	1.49439	0.25470	1.49989	46.82696	1.26E-03
BFA	0.7609	0.0094	60.0000	1.3809	0.0453	1.5255	0.0351	1.2E-03
GGHS	0.76056	0.37014	0.03562	1.49638	0.13504	1.92998	62.7899	1.07E-03
SSO	0.760651	0.287201	0.036255	1.510345	0.065979	1.433838	55.853271	9.9129E-04
IGHS	0.76079	0.97310	0.03690	1.92126	0.16791	1.42814	56.8368	9.8635E-4
ABC	0.760813	0.192684	0.036861	1.438003	0.999587	1.983721	55.933515	9.8387E-04
ABSO	0.76078	0.26713	0.03657	1.46512	0.38191	1.98152	54.6219	9.8344E-04
GOTLBO	0.760752	0.800195	0.036783	1.999973	0.220462	1.448974	56.075304	9.83177E-04
MSSO	0.760748	0.234925	0.036688	1.454255	0.671593	1.995305	55.714662	9.8281E-04
BMO	0.76078	0.21110	0.03682	1.44533	0.87688	1.99997	55.8081	9.8262E-04
FA	0.761006	0	0.0367134	2	0.292634	1.47134	49.1867	1.011E-03
Proposed HFAPS	0.760781	0.225974	0.0367404	1.45101	0.749358	2	55.4855	9.8248E-04

presented. Simulation and results are demonstrated in Section 4. Finally, the study is concluded in Section 5.

2. Photovoltaic modeling and problem formulation

To describe the *I–V* characteristics of solar cells many models have been developed in the literature, but mostly used only two models single and double diode model. In this study, we used three most used case studies to evaluate proposed HFAPS. A 57 mm diameter commercial (R.T.C. France) silicon solar cell from the system under 1 sun ($1000\ W/m^2$) at 33 °C (Easwarakhanthan et al., 1986) and solar module Photowatt-PWP 201 in which 36 polycrystalline silicon cells are connected in series under 1 sun ($1000\ W/m^2$) at 45 °C and a solar panel model STM6-40/36 consists of 36 Monocrystalline cells aligned in series at 51 °C and full irradiance.

2.1. Solar cell model

2.1.1. Double diode (DD) model

An ideal solar cell model consists of a photo-generated I_{ph} current source which is shunted with a rectifying diode. In practice, to model the space charge recombination current I_{ph} is shunted by another diode. Furthermore, for the partial short circuit current path near the cell's edges a shunt leakage resistor is considered. A series resistance is considered in the model to represent resistance due to metal contacts which combined with semiconductor materials. Fig. 1 shows the equivalent circuit for the DD model. According to Fig. 1, the cell terminal current is computed as follows (Ishaque and Salam, 2011; Ma et al., 2014):

Where I_t is the terminal current, I_{ph} the photo-generated current, I_{sd_1}, I_{sd_2} is the first and second diode currents whereas I_{sh} is the shunt resistor current. The Shockley diode equation is used to model the solar

Table 4
Comparison of actual and experimental values for single and double diode model.

Measurement	Measurement		Single diode model		Double diode model	
	V_t	I_t	$I_{t(Calculated)}$	Relative error	$I_{t(Calculated)}$	Relative error
1	−0.2057	0.764	0.7641	−0.00013089	0.7640	0
2	−0.1291	0.762	0.7627	−0.00091864	0.7626	−0.0007874
3	−0.0588	0.7605	0.7614	−0.0011834	0.7613	−0.0010519
4	0.0057	0.7605	0.7602	0.00039448	0.7602	0.00039448
5	0.0646	0.76	0.7591	0.0011842	0.7591	0.0011842
6	0.1185	0.759	0.7580	0.0013175	0.7581	0.0011858
7	0.1678	0.757	0.7571	−0.0001321	0.7572	−0.0002642
8	0.2132	0.757	0.7561	0.0011889	0.7563	0.0009247
9	0.2545	0.7555	0.7551	0.00052945	0.7552	0.00039709
10	0.2924	0.754	0.7537	0.00039788	0.7537	0.00039788
11	0.3269	0.7505	0.7514	−0.0011992	0.7514	−0.0011992
12	0.3585	0.7465	0.7474	−0.0012056	0.7473	−0.0010717
13	0.3873	0.7385	0.7401	−0.0021666	0.7400	−0.0020311
14	0.4137	0.728	0.7274	0.00082418	0.7272	0.0010989
15	0.4373	0.7065	0.7070	−0.00070771	0.7068	−0.00042463
16	0.459	0.6755	0.6753	0.00029608	0.6752	0.00044412
17	0.4784	0.632	0.6308	0.0018987	0.6308	0.0018987
18	0.496	0.573	0.5719	0.0019197	0.5720	0.0017452
19	0.5119	0.499	0.4996	−0.0012024	0.4997	−0.0014028
20	0.5265	0.413	0.4137	−0.0016949	0.4137	−0.0016949
21	0.5398	0.3165	0.3175	−0.0031596	0.3175	−0.0031596
22	0.5521	0.212	0.2122	−0.0009434	0.2121	−0.0004717
23	0.5633	0.1035	0.1023	0.011594	0.1021	0.013527
24	0.5736	−0.01	−0.0087	0.13	−0.0088	0.12
25	0.5833	−0.123	−0.1255	−0.020325	−0.1255	−0.020325
26	0.59	−0.21	−0.2084	0.007619	−0.2083	0.0080952
MAE				0.0075		0.0071

cell; therefore, from (1) we have (2).

$$I_t = I_{ph} - I_{d_1} - I_{d_2} - I_{sh} \tag{1}$$

$$I_t = I_{ph} - I_{sd_1}\left[\exp\left(\frac{q(V_t + R_S I_t)}{n_1 KT}\right) - 1\right] - I_{sd_2}\left[\exp\left(\frac{q(V_t + R_S I_t)}{n_2 KT}\right) - 1\right] - \frac{V_t + R_S I_t}{R_{sh}} \tag{2}$$

where I_{sd_1} is the diffusion current and I_{sd_2} is saturation current. The series and shunt resistances are R_s and R_{sh} respectively. V_t is the terminal voltage. $k = 1.380653*10^{-23}(j/k)$ is the Boltzmann constant. $q = 1.60217646*10^{-19}$ (Coulombs) is the magnitude of charge on an electron, n_1 and n_2 are the diffusion and recombination diode ideality factors, respectively. Finally, T is the cell temperature in Kelvin. Therefore, seven unknown parameters in (2) are R_s, R_{sh}, I_{ph}, I_{sd_1}, I_{sd_2}, n_1 and n_2. A precise estimation of such parameters allows projecting the desirable performance of a solar cell (Anne and Michel, 2006; Mohammed, 2011).

