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A robust parameter estimation approach based on stochastic fractal search optimization algorithm applied to solar PV parameters

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ABSTRACT

Modeling of solar photovoltaic (PV) cell/modules to estimate its parameters with the measured current–voltage (*I–V*) values is a very important issue for the control, optimization, and effectiveness of the PV systems. Therefore, in this research work, a robust approach based on Stochastic Fractal Search (SFS) optimization algorithm is introduced to estimate accurate and reliable values of solar PV parameters for its precise modeling. To assess the excellence of the proposed SFS algorithm, different solar PV equivalent circuit models, i.e. single-diode model (SDM), double-diode model (DDM), and PV module model are taken into consideration. The introduced algorithm is examined under three different case studies; (i) first case study: an experimental standard dataset of a commercial R.T.C. France silicon solar cell working at 33 °C, and solar radiance of 1000 W/m^2; (ii) second case study: using a polycrystalline solar panel STP6 120/36 with 36 cells in series working at 22 °C, and (iii) third case study: an experimental dataset of ESP-160 PPW PV module working at 45 °C, this experimentation were carried out in the Laboratory of Renewable Energy at Assiut University, Egypt. The results obtained using the proposed method are compared with other recently published works, and hence, the achieved results show the superiority, perfectness, and effective modeling concerning various performance parameters. Thereby, the proposed SFS approach can be used for effective PV modeling to improve the efficiency of the PV system.

1. Introduction

The reduction of global warming is a great challenge these days to build a sustainable environment. Reduction or complete elimination of fossil fuel usage and turning into renewable energy sources are the key factors to overcome global warming (Charfi et al., 2018). Renewable energy includes solar, wind, tidal, biomass, wave, and geothermal energies. Among the different accessible sustainable power sources, solar PV energy is the one cleanest, plenty available, can use maximum days in a year, and low running/maintenance costs for the implementation (Vinod et al., 2018). However, the solar PV system depends on the environmental aspects, *i.e.*, ambient temperature, solar radiance, the efficiency of solar PV panels may reduce (Bawazir and Cetin, 2020). Therefore, to achieve a better level of efficiency, the accurate modeling of solar PV is necessary and it is a well-known fact that any systems outcome completely depends on its effective modeling. With this observation, the modeling of solar PV has attained high interest by researchers and industrial experts. While the modeling of solar PV parameters is a challenging task due to its non-linear characteristics. After performing rigorous research, the authors identified various techniques for the effective modeling of solar PV.

To model an effective solar PV, the mathematical modeling of solar PV has been introduced. These models have been mainly classified into three types that are single-diode model (SDM), double-diode model (DDM), and three diode model (TDM). These three models have been evolved based on their structure of the circuit, the involvement of parameters, and application. Among these models, SDM has been a widely used model due to its simplicity in structure and involvement of fewer parameters. However, to overcome the drawback of SDM by considering the recombination losses, DDM has been introduced by adding an additional diode to SDM (Rezk et al., 2019a; Messaoud, 2020).

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Nomenclature

$\bar{I}_{(V_i,\xi)}$	The estimated value as a function of the unknown parameters ξ
P'_i	The new solution of the ith solution
P'_t and P'_r	Solutions selected randomly from the approach utilizing Gaussian distribution
DDM	Double-diode model
G	The number of iterations
GA	Genetic algorithm
HS	Harmony search
I_D, I_{D1}, and I_{D2}	Currents of diodes D_1 and D_2
IJAYA	Improved JAYA
IMFO	Improved moths–flames optimization
I_{PV}	Photo-generated current in *Ampere* (A)
I–V	Current–voltage of the solar cell
k	Boltzmann constant (1.380649×10^{-23} Joule/Kelvin)
N	Set of empirical points (I_i, V_i) measured with an index of i
n, n_1, and n_2	The ideality factor of the diodes D_1 and D_2
N_D	The population size
N_p	Number of parallel strings
N_s	Number of series cells
OF	The objective function
P_{a1} and P_{a2}	The random solutions of population
PS	Pattern search
PV	Solar photovoltaic
q	Charge of the electron ($1.602176634 \times 10^{-19}$ Coulomb)
R.T.C	France silicon solar cell
RACF	Residual autocorrelation function
$rand(0, 1)$	A random number generated within the range [0, 1]
$rank(P_i)$	The rank of the ith solution among different arrangements in the populace
R_p	Shunt/parallel resistance in *ohms* (Ω)
R_s	Series resistance in *ohms* (Ω)
SDM	Single-diode model
SFS	Stochastic Fractal search
T	The temperature of PV panel (Kelvin)
V_t	The thermal voltage in *Volt* (V)
X_D	The number of optimization variable
Y_D	The maximum diffusion number of generated solutions
P_i and P_B	The ith solutions and the best solution, respectively
UB_{ij} and LB_{ij}	The upper and lower boundaries of the jth value of the solution i
δ	The standard deviation
μ_G and μ_P	The means of Gaussian walk which are equal to $\lvert P_i \rvert$ and $\lvert P_B \rvert$ respectively

The other model TDM is used for industrial applications. Since the required parameters for the modeling are not provided by the manufacturer, the parameter estimation of a solar PV has attained high priority, which helps to improve the efficiency of the solar PV system. Also, due to the nonlinear characteristics of solar PV, more care should be taken while building the PV models.

With the noticeable importance, numerous researchers and practitioners proposed various methods on the modeling of solar PV, which can be mainly divided into three main categories; analytical (Chan and Phang, 1987), deterministic (Tong et al., 2015), and heuristic methods (Bastidasrodriguez et al., 2017). For the first category: analytical methods, it is a mathematical analysis to determine the parameters of PV panels (Saleem and Karmalkar, 2009). These methods simplify and accelerate the calculation, but the accuracy and the reliability of the solution are poor. In the second category, deterministic methods, the solution is so poor because it depends on the differentiability or convexity of the models (Tong et al., 2015). For the third category, heuristic methods, it can overcome the limitations of analytical and deterministic methods as well heuristics methods have a great capability of handling multi-objective functions, which plays a crucial role in PV system design (Bastidasrodriguez et al., 2017). Besides, the optimal results obtained using optimization techniques have highly enhanced their results in various fields of applications. Therefore, the various optimization algorithms have been introduced for the effective modeling of three types of solar PV models. The different introduced algorithms, type of PV module, and the method of estimating the parameters have been listed in Table 1. From the presented Table 1, all the algorithms implemented for the same objective of estimating unknown parameters of PV, however, these algorithms give better results, still there exists a chance to improve the intermingling pace of the algorithm, avoiding premature convergence, reducing the computational burden and easier tuning of parameters.

This article proposed a novel algorithm named stochastic fractal search (SFS) to improve the estimation of the parameters of PV cells/models. SFS has been nominated because it can converge to the best solution at a fast rate. Moreover, SFS has a good balance between exploration and exploitation capacities. For the first time, the mathematical concept of fractal was used in (Salimi, 2015) to develop the SFS algorithm. Where the diffusion property of random fractals was used by the SFS algorithm to increase the efficiency of the search space of particles. The SFS algorithm comprises two principal processes after initializing the population, (1) diffusion and (2) updating to improve the searching (Salimi, 2015). In the first process, diffusion, each point diffuses around the underlying situation to expand misuse trademark. In the subsequent procedure, SFS utilizes some factual methodologies for updating the situation of every specialist. The updating procedure is to investigate all the more encouraging hunt space. In SFS, the data between the points is transmitted quickly. This makes the algorithm reaches the optimal at a quicker rate. Also, SFS has a decent harmony among investigation and abuse limits.

With this advent features of the SFS algorithm, it is used to solve a lot of optimization problems; *i.e.* classify color images of galaxies (Hosny et al., 2020), solve the problem of the configuration of distribution network with the present of distribution generators (Tran et al., 2020), optimize the control system of plug-in electric vehicles in hybrid with pattern search (Padhy and Panda, 2017), fully automatic control of power generation systems with the assist of modified cost function algorithm (Çelik, 2020), solve the multi-area economic-dispatch optimization problem (Lin and Wang, 2019), finding the optimal reactive power dispatch of multi-static VAR compensator devices (Mahdad, 2019) and developed for solving reliability-redundancy allocation problems (Mellal and Zio, 2016). Consequently, the SFS strategy is extremely amazing and guarantee to adequately actualize to various optimization problems in our life.

The novelty in this research work is using the SFS algorithm to estimate the PV cell/module parameters as an optimization problem. To examine the effectiveness of SFS, this algorithm has been applied to solve the parameter estimation problem

Table 1
Recapitulation of Literature Review.

Authors	Optimization Algorithm	Modeling type	*I–V* Data
Liao et al. (2020)	Triple-Phase Teaching–Learning-Based Optimization (TPTLBO)	Single-diode Double-diode	Experimental
Elazab et al. (2020)	Grasshopper Optimization Algorithm	Three-diode	Experimental
Ziedan et al. (2020)	Particle Swarm Optimization	Single-diode	Experimental
Zhang et al. (2020)	Nelder–Mead simplex orthogonal learning moth flame optimization	Single-diode Double-diode	Experimental
Yu et al. (2019)	PJAYA algorithm	Single-diode Double-diode	Experimental
Sheng et al. (2019)	Improved moths–flames Optimization (IMFO) Algorithm	Single-diode Double-diode	Datasheet
Nunes et al. (2019)	Hybrid Metaheuristics Algorithm	Single-diode Double-diode	Experimental
Sabudin and Jamil (2019)	Mathematical Modeling Algorithm	Single-diode Double-diode Three-diode	Mathematical
Muhammad et al. (2019)	Approximation and Correction Technique	Single-diode	Experimental
Rezk et al. (2019b)	Moth Search Algorithm	Three-diode	Experimental
Qais et al. (2019)	Sunflower Optimization Algorithm	Three-diode	Experimental Datasheet
Hsieh et al. (2019)	Dynamic Equivalent Circuit Technique	Single-diode	Experimental Datasheet
Chen et al. (2019)	Perturbed Stochastic Fractal Search (pSFS)	Single-diode Double-diode	Experimental
Yu et al. (2018)	Multiple learning backtracking search algorithm (MLBSA)	Single-diode Double-diode	Experimental
Nunes et al. (2018)	Guaranteed Convergence Particle Swarm Optimization	Single-diode Double-diode	Experimental
Xiong et al. (2018)	Improved Whale Optimization Algorithm	Single-diode Double-diode	Experimental
Kang et al. (2018)	Improved Cuckoo Search Algorithm	Single-diode Double-diode	Experimental
Gao et al. (2018)	Improved Shuffled Complex Evolution Algorithm	Single-diode Double-diode	Experimental
Jadli et al. (2018)	Newton–Raphson Algorithm	Single-diode	Mathematical Datasheet
Kler et al. (2017)	Evaporation Rate based Water Cycle Algorithm	Single-diode Double-diode	Experimental
Et-torabi et al. (2017)	Gauss–Seidel Technique	Single-diode Double-diode	Experimental
Xu and Wang (2017)	Hybrid Flower Pollination Algorithm	Single-diode Double-diode	Experimental
Yu et al. (2017)	Improved JAYA Optimization Algorithm	Single-diode Double-diode	Experimental
Ali et al. (2016)	Multi-Verse Optimization Metaheuristic Approach	Single-diode	Experimental Datasheet
Tong and Pora (2016)	Parameter Extraction Technique	Single-diode	Experimental
Allam et al. (2016)	Moth–Flame Optimizer	Three-diode	Experimental
Belarbi et al. (2016)	Newton–Raphson Technique	Single-diode	Datasheet
Ma et al. (2016)	Bio-Inspired Algorithms	Single-diode	Experimental
Awadallah (2016)	Bacterial Foraging Algorithm	Single-diode Double-diode	Experimental
Bharadwaj et al. (2016)	Levenberg–Marquardt Algorithm	Single-diode	Experimental Datasheet
Muhsen et al. (2015)	Crossover Controlled adaptively Algorithm	Single-diode	Datasheet
Alam et al. (2015)	Flower Pollination Algorithm	Single-diode Double-diode	Experimental
Khanna et al. (2015)	Particle Swarm Optimization	Double-diode Three-diode	Datasheet
Jacob et al. (2015)	Artificial Immune Algorithm	Double-diode	Experimental
Park and Choi (2015)	Pattern Search Algorithm	Single-diode	Datasheet
Askarzadeh and Coelho (2015)	Bird Mating Optimizer Algorithm	Single-diode	Experimental
Park and Choi (2015)	Pattern Search Optimization	Single-diode	Experimental Datasheet
Muhsen et al. (2015)	Differential Evolution with Adaptive Mutation Algorithms	Single-diode	Experimental
Mares et al. (2015)	Simple and Accurate Algorithm	Single-diode	Experimental Datasheet
Lim et al. (2015)	Binary Search Algorithm	Single-diode	Experimental
Oliva et al. (2014)	Artificial Bee Colony Algorithm	Single-diode Double-diode	Experimental
Niu et al. (2014a,b)	Biogeography-Based Optimization Algorithm Chaotic-based Mutation Strategy Algorithm	Single-diode Double-diode	Experimental

(*continued on next page*)

Table 1 (*continued*).

Authors	Optimization Algorithm	Modeling type	*I–V* Data
Niu et al. (2014a,b)	Modified Teaching–Learning Based Optimization Algorithm	Single-diode Double-diode	Experimental
Yuan et al. (2014)	Modified Chaos Optimization	Single-diode Double-diode	Experimental
Dkhichi et al. (2014)	Hybridized Annealing and Levenberg–Marquardt Algorithms	Single-diode	Experimental
Dizqah et al. (2014)	Genetic Algorithm	Single-diode	Datasheet
Askarzadeh and Rezazadeh (2013a,b)	Modified Artificial Bee Colony Algorithm	Single-diode Double-diode	Experimental
Jiang et al. (2013)	Differential Evolution Algorithm	Single-diode	Experimental Datasheet
Gong and Cai (2013)	An Improved of JADE Algorithm	Single-diode Double-diode	Experimental
Askarzadeh and Rezazadeh (2013a,b)	Bird Mating Optimization Algorithm	Single-diode Double-diode	Experimental
Ismail et al. (2013)	Genetic Algorithm	Single-diode Double-diode	Experimental
Rajasekar et al. (2013)	Bacterial Foraging Optimization Algorithm	Single-diode	Datasheet
Ma et al. (2013)	Cuckoo Search Algorithm	Single-diode	Experimental Datasheet
Attivissimo et al. (2012)	Levenberg–Marquardt Algorithm	Double-diode	Mathematical
Soon and Low (2012)	Linearly decreasing inertia weight PSO Algorithm	Single-diode	Datasheet
Al Hajri et al. (2012)	Pattern Search Algorithm	Single-diode	Experimental
Askarzadeh and Rezazadeh (2012)	Innovative Global Harmony Search Algorithm	Single-diode Double-diode	Experimental
El-Naggar et al. (2012)	Simulated Annealing Algorithm	Single-diode Double-diode	Experimental
Ishaque et al. (2012)	Penalty-based Differential Evolution Algorithm	Double-diode	Datasheet
AlRashidi et al. (2011)	Pattern Search (PS) Algorithm	Single-diode Double-diode	Datasheet
Ishaque and Salam (2011)	Differential Evolution Algorithm	Single-diode	Experimental
AlRashidi et al. (2011)	Pattern Search Algorithm	Single-diode	Experimental

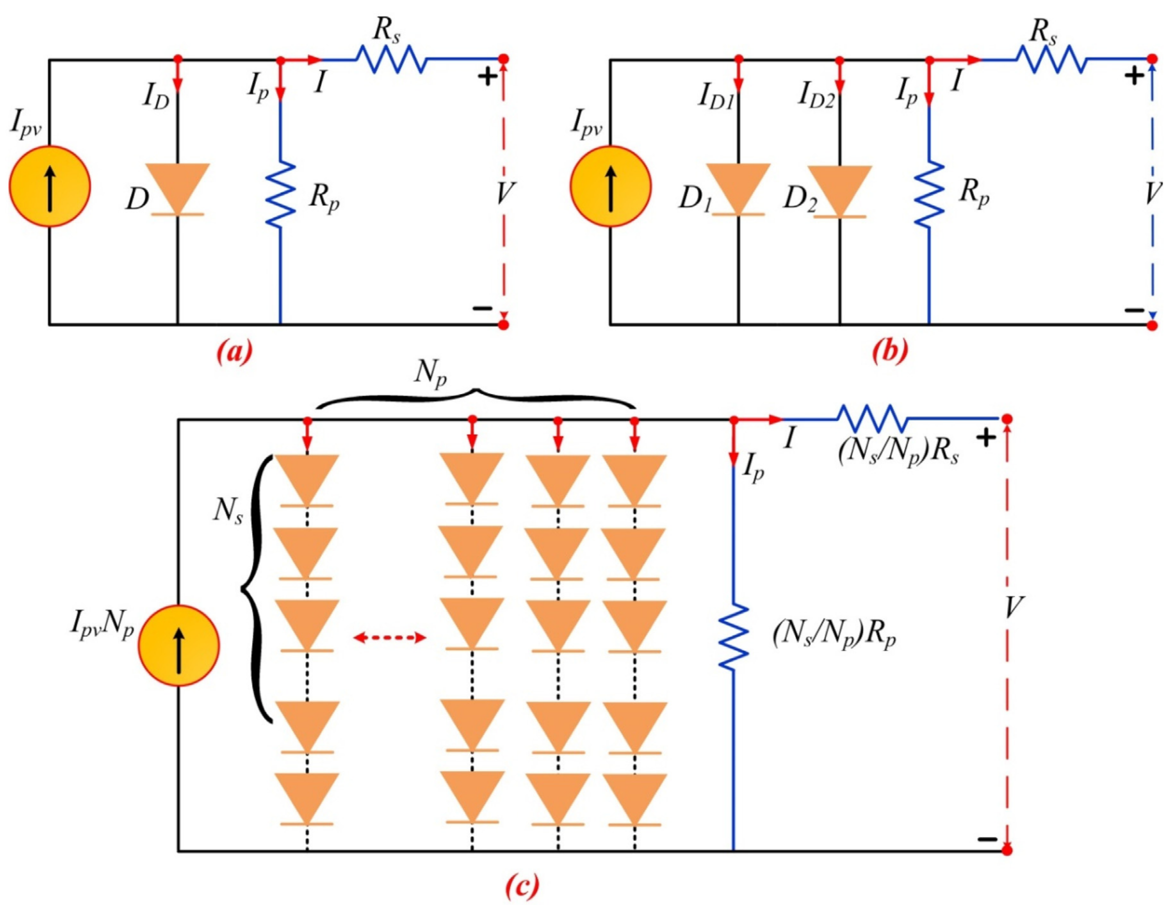

Fig. 1. Equivalent circuit of (a) single-diode model (SDM) (b) double-diode model (DDM), and (c) single-diode model (SDM) based solar PV module.

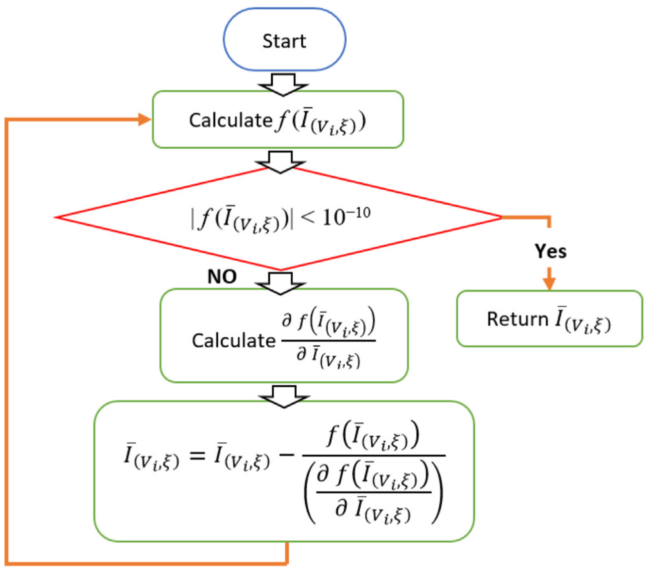

Fig. 2. Flowchart of the Newton–Raphson method (NRM).

of SDM and DDM for both single solar cells and PV modules. The performance of the proposed algorithm has been evaluated by an experimental setup installed on the university campus. In addition to the obtained results, statistical analysis has been performed by considering various parameters, which indicates the superiority and Excellency of the proposed method. Further, the achieved accuracy and robustness of the proposed algorithm are compared with several other competing algorithms that are recently developed. Table 1 summarizes the literature review on the modeling of PV cell/module based on several optimization algorithms, modeling type, and the I–V data.

However, the mentioned meta-heuristic algorithmic revealed high capability in convergence speed and global search, these algorithms suffered from few restrictions for example; most of them diverged their precision between SDM and DDM notably in outdoor circumstances. Consequently, the accuracy, reliability, and consistency in parameter estimation and accurate PV modeling yet to be done specifically with new optimizers. Also, SFS has been nominated because it can converge to the best solution at a fast rate. Moreover, SFS has a good balance between exploration and exploitation capacities.

A SFS optimization algorithm is used to handle the non-linear optimization problem of identifying the PV parameters using several experimental measured datasets. The following points sum up the main contributions and novelty of the research article.