2.1.2. Single diode (SD) model

A single solar cell model is shown in Fig. 2. The five parameters characterizing the single solar cell model are calculated. By using simple calculations on (3), the corresponding analytical in (4) is obtained:

$$I_t = I_{ph} - I_d - I_{sh} \tag{3}$$

$$I_t = I_{ph} - I_{sd}\left[\exp\left(\frac{q(V_t + R_S I_t)}{nKT}\right) - 1\right] - \frac{V_t + R_S I_t}{R_{sh}} \tag{4}$$

where I_{sd} is the inverse saturation current of the diode and n is the ideality factor. Five unknown parameters in (4) are R_s, R_{sh}, I_{ph}, I_{sd}, and n (Jain and Kapoor, 2004).

2.2. Single diode module (SDM)

This model consists of series of solar cells that are connected in parallel. A blocking diode is connected in series with each PV string to prevent extra current produced by other strings from flowing back in the string. Across each PV cell or number cells, a bypass diode is coupled to conduct the power output flow or the current in case some of the string's cells failed or shaded. Fig. 3 shows a PV module with N_S series cells and N_P parallel strings. The relation between the currents and voltages of a PV module with N_S series cells and N_P parallel strings is as (5).

$$I_t = I_{ph} N_p - I_{sd} N_p\left[\exp\left(\frac{q(V_t / N_s + R_S I_t / N_p)}{nKT}\right) - 1\right] - \frac{V_t . N_p / N_s + R_S I_t}{R_{sh}} \tag{5}$$

2.3. Parameter identification of a solar cell and module as an optimization problem

The following issues should be observed to solve the parameter identification problem of the solar cell models by optimization algorithm: (1) how to define a solution, (2) how to determine the search range, and (3) how to construct the objective function. In this study, a vector x, where $x = [R_s, R_{sh}, I_{ph}, I_{sd_1}, I_{sd_2}, n_1 \, and \, n_2]$, is considered as a solution for the double diode model and for single diode model x is$x = [R_s, R_{sh}, I_{ph}, I_{sd}, n]$. Table 1 shows upper and lower bounds of the parameters that obtained by the literature survey for single and double diode model solar cell (Askarzadeh and Rezazadeh 2013a, 2013b) and PV modules (Kler et al., 2017). The objective functions for the problem can be constructed as following. For each pair of the experimental data for single diode solar cell model, double diode solar cell model and PV module model we have (6), (7) and (8), respectively (Easwarakhanthan et al., 1986):

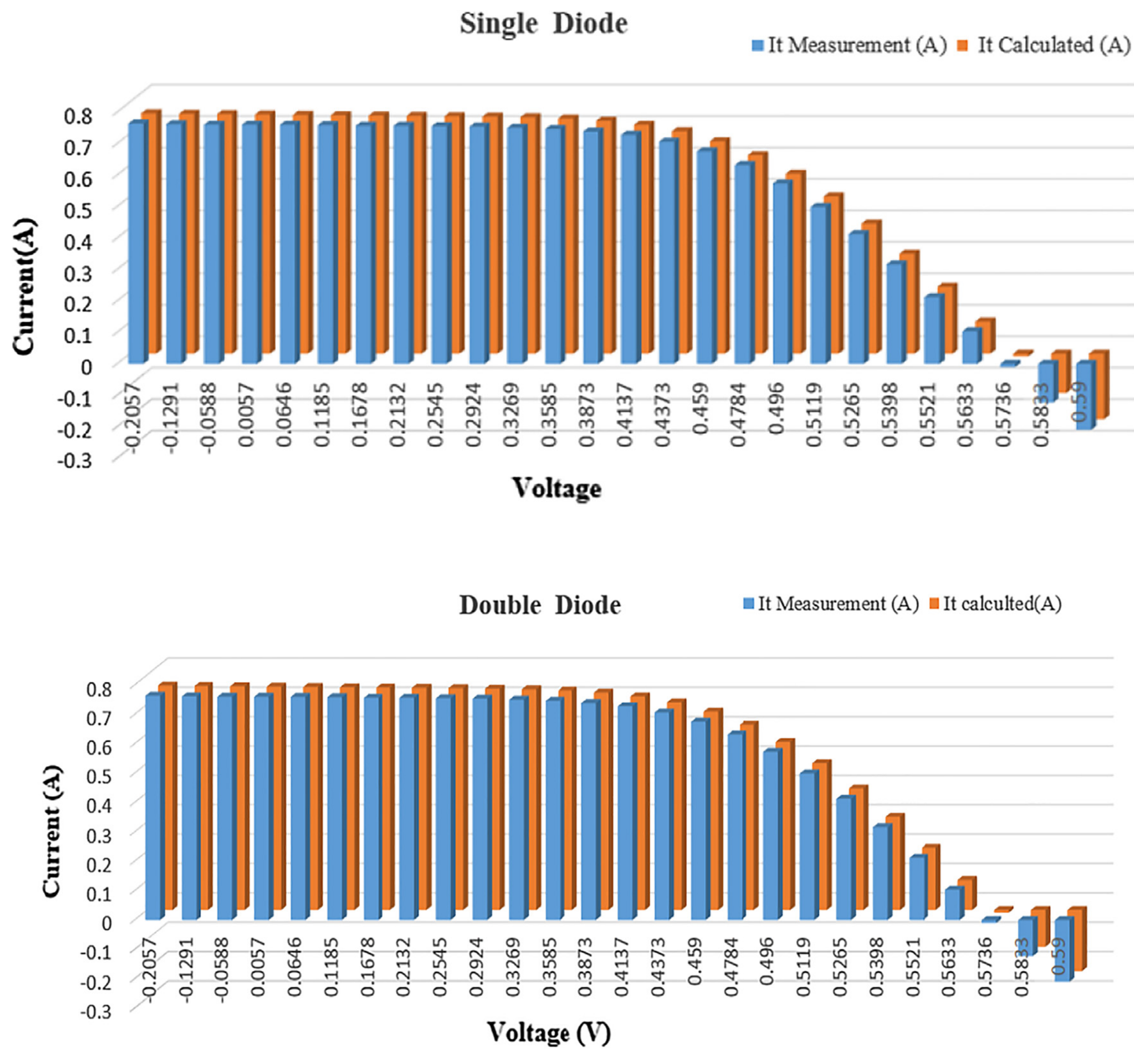

Fig. 7. Comparison between the *I–V* characteristics of the experimental data and models for the single and double diode identified by HFAPS algorithm.

$$f_{SD}(V_t, I_t, x) = I_t - I_{ph} + I_{sd}\left[\exp\left(\frac{q(V_t + R_s I_t)}{nKT}\right) - 1\right] + \frac{V_t + R_s I_t}{R_{sh}} \tag{6}$$

$$f_{DD}(V_t, I_t, x) = I_t - I_{ph} + I_{sd_1}\left[\exp\left(\frac{q(V_t + R_s I_t)}{n_1 KT}\right) - 1\right] + I_{sd_2}\left[\exp\left(\frac{q(V_t + R_s I_t)}{n_2 KT}\right) - 1\right] + \frac{V_t + R_s I_t}{R_{sh}} \tag{7}$$

$$f_{SDM} = I_t - I_{ph}N_p + I_{sd}N_p\left[\exp\left(\frac{q(V_t/N_s + R_s I_t/N_p)}{nKT}\right) - 1\right] + \frac{V_t . N_p/N_s + R_s I_t}{R_{sh}} \tag{8}$$

The value of $f_{SD}(V_t, I_t, x)$, $f_{DD}(V_t, I_t, x)$and f_{SDM} are calculated for each pair of the experimental data. We use the root mean square error (RMSE) as a criterion to quantify the difference between the model results and the experimental data. RMSE is defined by (9).

$$RMSE = \begin{cases} \sqrt{\frac{1}{N}\sum_{t=1}^{N} f_{SD}(V_t, I_t, x)^2}; & \text{For single diode} \\ \sqrt{\frac{1}{N}\sum_{t=1}^{N} f_{DD}(V_t, I_t, x)^2}; & \text{For double diode} \\ \sqrt{\frac{1}{N}\sum_{t=1}^{N} f_{SDM}(V_t, I_t, x)^2}; & \text{For PV Single diode module} \end{cases} \tag{9}$$

where N is the number of the experimental data.

The objective function should be minimized with respect to the parameters range. The five parameters of single diode model or seven parameters of double diode model are adjusted by optimization algorithm until one of the termination criteria is met.

3. Proposed algorithm for optimizing the parameters of a solar cell model

3.1. Firefly optimizer

The Firefly algorithm (FA) was firstly proposed by Yang (2010), which imitate the social behavior of fireflies in the tropical summer sky. The main rules of this algorithm can be specified as follows:

(1) All firefly will be attracted to other fireflies regardless of their sex.
(2) Attractiveness depends on the firefly brightness. For any two of

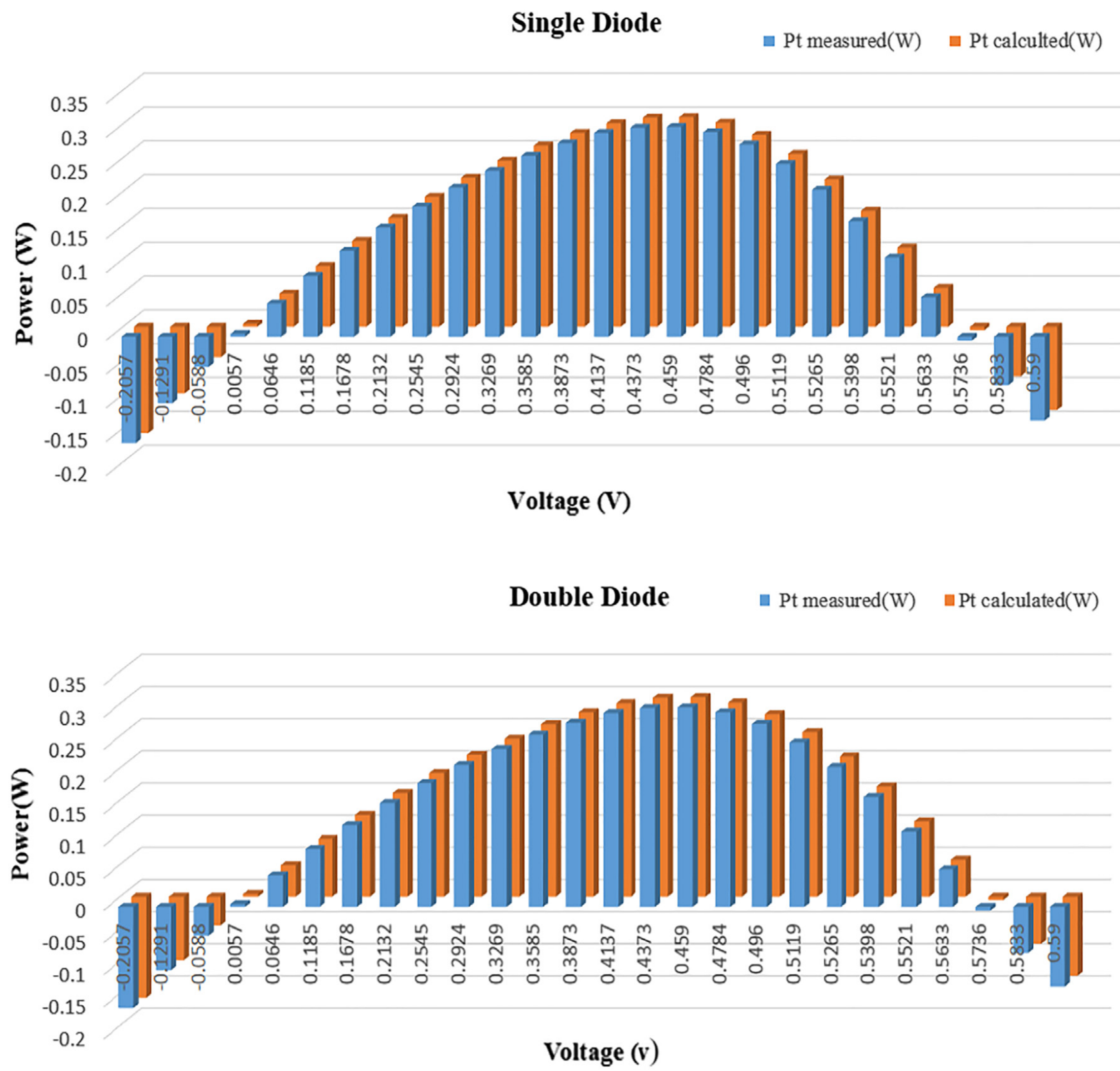

Fig. 8. Comparison between the *P–V* characteristics of the experimental data and models for the single and double diode (R.T.C France) identified by HFAPS algorithm.

flashing fireflies, the brighter one attracts the less bright towards itself. The brightness decreases with increasing distance between fireflies, thus attractiveness that is proportional to the brightness will decrease. If a particle firefly brighter than all other fireflies this particle will move randomly in the space.