- A new application of the SFS optimization method is proposed in this paper for determining the parameters of SDM and DDM of PV cell/module. The proposed method benefits in using adaptive weights in its searching process for the global optima.
- The SDM's and DDM's parameters have been evaluated over real-time measurements at different weather conditions.
- The parameters of the SDM and DDM for commercial R.T.C. France silicon solar cell working at 33 °C, a polycrystalline solar panel STP6 120/36 with 36 cells in series working at 22 °C and of ESP-160 PPW PV module working at 45 °C, are determined. The experimentations were carried out in the Laboratory of Renewable Energy at Assiut University, Egypt.
- The performance of the SFS optimization method is fully detailed and an extensive relative investigation has been completed between SFS and the well-established algorithms, namely; an improved JAYA optimization algorithm, harmony search algorithm, genetic algorithm, improved moths–flames optimization, Perturbed Stochastic Fractal Search, a biogeography-based optimization algorithm with mutation strategies (BBO-M) and Nelder–Mead simplex orthogonal learning moth flame optimization (NMSOLMFO) on extracting the parameters of three PV models.

The rest of this paper is sorted out as follows: section two: a mathematical model of solar PV cell/module is explained based on SDM and the DDM; section three: problem formulation of modeling solar PV cell/module; section four: an explanation of implementation SFS algorithm; section five: results of theoretical and experimental work with its discussions; section six: conclusion and outcomes of this work.

2. Mathematical models of solar PV cell/module

A mathematical model of the single-diode model (SDM) and double-diode model (DDM) and PV modules are presented in this part. The equivalent circuit of SDM solar PV cell is illustrated in Fig. 1a.

By applying Kirchhoff's law to the equivalent circuit of SDM, the output current I is expressed as (Chen et al., 2019; Hsieh et al., 2019; Muhammad et al., 2019).:

$$I = I_{pv} - I_D - \left(\frac{V + IR_s}{R_p}\right) \tag{1}$$

Where; I_{PV}: photo-generated current in *Ampere* (A); I_D: diode current in *Ampere* (A); R_s: series resistance in *ohms* (Ω); R_p: shunt/parallel resistance in *ohms* (Ω).

The supply current I_{pv} is linked with a parallel diode D of current I_d which is defined by Shockley formula as (Mohamed et al., 2019; Ziedan et al., 2020):

$$I_D = I_0 \left[Exp\left(\frac{V + IR_s}{nV_t}\right) - 1\right] \tag{2}$$

where; n: the ideality factor of the diode, which depends on the fabrication design of semiconductor material; V_t: the thermal voltage in *Volt* (V), which is calculated as (Xu and Wang, 2017; Yu et al., 2017):

$$V_t = \frac{N_s\, k\, T}{q} \tag{3}$$

where; k: Boltzmann constant (1.380649×10^{-23} Joule/Kelvin); T: temperature of PV panel (Kelvin); N_s: number of series PV cells; q: charge of the electron ($1.602176634 \times 10^{-19}$ Coulomb). By substituting Eq. (2) in Eq. (1), output current I of SDM can be calculated as:

$$I = I_{pv} - I_0 \left[Exp\left(\frac{V + IR_s}{nV_t}\right) - 1\right] - \left(\frac{V + IR_s}{R_p}\right) \tag{4}$$

For the solar PV module, which consists of several parallel strings (N_p) and several series cells (N_s) as shown in Fig. 1c, the output current I is described as:

$$I = I_{pv}N_P - I_0 N_P \left[Exp\left(\frac{\left(\frac{V}{N_s} + \frac{IR_s}{N_p}\right)}{nV_t}\right) - 1\right] - \left[\frac{\left(\frac{VN_p}{N_s} + IR_s\right)}{R_p}\right] \tag{5}$$

The model is characterized by five unknown parameters which is summarized as in the following equation:

$$\xi = [I_{pv}, I_0, n, R_s, R_p] \tag{6}$$

The double-diode model (DDM) of a solar PV cell is presented in Fig. 1b which is similar to the SDM but differs in having two diodes, D_1 and D_2, connected in parallel with a current source

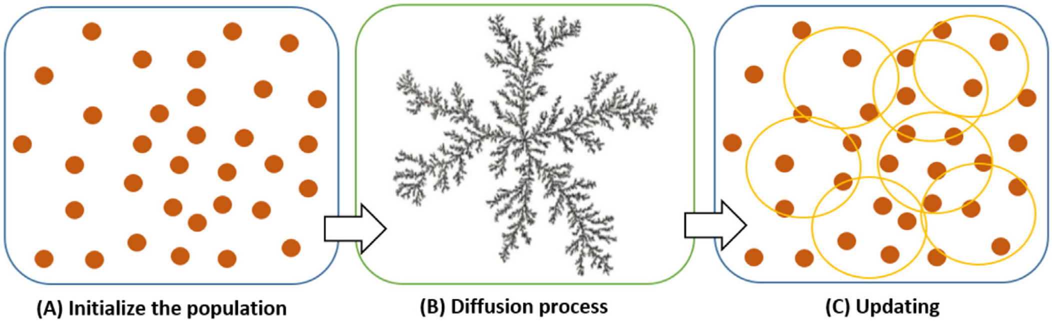

Fig. 3. Main processes of stochastic fractal search algorithm; (A) initialize the population, (B) diffusion process, and (C) updating process.

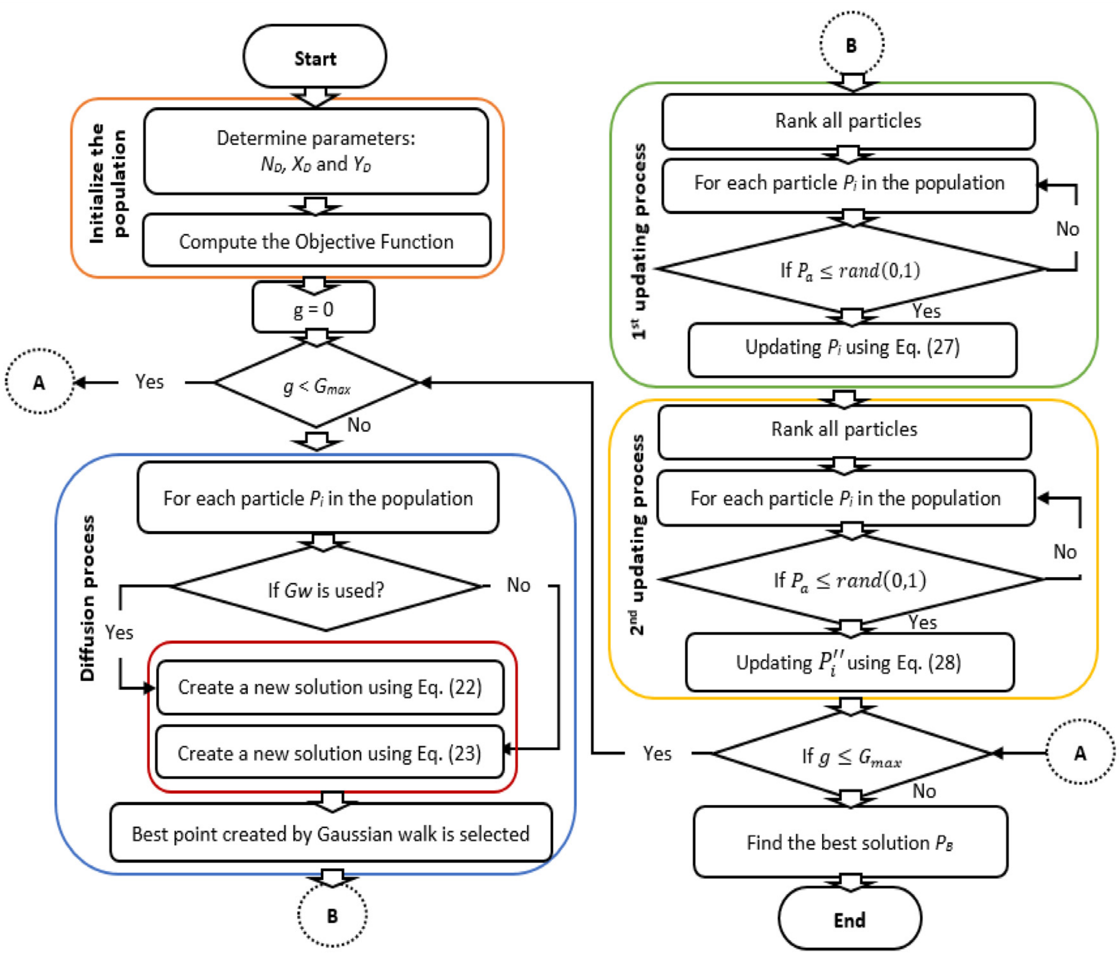

Fig. 4. Flowchart of the stochastic fractal search (SFS) algorithm.

(Nunes et al., 2018; Xiong et al., 2018; Nunes et al., 2019; Sabudin and Jamil, 2019). At low solar radiance levels, the DDM model is more accurate to describe the physical phenomena of the P-N junction. Diffusion current in the junction is presented by the first diode, while the other one is for the recombination impacts at the space–charge area. This model is more complex than SDM due to an increasing number of parameters.

By applying Kirchhoff's law to the circuit in Fig. 1b, the current I is expressed as:

$$I = I_{pv} - I_{D1} - I_{D2} - \left(\frac{V + IR_s}{R_p}\right) \tag{7}$$

Where, I_{D1} and I_{D2} are the currents of diodes D_1 and D_2 which Shockley equation describes them as (Chen et al., 2019; Jadli et al., 2018):

$$I_{D1} = I_{01}\left[Exp\left(\frac{V + IR_s}{n_1 V_t}\right) - 1\right] \tag{8}$$

$$I_{D2} = I_{02}\left[Exp\left(\frac{V + IR_s}{n_2 V_t}\right) - 1\right] \tag{9}$$

Where n_1 and n_2 are ideality factors of diodes D_1 and D_2. The output current I of DDM is obtained by substituting Eqs. (8) and

Fig. 5. The experimental set-up; (A) Solar PV panel, (B) measuring devices, and (C) electric load (variable resistance).

(9) in Eq. (7):

$$I = I_{pv} - I_{01}\left[Exp\left(\frac{V+IR_s}{n_1V_t}\right)-1\right] - I_{02}\left[Exp\left(\frac{V+IR_s}{n_2V_t}\right)-1\right] - \left(\frac{V+IR_s}{R_p}\right) \tag{10}$$

From the above Eq. (10), it can be observed that three exist seven unknown parameters that need to estimate for effective modeling of DDM. Which are summarized as in the following equation:

$$\xi = [I_{pv}, I_{01}, I_{02}, n_1, n_2, R_s, R_p] \tag{11}$$

The unknown parameters of both SDM and DDM can be obtained either analytically, numerically, or using any optimization algorithm.

3. Problem formulation

The unknown parameters of SDM and DDM of Eqs. (6) and (11) need to be determined. During the optimization process, the unknown parameters are used as a decision variable whereas the root mean square error between the estimated and experimental data is used as a cost function. The following equations are used to calculate Absolute error (AE), Mean absolute error (MAE) and Root mean square error (RMSE) (Chen et al., 2019; Nunes et al., 2019; Qais et al., 2019; Elazab et al., 2020):

$$AE = \sum_{i=1}^{N}\left|I_i - \bar{I}_{(V_i,\xi)}\right| \tag{12}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|I_i - \bar{I}_{(V_i,\ \xi)}\right| \tag{13}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(I_i - \bar{I}_{(V_i,\xi)}\right)^2} \tag{14}$$

Where, N: set of empirical points (I_i, V_i) measured with an index of i; $\bar{I}_{(V_i,\xi)}$: the estimated value as a function of the unknown parameters ξ which are characterized by Eqs. (6) and (11).

The objective function (OF) can define as a function that assesses the level of correspondence between the arrangement of parameters (each inside a given range), which describe the model, and the exploratory information.

In this study, OF is RMSE which measures the difference between measured and estimated values.

The problem is formulated to minimize the error of the estimated parameters ξ of the model and the measured data which is expressed as:

$$\min(RMSE) = min\sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(I_i - \bar{I}_{(V_i,\xi)}\right)^2} \tag{15}$$

Theoretically, OF ought to be zero when the specific estimations of the parameters are acquired. Since the models are very much determined and no data is accessible about the exact estimations of the model parameters, the level of correspondence relies just on the trial information. In this way, any decrease in the OF (RMSE) esteem is critical, relating to an improvement of the creator's information about the genuine estimations of the parameters.

3.1. Single-diode model

The optimum values of the unknown five parameters, which are shown in Fig. 1b, are obtained by evaluating the present values that produce the least error. However, since Eq. (6) does not concede an unequivocal arrangement, there is a critical impediment, in parameter extraction of the model, yet besides in its recreation. This confinement can be overwhelmed by using numerical methods, *i.e.*, the Bisection Method (BM) or the Newton–Raphson method (NRM) (Jordehi, 2016; Rezk and Fathy, 2017a,b; Chen et al., 2019).

So, the estimated current $\bar{I}_{(V_i,\xi)}$ is obtained by using NRM, whose flowchart is shown in Fig. 2, the value of the function $f\ (\bar{I}_{(V_i,\xi)})$, successively, until fulfilling the halting condition, $|f\ (\bar{I}_{(V_i,\xi)})| < 10^{-10}$. During progressive iterations, the method requires information on the derivative of the function $f\ (\bar{I}_{(V_i,\xi)})$ concerning $\bar{I}_{(V_i,\xi)}$ to compute the new estimation of the evaluated current $\bar{I}_{(V_i,\xi)}$ as expressed as (Rezk et al., 2019e,f):

$$f\left(\bar{I}_{(V_i,\xi)}\right) = I_{ph} - I_0\left[Exp\left(\frac{V+\bar{I}_{(V_i,\xi)}R_s}{nV_t}\right)-1\right]$$

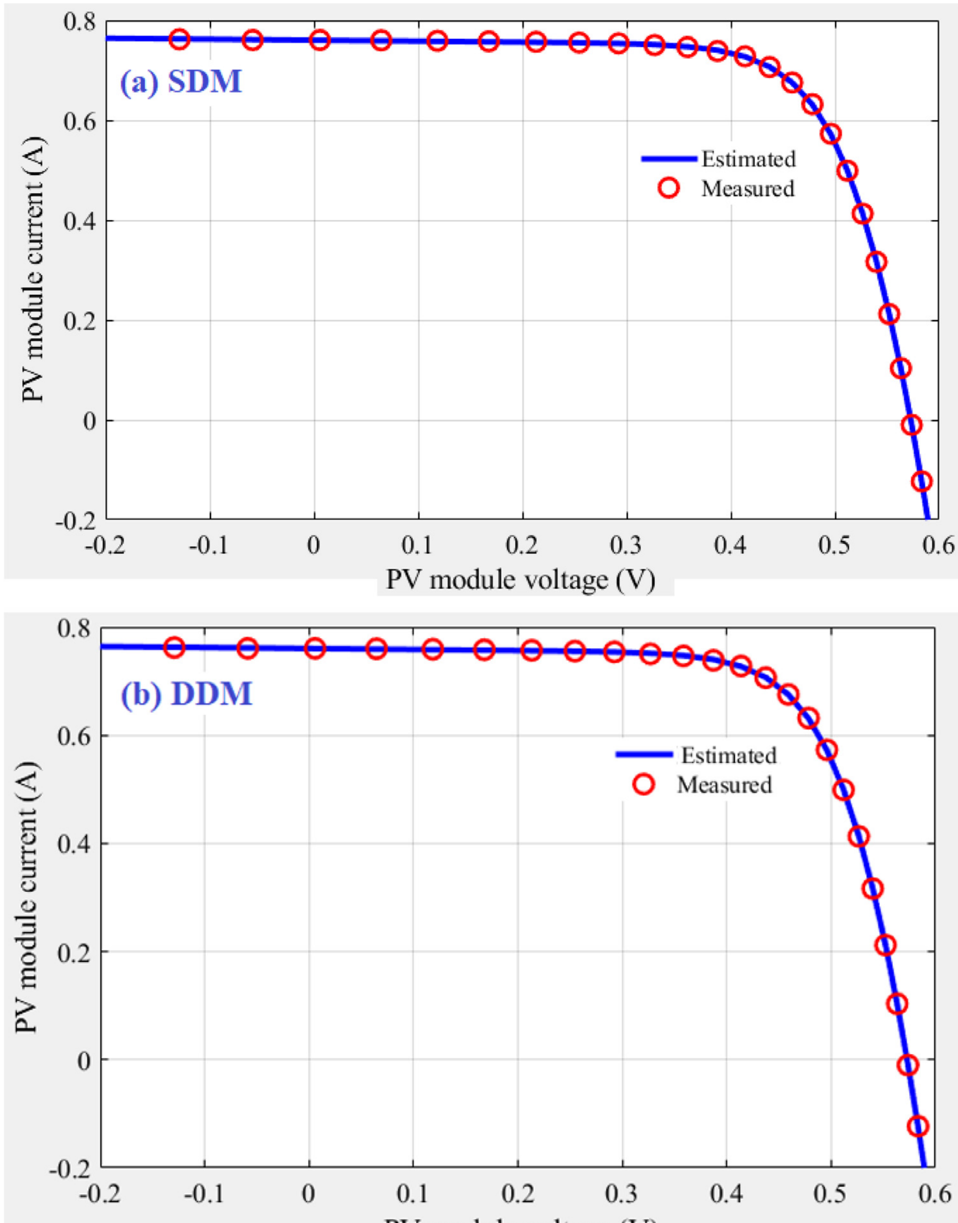

Fig. 6. The experimental dataset versus the estimated for R.T.C France silicon solar cell. (a) SDM; (b) DDM.

$$- \left(\frac{V_i + \bar{I}_{(V_i,\xi)} R_s}{R_p} \right) - \bar{I}_{(V_i,\xi)} \tag{16}$$

$$\frac{\partial f\left(\bar{I}_{(V_i,\xi)}\right)}{\partial \bar{I}_{(V_i,\xi)}} = - \left(\frac{I_0 R_s \left[Exp\left(\frac{V_i + \bar{I}_{(V_i,\xi)} R_s}{nV_t} \right) \right]}{nV_t} - \left(\frac{V_i + \bar{I}_{(V_i,\xi)} R_s}{R_p} \right) \right) - \frac{R_s}{R_p} - 1 \tag{17}$$

3.2. Double-diode model

The optimum estimations of the seven obscure parameters, as shown in Fig. 1b, are acquired by assessing the present qualities that produce the least mistake. Likewise with the previous model, the extracted current $\bar{I}_{(V_i,\xi)}$ is also obtained by using NRM, whose flowchart is shown in Fig. 2, and with Eqs. (16) and (17) being replaced by the following equations (Rezk et al., 2019a,f):

$$f\left(\bar{I}_{(V_i,\xi)}\right) = I_{ph} - I_{01} \left[Exp\left(\frac{V + \bar{I}_{(V_i,\xi)} R_s}{n_1 V_t} \right) - 1 \right] - I_{02} \left[Exp\left(\frac{V + \bar{I}_{(V_i,\xi)} R_s}{n_2 V_t} \right) - 1 \right] - \left(\frac{V_i + \bar{I}_{(V_i,\xi)} R_s}{R_p} \right) - \bar{I}_{(V_i,\xi)} \tag{18}$$

$$\frac{\partial f\left(\bar{I}_{(V_i,\xi)}\right)}{\partial \bar{I}_{(V_i,\xi)}} = - \left(\frac{I_{01} R_s \left[Exp\left(\frac{V_i + \bar{I}_{(V_i,\xi)} R_s}{n_1 V_t} \right) \right]}{n_1 V_t} - \left(\frac{V_i + \bar{I}_{(V_i,\xi)} R_s}{R_p} \right) \right)$$