(3) The brightness of a firefly is associated with the cost function of the problem. The pseudo code of FA is shown in Fig. 4 (Yang, 2010a, Fateen and Bonilla-Petriciolet, 2014).

(4) The mentioned attractiveness can be calculated by the Eq. (10):

$$\beta = \beta_{\min} + (\beta_0 - \beta_{\min}) * \exp(-\gamma r^2) \tag{10}$$

where r is the distance between two fireflies and β_0 is the attractiveness at $r = 0$ and β is the attractiveness for distance r, $\beta_{\min}$ is attractiveness when the distance between two fireflies is very high ($r \to +\infty$) and γ is the light absorption coefficient. The r_{ij} is the Cartesian distance between two fireflies i and j can be calculated as Eqs. (11) and (12):

$$r_{ij} = x_i - x_j = \sqrt{\sum_{k=1}^{d} (x_{i,k} - x_{j,k})^2} \tag{11}$$

The movement is obtained as follows:

$$x_i = x_i + \beta(x_j - x_i) + \alpha \in_i \tag{12}$$

The second term in (12) i.e. β is for the attraction, while $\in_i$ is a vector of random numbers from a uniform random variable in the range $[-0.5, 0.5]$. α is a parameter that controls the step. It can also vary with time, gradually reducing to zero.

3.2. Pattern search

The Pattern Search (PS) optimization routine is an evolutionary technique that is suitable to solve a variety of optimization problems that lie outside the scope of the standard optimization methods (Holland and Goldberg, 1989; Michalewicz and Hartley, 1996). The convergence properties for a wide variety of pattern search discussed in (Torczon, 1997). Generally, pattern search methods consider the pattern of points that have offsets from the current best point. If there is a better solution between these points it accepted as a new best point and iterate sampling around it again. If not, the scale of pattern reduced and pattern of point again produced about the best point. A flexible and well-balanced operator to enhance and adapt the fine tune local search exist in pattern search (Lewis et al., 2000). Refinement of a new point: using a local optimization procedure starting in $\hat{U}_T$ to find local minimum U_T a direct search method called pattern search is used as following steps (See Fig. 5).

Step 1: Set $U_0 = \hat{U}_T$, $\Delta_p = \Delta_0$ where p is the iteration index.

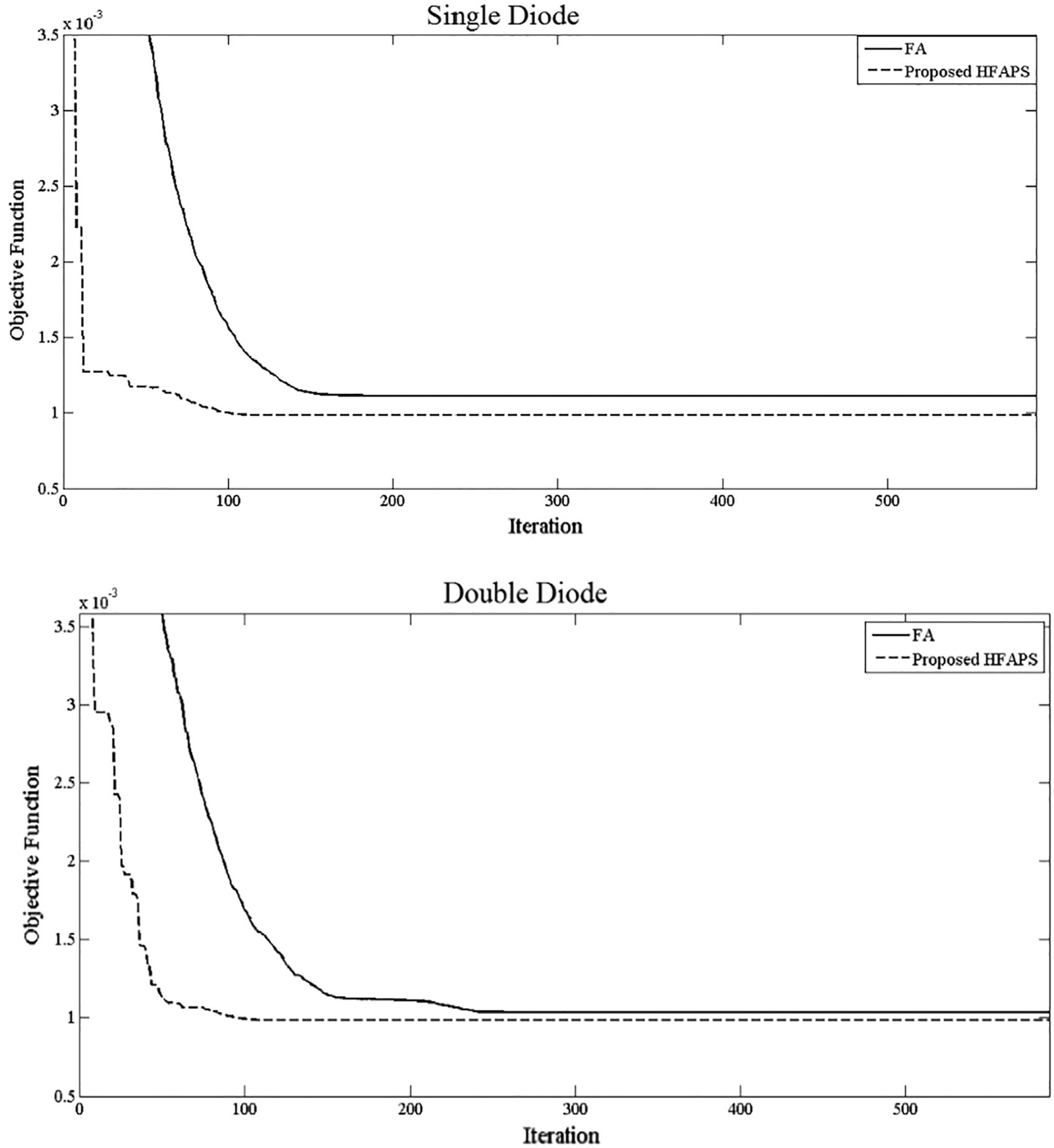

Fig. 9. Convergence process of HFAPS algorithm during the identification for (R.T.C. France) silicon solar cell single and double diode model.