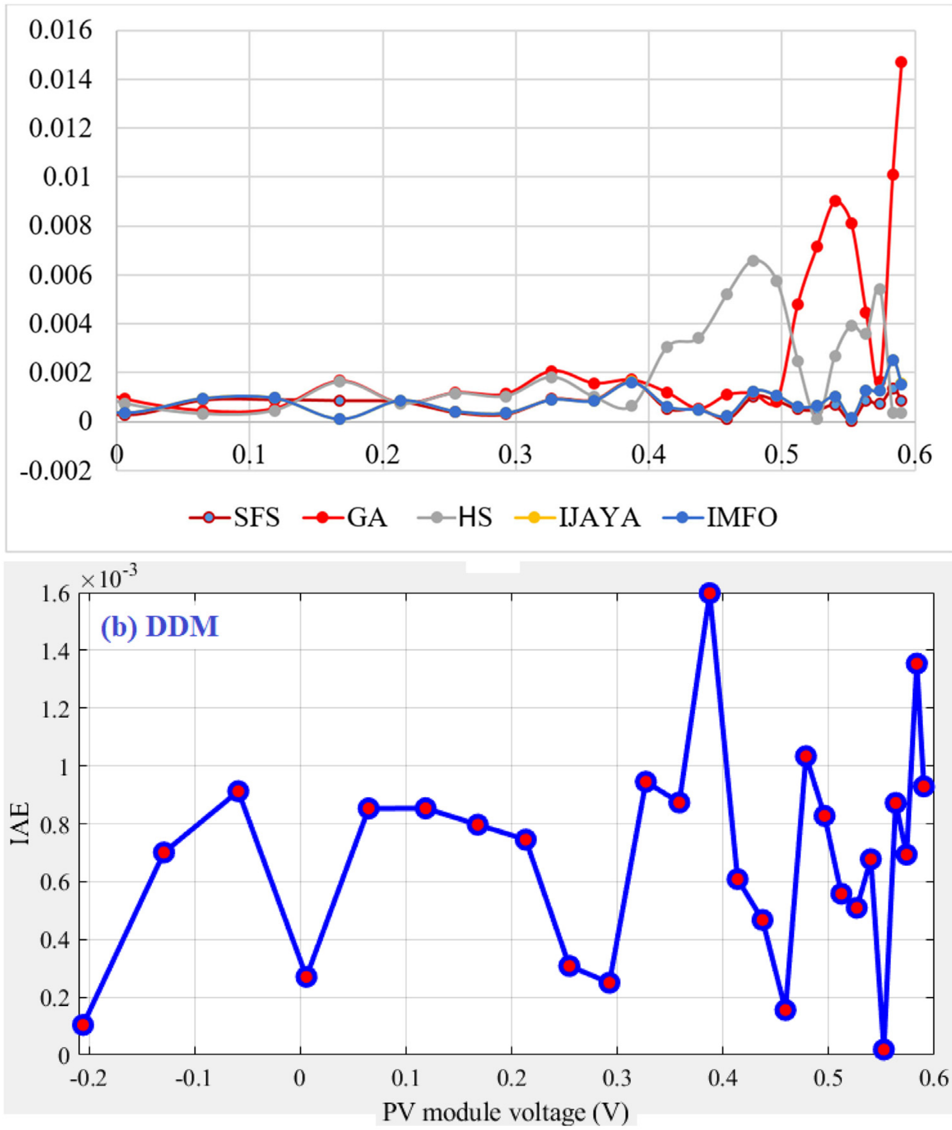

Fig. 7. Absolute error against measured PV module voltage for R.T.C France silicon solar cell using different strategies. (a) SDM and (b) DDM.

$$- \left(\frac{I_{02} R_s \left[Exp\left(\frac{V_i + \bar{I}_{(V_i,\xi)} R_s}{n_2 V_t} \right) \right]}{n_2 V_t} - \left(\frac{V_i + \bar{I}_{(V_i,\xi)} R_s}{R_p} \right) \right) - \frac{R_s}{R_p} - 1 \tag{19}$$

4. The stochastic fractal search algorithm

The stochastic fractal search (SFS) algorithm is a recently created by Salimi (2015), inspiring by the characteristic development marvel of a random fractal. The SFS algorithm essentially utilizes two procedures after initializing the population, (1) diffusion and (2) updating to improve the searching, Fig. 3. In initialize the population process, determine the population size N_D, and determine the number of optimization variable X_D. In the diffusion process, each particle diffuses around its location and completes the misuse task (Salimi, 2015; Chen et al., 2019; Hosny et al., 2020; Tran et al., 2020). On the other hand, in the updating procedure, every molecule is updated by the area of different particles, and this procedure prompts investigation properties. The three processes of SFS are shown in Fig. 3.

In the mathematical model of the SFS, the best solution only selected in the diffusion process to produce new arrangements, while overlooking different arrangements as shown in the flowchart of Fig. 4. The process toward creating new arrangements is represented by Gaussian walks (Gw) that can be defined as follows (Salimi, 2015; Padhy and Panda, 2017; Chen et al., 2019; Çelik, 2020):

$$Gw_1 = Gaussian\left(\mu_G, \sigma\right) + \left(rand\left(0,1\right) \times P_B - rand\left(0,1\right) \times P_i\right) \tag{20}$$

$$Gw_2 = Gaussian\left(\mu_P, \delta\right) \tag{21}$$

Where; $rand(0, 1)$ is a random number generated within the range [0, 1]; P_i and P_B are the ith solutions and the best solution, respectively; μ_G and μ_P are the means of Gaussian walk which are equal to $|P_i|$ and $|P_B|$ respectively; δ is the standard deviation which is computed as (Salimi, 2015; Lin and Wang, 2019):

$$\delta = \left| \frac{\log\left(g\right)}{g} \left(P_i - P_B\right) \right| \tag{22}$$

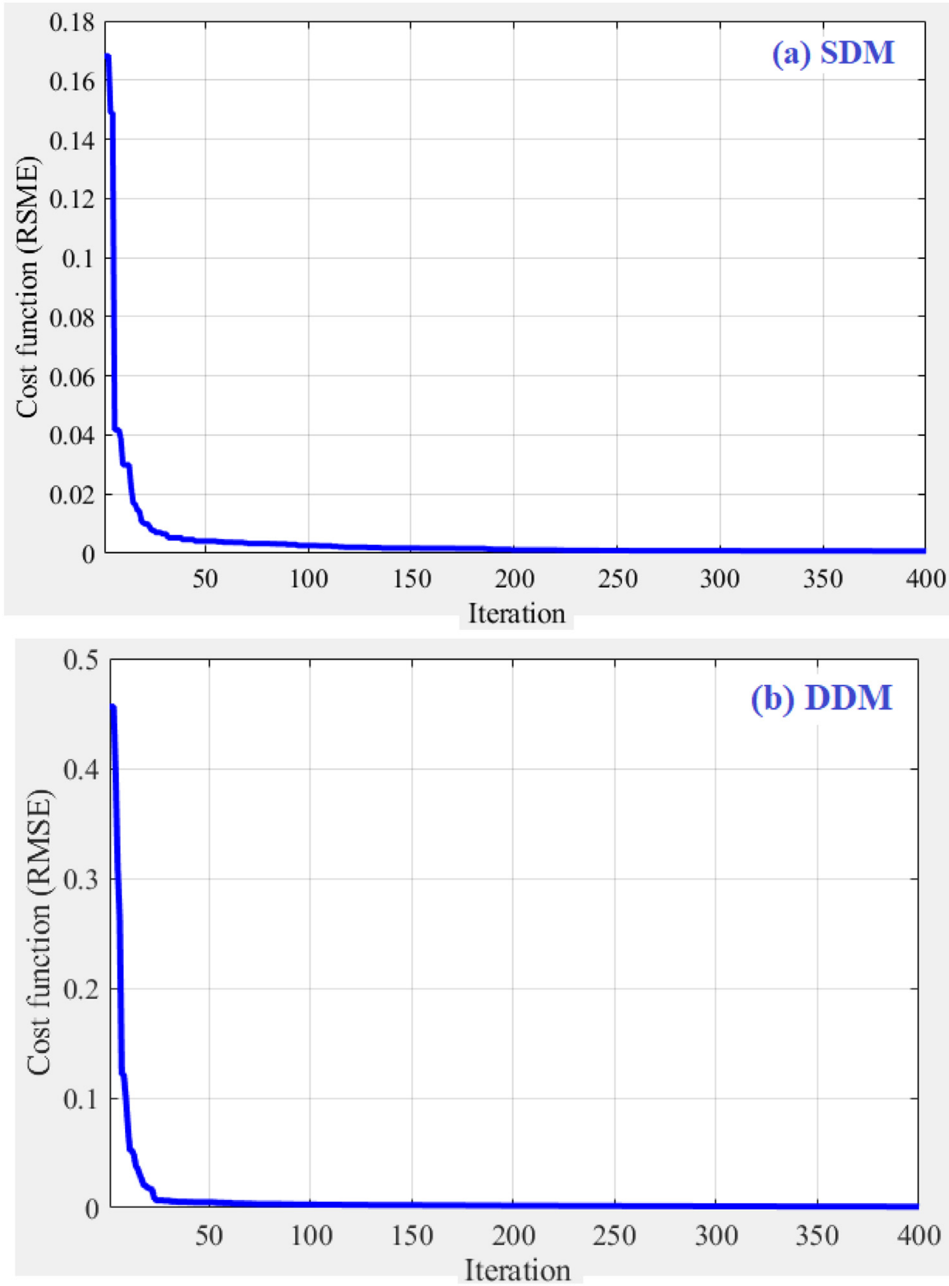

Fig. 8. The variation cost function during parameter estimation of R.T.C France silicon solar cell using SFS strategy. (a) SDM and (b) DDM.

Where; g is the number of iterations. During the optimization process, g is increased but less than terminated condition G_{max}, δ is dynamically adjusted due to Eq. (22).

Every particle is diffused around its present situation by utilizing the Gaussian walks then again until a predefined most extreme dissemination number YD is reached, Fig. 4. Several generated solutions are obtained using the algorithm, based on the following equation:

$$P_{ij} = LB_{ij} + rand\,(0, 1) \times \left(UB_{ij} - LB_{ij}\right),\ j = 1, 2, 3, \ldots.., Y_D \quad (23)$$

Where; UB_{ij} and LB_{ij} are the upper and lower boundaries of the jth value of the solution i; Y_D is the maximum diffusion number of generated solutions using SFS algorithm.

In the next step, the quality of each solution is computed and the best solution P_B is determined. Two approaches are used in this step; the first approach is aimed to update the solution of each element probability (P_a) based on the value of the Pa < $rand\,(0, 1)$ as expressed in the following equation (Salimi, 2015; Chen et al., 2019; Mahdad, 2019):

$$P_a = \frac{rank\,(P_i)}{N_D} \quad (24)$$

$$P'_{ij} = P_{aj} - rand\,(0, 1) \times (P_{a1} - P_{a2}) \quad (25)$$

Where; $rank(P_i)$ is the rank of the ith solution among different arrangements in the populace; P'_i is the new solution of the ith solution; P_{a1} and P_{a2} are the random solutions of population.

The second approach is aimed to enhance the exploration which means applying the changes to the solution dependent on different solutions in the populace. However, this approach begins by ranking all arrangements dependent on Eq. (26), like similar strides in the primary approach. If $P_a < rand\,(0, 1)$ for the

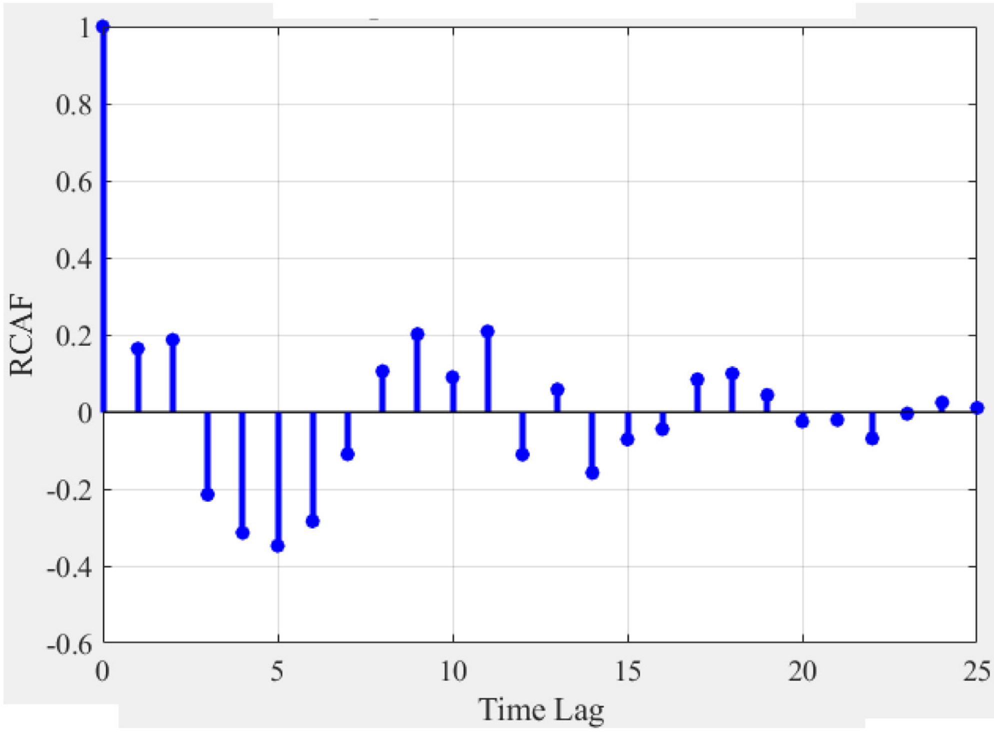

Fig. 9. RCAF results for SDM of R.T.C France silicon solar cells using SFS strategy.

P'_i, there is no update for the current solution P'_i; otherwise the solution is updated utilizing the accompanying equation (Chan and Phang, 1987; Padhy and Panda, 2017):

$$P''_i = \begin{cases} P'_i - rand\,(0, 1) \times \left(P'_t - P_B\right) & rand\,(0, 1) \leq 0.5 \\ P'_i + rand\,(0, 1) \times \left(P'_t - P'_r\right) & rand\,(0, 1) > 0.5 \end{cases} \tag{26}$$

Where P'_t and P'_r are solutions selected randomly from the approach utilizing Gaussian distribution. The subsequent stage is to compare the quality of the P''_i with P'_i and if (P''_i) is better than (P'_i) then P''_i is replaced P'_i; otherwise P'_i not updated.

Table 2
Specifications of R.T.C France silicon solar cell, STP6 120/36, and ESP-160 PPW.

Parameter	Type of solar cell and panel		
	R.T.C solar cell	STP6 120/36	ESP-160 PPW
Number of samples	26	22	45
Test Temperature, C	33	55	43
Test radiation, W/m^2	1000	na	na
Short circuit current, A	0.7605	7.48	5.51
Open circuit voltage, V	0.5727	19.21	20.65
Current @ MPP, A	0.6755	9.83	16
Voltage @ MPP, V	0.4590	14.93	4.95
Number of cells	1	36	72

5. Experimental results, analysis, and discussion

To prove the legitimacy of the proposed SFS approach, it is applied to determine the parameters of different solar PV equivalent circuit models including the SDM and DDM for both solar cell and PV module.

The control parameters of SFS are 30, 400 and 1 respectively for the population size, maximum number of iterations and Maximum Diffusion Number. Three different case studies are considered for the evaluation. The first case study, an experimental standard dataset of a commercial R.T.C. France silicon solar cell operating at a temperature of 33 °C and solar radiance of 1000 W/m^2 is adopted (AlRashidi et al., 2011). A polycrystalline solar panel STP6 120/36 is used for the second case study. It consists of 36-cells in series of polycrystalline silicon cells. The test has been performed at 22 °C (Liao et al., 2020). For the last case study, an experimental dataset is extracted using the ESP-160 PPW PV module at a temperature of 45 °C is taken into account. To assess the system performance of the proposed method 45 measurements of voltage and current are considered. This experimentation with real-prototype has been examined in the Laboratory of Renewable Energy at Assiut University, Egypt. The experimental set-up used for the assessment is shown in Fig. 5 where as the dataset are presented in Appendix. Table 2 highlights the specifications of PV panels and solar cells considered in this research.

5.1. Results of first case study

Based on the dataset on R.T.C France silicon solar cell, the proposed strategy of SFS is used to determine the optimal parameters for both SDM and DDM of the cell, and obtained parameters are listed in Tables 3 and 4 respectively. Tables 3 and 4 stat comparison between the SFS algorithm and an improved JAYA (IJAYA) optimization algorithm (Yu et al., 2017), harmony search (HS) algorithm (Askarzadeh and Rezazadeh, 2012), genetic algorithm (GA) (AlRashidi et al., 2011), improved moths–flames optimization (IMFO) (Sheng et al., 2019), Perturbed Stochastic Fractal Search (pSFS) (Chen et al., 2019), A biogeography-based optimization algorithm with mutation strategies (BBO-M) and Nelder–Mead simplex orthogonal learning moth flame optimization (NMSOLMFO) (Zhang et al., 2020). From the presented results in Table 3, it can be easily understood that when applied the objective function (RMSE), via SFS algorithm is more accurate than other competent algorithms.

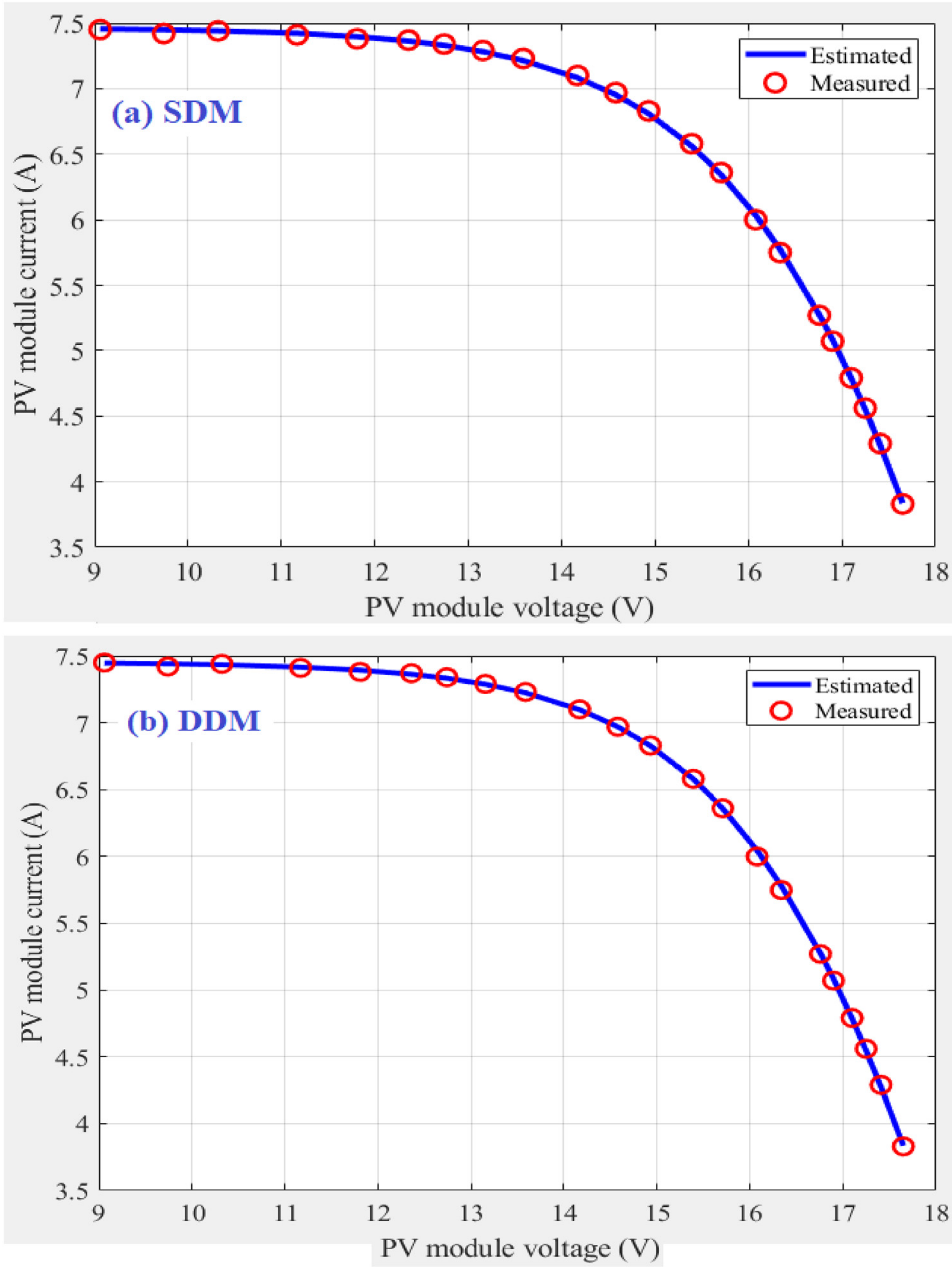

Fig. 10. The experimental dataset versus the estimated for STP6 120/36 PV panel. (a) SDM and (b) DDM.

Table 3
Boundaries and optimal values of SDM parameters of R.T.C France silicon solar cell.

Parameter	Boundary		Optimal parameters							
	Min.	Max.	SFS	IJAYA (Yu et al., 2017)	HS (Askarzadeh and Rezazadeh, 2012)	GA (AlRashidi et al., 2011)	IMFO (Sheng et al., 2019)	pSFS (Chen et al., 2019)	BBO-M (Niu et al., 2014a,b)	NMSOL-MFO
I_{sc} (A)	0	1	**0.7609**	0.7608	0.7607	0.7619	0.76078	0.76078	0.76078	0.760773131
Io_1 (A)	1e−08	1e−05	**3.167e−07**	3.228e−07	3.049e−07	8.087e−07	3.2296e−07	3.230e−07	3.187e−07	3.23641e−07
n_1	0	2	**1.47918**	1.4811	1.47538	1.5751	1.48117	1.48118	1.47984	0.036369754
R_s (Ω)	0	5	**0.03648**	0.0364	0.03663	0.0299	0.03638	0.03638	0.03642	1.481376399
R_p (Ω)	0	100	**53.2805**	53.7595	53.5946	42.372	53.71456	53.71852	53.36227	53.78931534
RMSE			**7.931e−04**	9.89e−04	1.50e−02	4.77e−03	9.86e−04	9.860e−04	9.8634e−04	9.8603e−04
MAE			**7.054e−04**	na	na	na	na	na	na	na
R^2			**1**	na	na	na	na	na	na	na

For SDM, the minimum value of RMSE is achieved by SFS strategy. The values of RMSE are 7.931e−04, 9.89e−04, 1.50e−02, 4.77e−03, 9.86e−04, 9.8602e−04, 9.8634e−04 and 9.8603e−04 respectively for SFS, IJAYA, HS, GA, IMFO, pSFS, BBO-M and NMSOLMFO. This means that using SFS decreased the cost function by 19.56% compared with pSFS. The coefficient of determination is 1 using for SFS. This is confirmed that there is a