Table 5
Circuit model parameters STM6-40/36 at 51 °C and full irradiance, for single diode model, achieved by different optimization algorithms.

Approaches	Parameters					
Algorithm	$I_{ph}(A)$	$I_{sd}(\mu A)$	$R_S(\Omega)$	n	$R_{sh}(\Omega)$	RMSE
LSP	1.6635	1.4142	0.1756	53.9496	555.084	0.00218
ABC	1.5	1.6644	0.1796	53.5176	547.416	0.19253
CIABC	1.6642	1.676	0.1584	53.9136	562.212	0.02518
ELPSO	1.666268	0.46	0.5	50.458643	497.7473	0.00218
FA	1.6903	0.1603	0.3424	46.7149	209.6324	0.009142
Proposed HFAPS	1.6663	1.0703	0.24849	53.016	490.03	0.00197

Step 2: In iteration p we have solution U_p and step-length parameter $\Delta_p > 0$ Let e_i, i = 1, …, n, denote the standard unit basis vectors.
Step 3: Look at the point $U_{pattern} = U_p \pm \Delta_p e_i,\ i = 1, ..., n$ to find $U_{pattren}$ for which $f(U_{pattren}) < f(U_p)$. If you find no $U_{pattren}$ such that $f(U_{pattren}) < f(U_p)$, then, reduce Δ_p by a half and continue. Otherwise, leave the step length parameter alone, set $\Delta_{p+1} = \Delta_p$ and $U_{p+1} = U_{pattern}$. In the latter case, we can also increase the step length parameter by factor of 2 ($\Delta_{p+1} = 2\Delta_p$), if we feel a longer step might be justified. We used $\Delta_{p+1} = 2\Delta_p$ when for four successive times we achieve better objective function.
Step 4: Repeat the iteration just described until Δ_p is deemed sufficiently small.
Step 5: At the end update the solution U_T by $U_{\text{number of pattern iteration}}$ (i.e. $U_T = U_{\text{number of pattern iteration}}$)

3.3. Proposed hybrid firefly algorithm and pattern search algorithm

In this study, a combination of Firefly and pattern search methods called hybrid firefly and pattern search HFAPS was proposed. Firefly that is a global optimizing method that explores the space of solution and most likely gives an optimal or near-optimal solution if applied alone. Thus, it can be combined with local optimization algorithms like pattern search. Pattern search is good to exploit a local area, but it is usually not good at exploring the wide area (Bao et al., 2013; Chiranjeevi and Jena, 2017). The balance between exploration and exploitation is achieved by combining Firefly and pattern search. The search of the hybrid algorithm is started with the Firefly, then pattern search has chances to exploit solution generated by Firefly. In this

Table 6
The results of parameters extraction for Photo watt-PWP 201 PV module by various methods.

Approaches	Parameters					
	$I_{ph}(A)$	$I_{sd}(\mu A)$	$R_s(\Omega)$	n	$R_{sh}(\Omega)$	RMSE
Newton	1.0318	3.2875	1.2057	48.45	555.5556	0.7805
CPSO	1.0286	8.301	1.0755	48.821	1850.1	3.5 E-3
SA	1.0331	3.6642	1.1989	48.289	833.33	2.7 E-3
PS	1.0313	3.1756	1.2053	48.6766	714.29	0.0118
TLABC	1.0307	3.5124	1.1995	48.45	969.9313	2.4266E-3
FA	1.0370	7.7289	1.0907	51.9452	705.7378	4.7961 E-3
Proposed HFAPS	1.0305	3.4842	1.2013	48.6449	984.2813	2.4251 E-3

study, proportion of iteration to maximum iteration is considered for the rate of PS application. Thus, in the first iterations (exploring stage) PS has low chance to work over solutions. Thus, the role of PS in the first iterations (exploration stage) is low and mostly Firefly is applied while in the last iterations (exploitation stage) PS plays an important role in improving results. The flowchart for the proposed HFAPS algorithm is presented in Fig. 6.

4. Simulation results

In this section, parameter estimation of single and double diode solar cell models and PV modules by proposed HFAPS were conducted and performance of algorithm compared with the results of recent works. Several experiments were simulated to obtain control parameters of FA and HFAPS, properly. The number of maximum iteration has been chosen 5000 that is adopted from previous studies (Askarzadeh and Rezazadeh, 2012, 2013a, 2013b). The number of fireflies is 50, randomization parameter$\alpha = 0.02$, the attractiveness $\beta_0 = 2$, and the light absorption coefficient $\gamma = 1$. The PS is executed with an initial step-length parameter Δ_0 is equal to quadrature of space search for each dimension i.e. $\Delta_0 = (UB{-}LB)/4$ that UB and LB are upper and lower bound of variables respectively mentioned in Table 1, when improvement not attained theΔ is reduced by factor 2 i.e.$\Delta = \Delta/2$. Simulations have been done on an Intel, core i5 core CPU, 2.4 GHz and 6 GB RAM computer. The program implemented in MATLAB 2014. A 57 mm diameter commercial (R.T.C. France) silicon solar cell is considered to study the effectiveness of HFAPS. The experimental data has been adopted from the system under 1 sun (1000 W/m^2) at 33 °C (Askarzadeh and Rezazadeh 2013a; Easwarakhanthan et al., 1986). A solar module (Photowatt-PWP 201) in which 36 polycrystalline silicon cells are connected in series under 1 sun (1000 W/m^2) (Easwarakhanthan et al., 1986) and commercial solar panel model STM6-40/36 manufactured consists of 36 Monocrystalline cells (Tong and Pora, 2016).