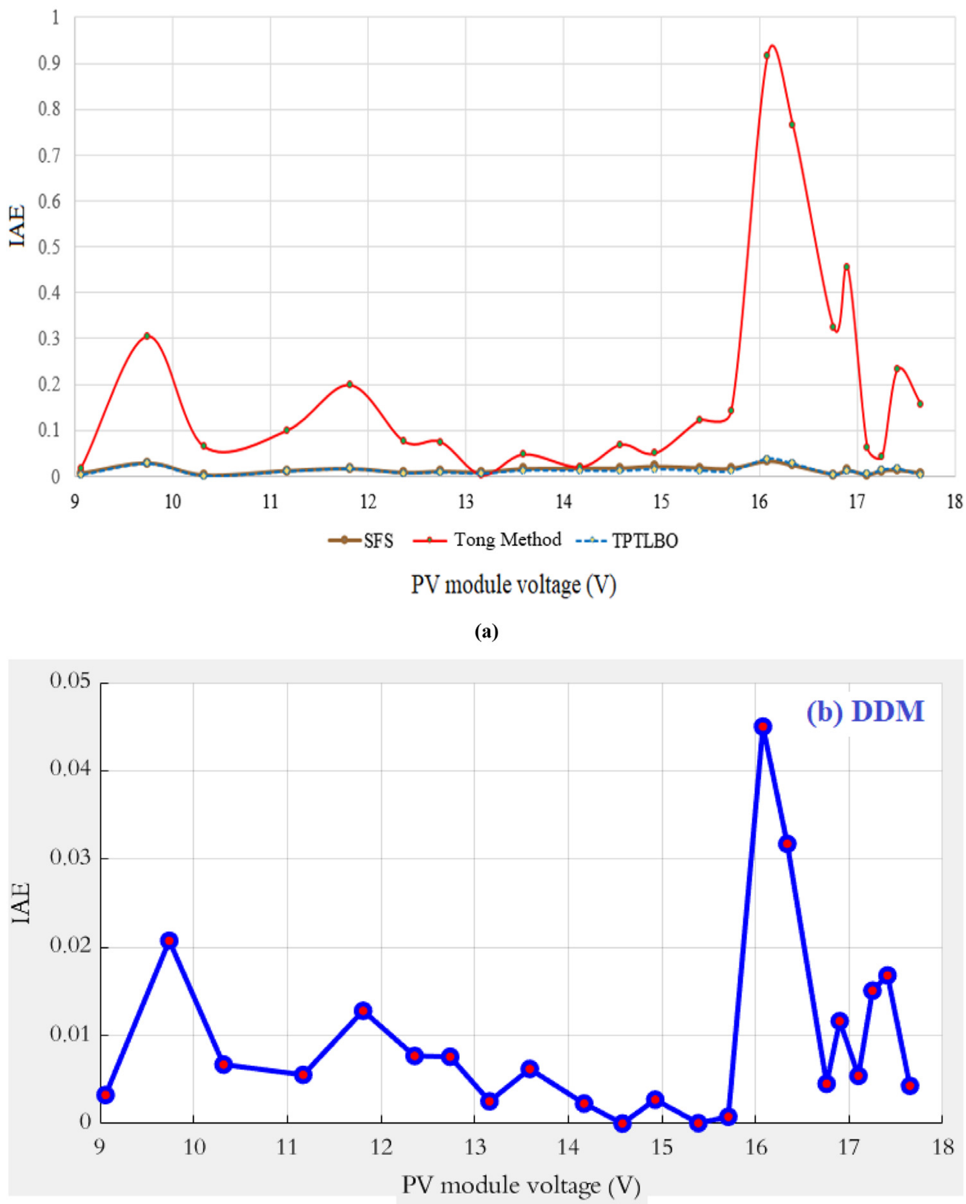

Fig. 11. Absolute error against measured PV module voltage for STP6 120/36 PV panel using different strategies. (a) SDM and (b) DDM.

Table 4
Boundaries and optimal values of DDM parameters of R.T.C France silicon solar cell.

Parameter	Boundary		Optimal parameters						
	Min.	Max.	SFS	IJAYA (Yu et al., 2017)	HS (AlRashidi et al., 2011)	IMFO (Sheng et al., 2019)	pSFS (Chen et al., 2019)	BBO-M	NMSOL-MFO
I_{sc} (A)	0	1	**0.7608**	0.7601	0.76176	0.76078	0.76078	0.76083	0.760781079
Io_1 (A)	1e−08	1e−05	**2.183e−07**	5.0445e−09	1.2545e−07	2.335e−07	8.4161e−07	5.9115e−07	7.49349e−07
Io_2(A)	1e−08	1e−05	**3.681e−07**	7.5094e−07	2.547e−07	6.8372e−07	2.1545e−07	24523e−07	0.036740432
n_1	0	2	**1.450**	1.2186	1.49439	1.45374	2	2	2.25974E−07
n_2	0	2	**1.820**	1.6247	1.49989	2	1.44705	1.45798	1.451016656
$R_s(\Omega)$	0	5	**0.03675**	0.0376	0.03545	0.03671	0.03679	0.03664	55.48543807
R_p (Ω)	0	100	**54.5464**	77.8519	46.82696	55.2997	55.72835	55.0494	2
RMSE			**7.7827e−04**	9.8292e−04	1.26e−03	9.8252e−04	9.8255e−04	9.8272e−04	9.8248e−04
MAE			**6.8889e−04**	na	na	na	na	na	na
R^2			**0.99999**	na	na	na	na	na	na

perfect agreement between the estimated datasets and the experimental data. For DDM, the minimum value of RMSE is also achieved by SFS strategy. The values of RMSE are 7.7827e−04, 9.8292e−04, 1.26e−03, 9.8252e−04, 9.8255e−04, 9.8272e−04 and 9.8248e−04 respectively for SFS, IJAYA, HS, IMFO, pSFS, BBO-M and NMSOLMFO. This means that using SFS decreased the

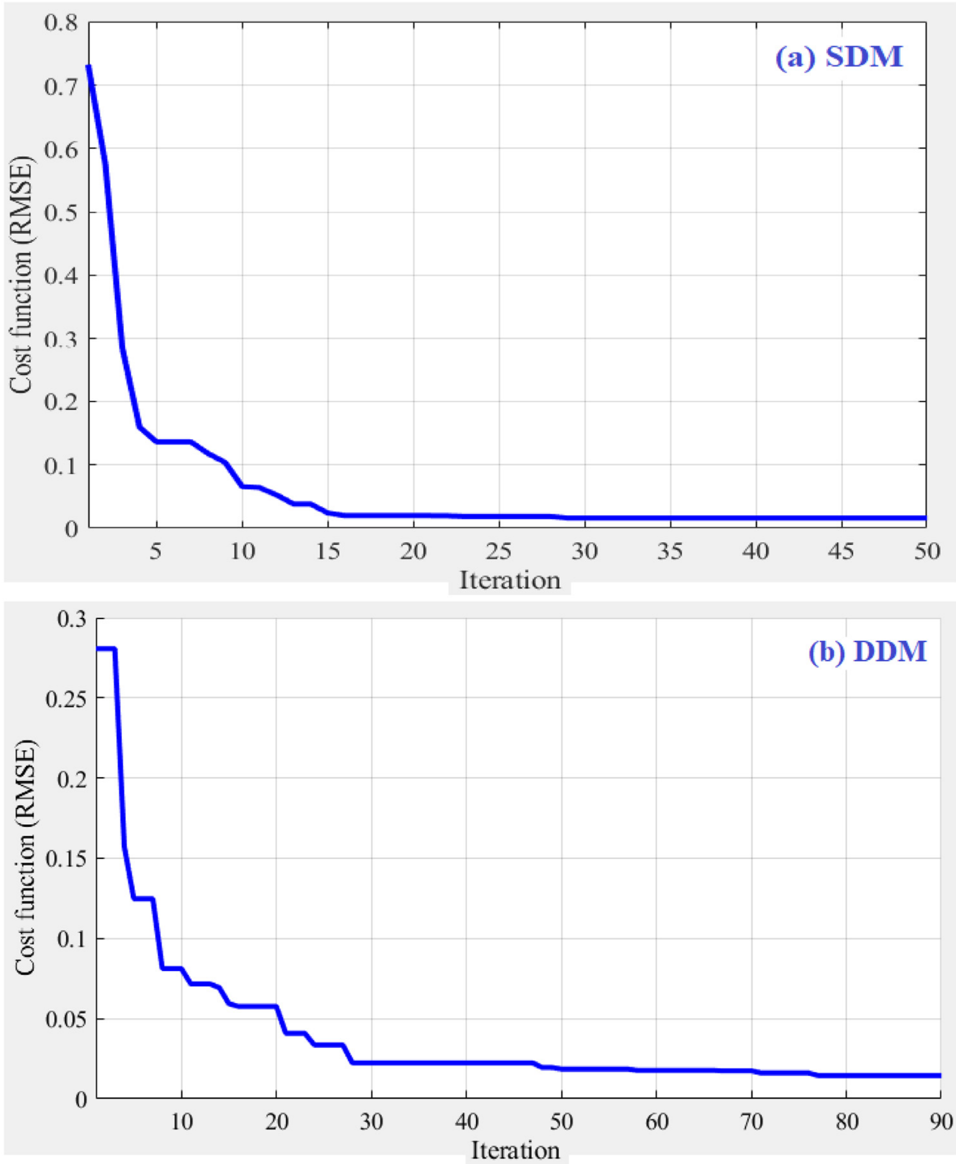

Fig. 12. The variation cost function during parameter estimation of STP6 120/36 PV panel using SFS strategy. (a) SDM and (b) DDM.

cost function by 20.79% compared with pSFS. The coefficient of determination is 0.99999 using for SFS. This is confirmed that there is a perfect agreement between the estimated datasets and the experimental data. Fig. 6(a) and (b) show the experimental dataset versus the estimated, respectively for both SDM and DDM.

The absolute error against measured PV module voltage for both SDM and DDM using different strategies are shown in Fig. 7. For SDM, the maximum values for the absolute error are 1.65E−03, 7.16E−03, 6.58E−03, 1.62E−03, and 1.62E−03 respectively for SFS, IJAYA, HS, GA, and IMFO. Whereas the maximum absolute error for DDM is 1.60E−03 using the proposed strategy. This confirms the superiority of SFS compared with other methods.

The variation cost function during parameter estimation of R.T.C France silicon solar cell using SFS strategy for both SDM and DDM is presented in Fig. 8. It is noted that for both models consume approximately 200 iterations to catch the optimal solution. The best solution values are 7.931e−04 and 7.7827e−04 for SDM and DDM, respectively.

The results of the whiteness test for R.T.C France silicon solar cells using SFS strategy are shown in Fig. 9. The main target of this test is to ensure that the selected model parameters describe the experimental dataset perfectly without any mismatch. It calculated using the residual autocorrelation function (RACF) at different time lags. Considering Fig. 9, the RCAF values range from −1 to +1.