4.1. Results for solar cell

To show the effectiveness of HFAPS method, In Tables 2 and 3 the results of the proposed method for single, double diode solar cell of RTC France are compared with some of the recent works. It can be seen from Tables 2 and 3 that HFAPS can achieve the lowest RMSE value (9.8602e-4 for the single diode, 9.8248e-4 for the double diode solar cell). In Tables 2 and 3 the optimum values of parameters from different algorithms were tabulated along with the RMSE. Based on error analysis can be efficiently judged validation between actual and computed values. Thus, mean absolute error (MAE) between actual and computed values should be calculated. The relationship between relative error and MAE are as follows:

$$e = \frac{I_{t(measurea)} - I_{t(Calculated)}}{I_{t(measurea)}} \tag{13}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{\mathrm{I}_{t(measurea)} - I_{t(Calculated)}}{\mathrm{I}_{t(measurea)}}\right| \tag{14}$$

Table 4 shows the relative error and MAE of actual and measured current in the case of single and double diode. MAE is 0.0075 for the single diode model and 0.0071 for the double diode model. The calculated value of the MAE in Table 4 indicates the high accuracy of the identification process.

The optimal parameters obtained by the HFAPS algorithms are altered to the single and double diode model and the *I–V* characteristic is plotted along with the experimental data to observe the agreement between them. In Fig. 7, correlation coefficient and root mean square percentage deviation between the computed values and the measured values are 1 and 0.024, for single diode and 1 and 0.023 for double diode respectively. Results of the correlation coefficients and root mean square percentage deviations show there is a good agreement between real data and results of model. Based on the correlation coefficients and root mean square percentage deviations, it is observed that there is good agreement between the experimental data and the model results.

As shown in Fig. 8 the computed values of P-V characteristic for model are matched with the experimental data. Correlation coefficient and root mean square percentage deviation between the calculated values and the measured values are 1 and 0.0273, for single diode and 1 and 0.026 for double diode, respectively. These values verified the accuracy of the proposed method. In Fig. 9 the values of objective function (RMSE) is plotted against the iteration number. As it is expected the RMSE decrease during the iterations. As shown in Fig. 9, the convergence of proposed HFAPS is better than FA.

4.2. Results for PV modules

In this study, commercial solar panel model STM6-40/36 manufactured consists of 36 Monocrystalline cells (of size 38–128 mm) aligned in series has also been chosen to evaluate the performance of proposed HFAPS. Experiment data available in (Tong and Pora, 2016). The comparison results of the HFAPS and the other algorithms have been shown in Table 5. Results show that HFAPS has comparative performance in the respect with Artificial Bee Colony (CIABC) (Oliva et al., 2017), ABC (Oliva et al., 2017), Chaotic Improved Artificial Bee Colony (CIABC) (Oliva et al., 2017) and loop of search process called (LSP) (Tong and Pora, 2016) and ELPSO (Jordehi, 2018). The results

Table 7
Comparison of I_{MP}, V_{MP} and P_{MP} for proposed approach and other works.

Approach	R.T.C. France			PWP 201			STM6-40/36		
	I_{MP} (A)	V_{MP} (v)	P_{MP} (w)	I_{MP} (A)	V_{MP} (v)	P_{MP} (w)	I_{MP} (A)	V_{MP} (v)	P_{MP} (w)
Real value	0.6894	0.4507	0.3107	0.9120	12.649	11.5359	1.50	16.98	25.47
BMO	0.692	0.449	0.3107	–	–	–	–	–	–
OPAM	0.6874	0.4529	0.3113	0.9157	12.6174	11.553	–	–	–
ASADM	–	–	–	–	–	–	1.499	17.006	25.492
FA	0.6894	0.4509	0.31085	0.9085	12.618	11.463	1.494	17.045	25.477
Proposed HFAPS	0.6894	0.4506	0.31064	0.9125	12.645	11.539	1.500	16.973	25.459

Table 8
Extracted Parameters by HFAPS for different PV modules at irradiance 1000 W/m^2 and different cell temperature values.

Parameters	KC200GT	SX3200N	1STH-235-WH
T = 25 °C			
$I_{ph}(A)$	8.199247	8.95992	8.566311
$I_{sd}(\mu A)$	0.154161	0.036687	0.002726
$R_s(\Omega)$	0.239552	0.29941	0.371804
n	74.57945	52.84662	65.84608
R_{sh}	1448.259	407.8471	671.966
RMSE	0.049863	0.033926	0.036652
T = 50 °C			
$I_{ph}(A)$	8.321374	9.209045	8.730813
$I_{sd}(\mu A)$	0.129957	0.839121	0.274116
$R_s(\Omega)$	0.301042	0.301612	0.344275
n	63.22531	51.96229	70.8916
R_{sh}	1017.667	231.6561	1756.071
RMSE	0.038852	0.042428	0.042834
T = 75 °C			
$I_{ph}(A)$	8.451032	9.358777	8.910162
$I_{sd}(\mu A)$	1.288778	1.974022	0.732474
$R_s(\Omega)$	0.310513	0.336897	0.381467
n	61.96239	44.98408	64.07
R_{sh}	1023.943	1091.568	1901.529
RMSE	0.029724	0.077988	0.037194

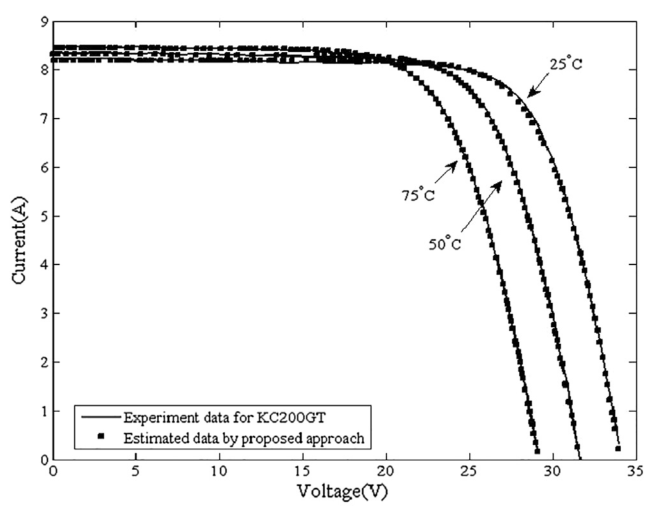

Fig. 10. Experimental and estimated I-V characteristics of PV modules at different cell temperature values for KC200GT.

show that the proposed HFAPS achieved good results and can be considered as a competitive algorithm for parameter extraction of solar cell modules.

Another case study has been used to evaluate HFAPS is solar module Photowatt-PWP 201 in which 36 polycrystalline silicon cells are connected in series under 1 sun (1000 W/m^2) at 45 °C (El-Naggar et al., 2012). The proposed HFAPS compared with previous studies including Newton (Easwarakhanthan et al., 1986), CPSO (Wei et al., 2011), SA (El-Naggar et al., 2012), TLABC (Chen et al., 2018) in Table 6. Results show that HFAPS algorithm achieves better or near performance in the compared with the previous studies.

4.3. Maximum power point (MPP)

At the MPP derivative of Pt (output power) with respect to Vt (terminal voltage), should be zero. Using the standard numerical nonlinear method for (5) and (15) that their parameters are extracted by HFAPS in Table 2 can obtain the current of maximum power (I_{MP}), the voltage of maximum power (V_{MP}) and power of maximum power point

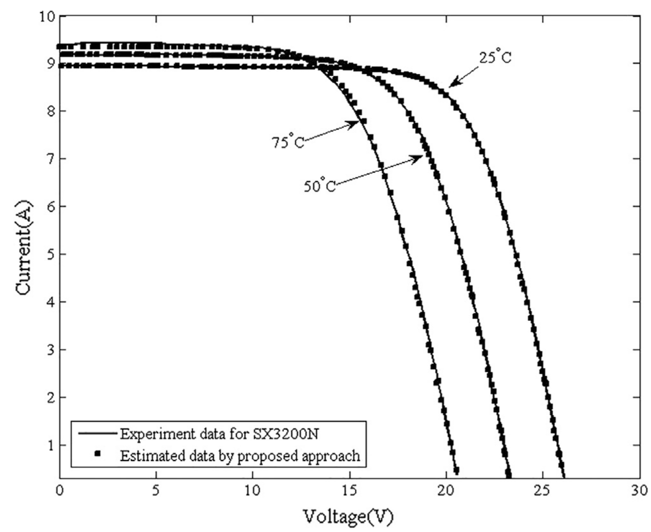

Fig. 11. Experimental and estimated I-V characteristics of PV modules at the different cell temperature values for SX3200N.

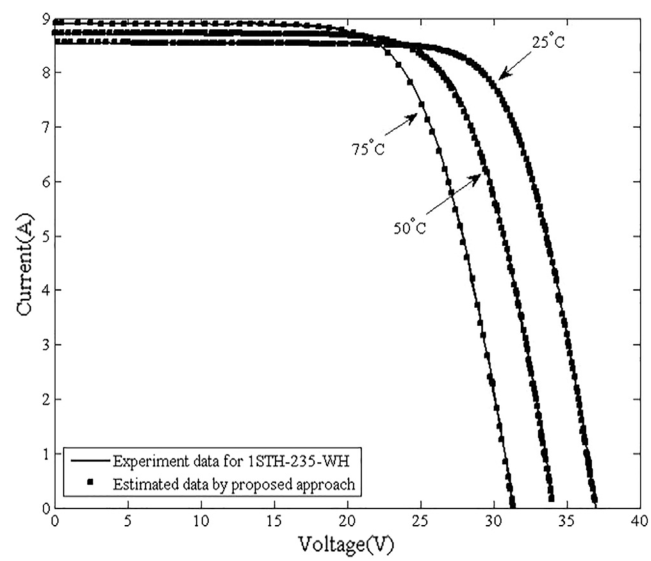

Fig. 12. Experimental and estimated I-V characteristics of PV modules at the different cell temperature values for 1STH-235-WH.

(P_{MP}). The current and voltage that satisfy (5) and (15) are shown in Table 7.

It is notable, the many used approaches to acquire the MPP in a solar cell is obtained according to the maximum power of I-V multiplication. Thus, the accuracy of this approach is related to the precision of the experimental data around the actual MPP. However, mathematical models like our proposed approach have no these restriction and estimated model can be used to obtain MPP.

$$\frac{dP_t}{dV_t} = I_t - V_t\left[\frac{\frac{q}{nKT}\left(I_{ph} + I_d - I_t - \frac{V_t + R_s I_t}{R_{sh}}\right) + \frac{1}{R_{sh}}}{1 + \frac{qR_s}{nKT}\left(I_{ph} + I_d - I_t - \frac{V_t + R_s I_t}{R_{sh}}\right) + \frac{R_s}{R_{sh}}}\right] = 0 \quad (15)$$

The real value characteristic of R.T.C. France, PWP 201 and STM6 40–36 available with the datasheet (Pindado and Cubas, 2017; Jadli et al., 2018). The operation point based analytical method (OPAM) introduced by Cubas et al. (2017) that uses short-circuit current, the slope of the I-V curve at that point, the open-circuit voltage, and the current and voltage levels, together with the slope of the I-V curve at the instantaneous operation point to extract parameters of solar cell

Table 9
Extracted Parameters by HFAPS for different PV modules at 25 °C and different irradiance.

Parameters	KC200GT	SX3200N	1STH-235-WH
G = 1000 W/m²			
$I_{ph}(A)$	8.199247	8.95992	8.566311
$I_{sd}(\mu A)$	0.154161	0.036687	0.002726
$R_s(\Omega)$	0.239552	0.29941	0.371804
n	74.57945	52.84662	65.84608
R_{sh}	1448.259	407.8471	671.966
RMSE	0.049863	0.033926	0.036652
G = 600 W/m²			
$I_{ph}(A)$	4.93922	5.372796	5.147846
$I_{sd}(\mu A)$	0.314512	0.054622	0.0015
$R_s(\Omega)$	0.132137	0.287199	0.377745
n	78.3876	54.02059	64.11109
R_{sh}	359.1577	333.8148	764.5885
RMSE	0.04085	0.023729	0.0195
G = 200 W/m²			
$I_{ph}(A)$	8.177455	1.781057	1.736608
$I_{sd}(\mu A)$	0.044417	0.027915	4.50E-05
$R_s(\Omega)$	0.272048	0.337609	0.538067
n	69.80604	52.08052	54.91253
R_{sh}	1161.409	2000	388.6414
RMSE	0.044282	0.009984	0.019351

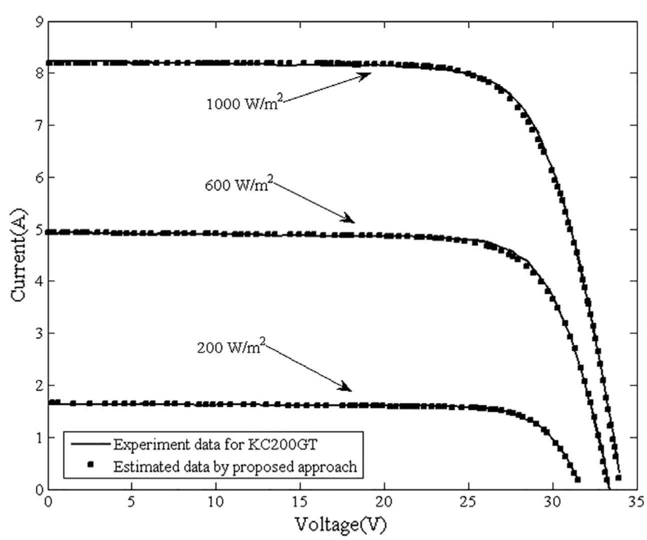

Fig. 13. Experimental and estimated I-V characteristics of PV modules at different irradiance for KC200GT.

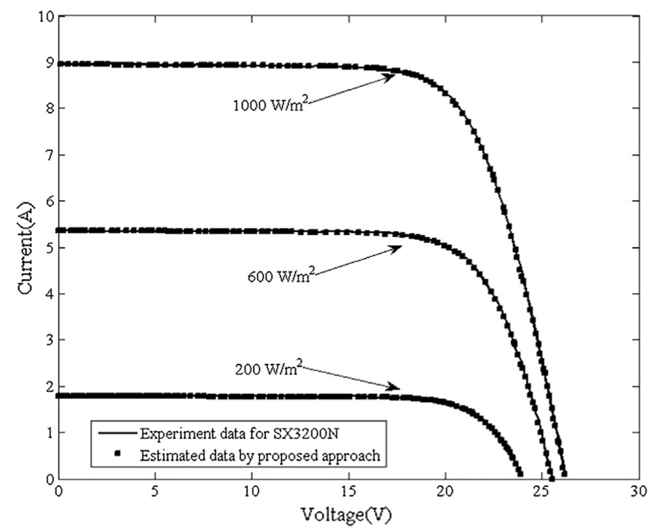

Fig.14. Experimental and estimated I-V characteristics of PV modules at different irradiance for SX3200N.

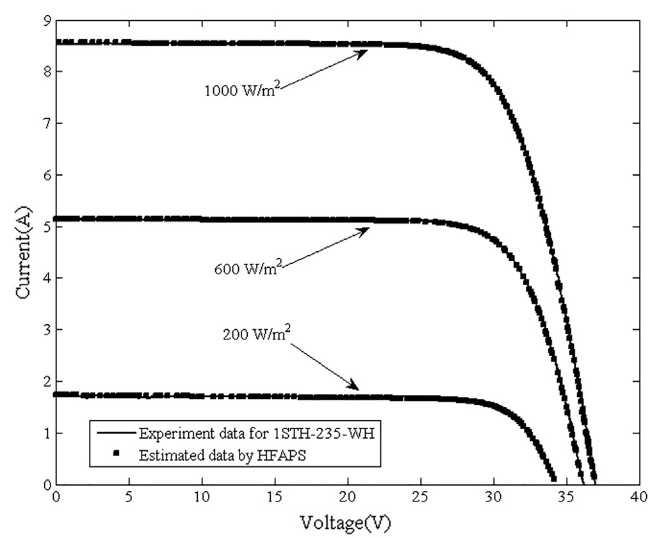

Fig.15. Experimental and estimated I-V characteristics of PV modules at different irradiance for 1STH-235-WH.

model. A new parameter estimation technique has been introduced based on a combination of a Derived Model, Analytical and Simulated Annealing methods, called ASADM by Jadli et al. (2018). The MPP of proposed HFAPS is compared with BMO, OPAM, ASADM and FA. In the most cases, V_{MP} and I_{MP} of HFAPS are better than other works. It is notable, even with the bigger error in estimated I_{MP} and V_{MP} can have better P_{MP} (their multiply) in the respect to the case with the low error in estimated I_{MP} and V_{MP}. This happens when estimated I_{MP} greater than real I_{MP} and V_{MP} is less than real V_{MP} or vice versa (See I_{MP}, V_{MP} and P_{MP} for BMO and HFAPS for R.T.C. France).

4.4. Temperature and irradiance analysis

In this section three PV modules M/S Kyocera KC200GT, M/S BP SX3200N and M/S 1Soltech 1STH-235WH with number of cell series (Ns) equal to 52, 50 and 60 respectively are used to test cell temperature and irradiance analysis (Kler et al., 2017). The modules with different cell temperature values 25 °C, 50 °C and 75 °C at the irradiance (1000 W/m²) were considered to evaluate proposed HFAPS. The data were collected from digitalize figures in (Kler et al., 2017). The optimal extracted parameters by HFAPS with RMSE values for different cell temperature are tabulated in Table 8. The estimated and reference values of I-V characteristic for the different cell temperature values have been shown in Figs. 10–12. From Figs. 10–12 can be seen that the estimated I-V values for different temperature are accurate in the respect to expected values along the range.

For irradiance analysis three different irradiance values 200 W/m², 600 W/m² and 1000 W/m² at a constant temperature 25 °C are used to test HFAPS. Extracted parameters for different irradiance are showed in Table 9. Results show that HFAPS can achieve low RMSE in different irradiance. The comparison between expected and estimated results are illustrated in Figs. 13–15 for M/S Kyocera KC200GT, M/S BP SX3200N and M/S 1Soltech 1STH-235WH modules, respectively. Results show the estimated values by HFAPS and expected value in different irradiance along the entire range.

5. Conclusion

In this study, the hybrid of Firefly and Pattern Search algorithm was used for identifying the unknown parameters of the model for single and double diode solar cell and PV module to acquire an accurate *I–V* characteristic of real systems. The proposed algorithm utilized the exploration benefits of Firefly along with exploitation advantage of Pattern Search to convergence to the global solutions. The different simulations were conducted on the different case studies in this work. Simulation results showed that the presented hybrid algorithm is a competitive algorithm to be considered in the modeling of solar cell systems. Furthermore, proposed algorithm could successfully extract parameters of PV models in different temperatures and irradiance.

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