5.2. Results of second case study

Based on the experimental dataset on the STP6 120/36PV solar module, the proposed strategy of SFS is used to determine the optimal parameters for both SDM and DDM of the panel. The number of I–V points is 36. Table 5 presents the maximum and minimum boundaries of each unknown parameter and optimal values of SDM parameters of the STP6 120/36 PV solar module

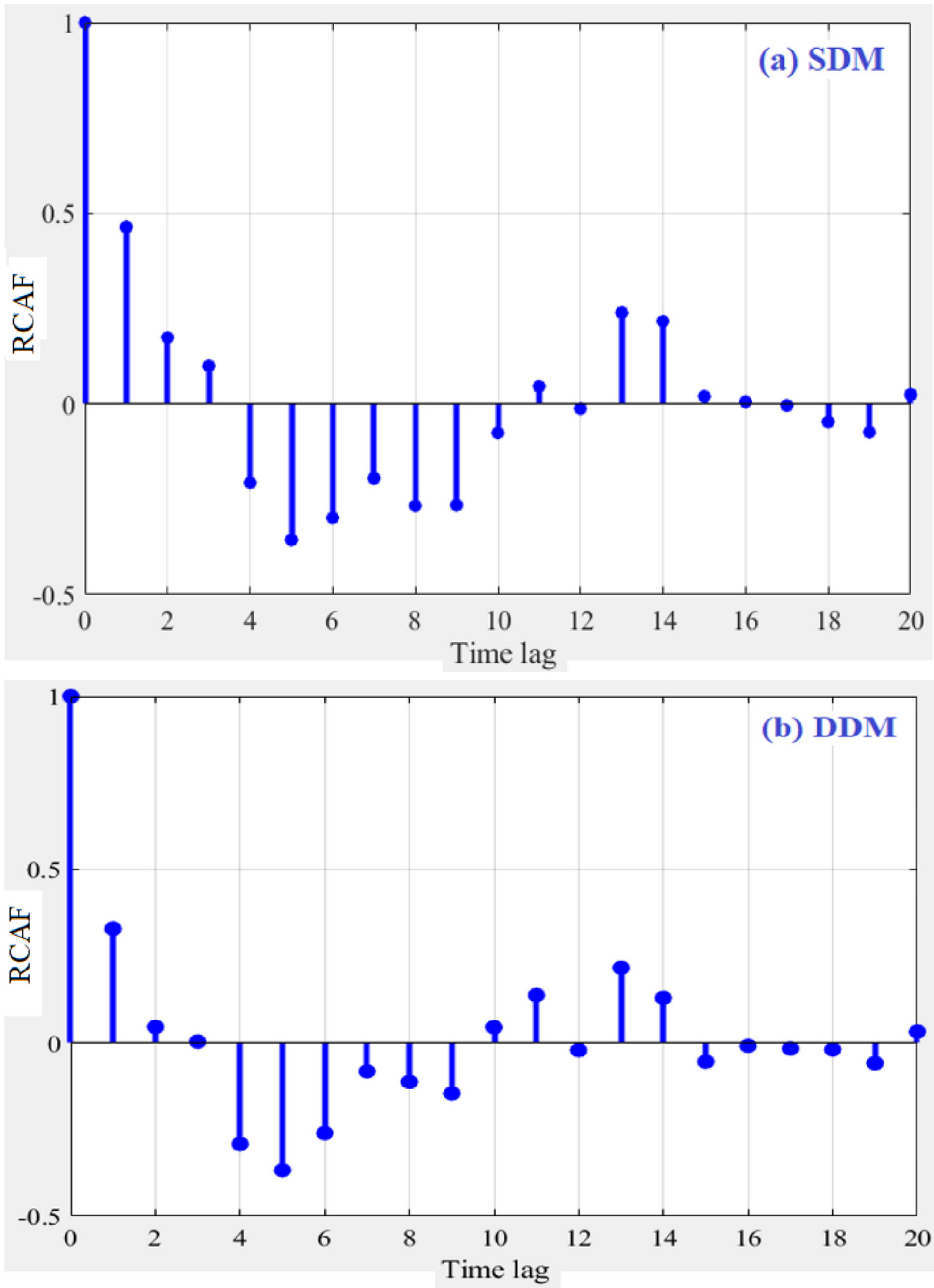

Fig. 13. RCAF results for STP6 120/36 PV panel using SFS strategy. (a) SDM and (b) DDM.

using SFS, TPTLBO (Liao et al., 2020)), and method in Ref. (Tong and Pora, 2016).

For SDM, the minimum value of RMSE is achieved by SFS strategy. The values of RMSE are 0.0159, 0.30343, and 0.0166, respectively for SFS, TPTLBO, and Tong Method (Tong and Pora, 2016). The coefficient of determination is 0.9998 using SFS. This confirms that there is a perfect agreement between the estimated datasets and the experimental data. Fig. 10(a) and (b) illustrate the experimental dataset versus the estimated, respectively for both SDM and DDM. For the DDM, the RMSE and MAE are 0.0145 and 0.0097, respectively.

The absolute error against measured PV module voltage for both SDM and DDM using different strategies is shown in Fig. 11. For SDM, the maximum values for the absolute error are 0.0335, 0.917, and 0.03749, respectively for SFS, TPTLBO, and Tong Method (Tong and Pora, 2016). Whereas the maximum absolute error for DDM is 0.046 using the proposed strategy. This exhibits the superiority of SFS compared with other methods.

The variation cost function during parameter estimation STP6 120/36 PV panel using SFS strategy for both SDM and DDM is presented in Fig. 12. It is noted that both models can achieve optimal solution approximately by 30 and 80 iterations for SDM

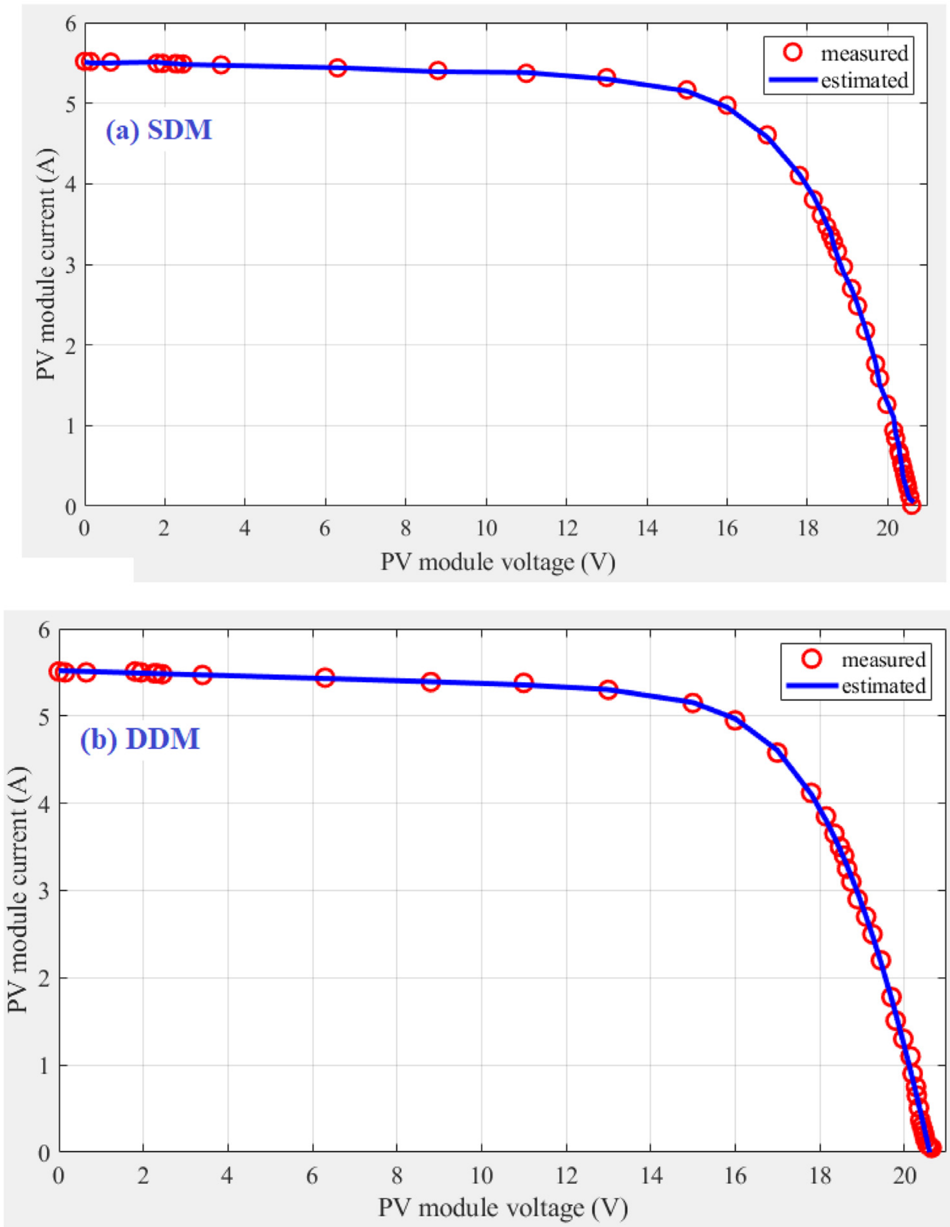

Fig. 14. The experimental dataset versus the estimated for ESP-160 PPW PV module. (a) SDM and (b) DDM.

Table 5
Boundaries and optimal values of SDM and DDM parameters of the STP6 120/36 PV module.

Parameter	Boundary			Optimal parameters (SDM/DDM)		
	Min.	Max.	SFS	TPTLBO (Liao et al., 2020)	Tong Method (Tong and Pora, 2016)	SFS
I_{sc} (A)	0	10	**7.4757**	7.4725	7.4838	**7.480**
I_{o1} (A)	1e−08	1e−04	**3.01e−06**	2.335e−06	1.2e−06	**8.3127e−07**
I_{o2} (A)	1e−08	1e−04	**na**	na	na	**3.1635e−06**
n_1	0.5	2	**1.2816**	1.2601	1.2072	**1.1827**
n_2	0.5	2	**na**	na	na	**1.76786**
R_s (Ω)	0	5	**0.1600**	0.0046	4.9	**0.1874**
R_p (Ω)	0	1000	**827.5815**	22.2199	9.745	**376.625**
RMSE			**0.0159**	0.30343	0.0166	**0.0145**
MAE			**0.0137**	na	na	**0.0097**
R^2			**0.9998**	na	na	**0.9998**

and DDM, respectively. The best solution values are 0.0159 and 0.0145 for SDM and DDM, respectively.

The results of the whiteness test for STP6 120/36 PV panel using the STS strategy for both SDM and DDM are shown in Fig. 13. The RCAF values range from −1 to +1 for both strategies. If the RCAF values appear between the system can be considered effective, this test can be widely used to decide the effectiveness

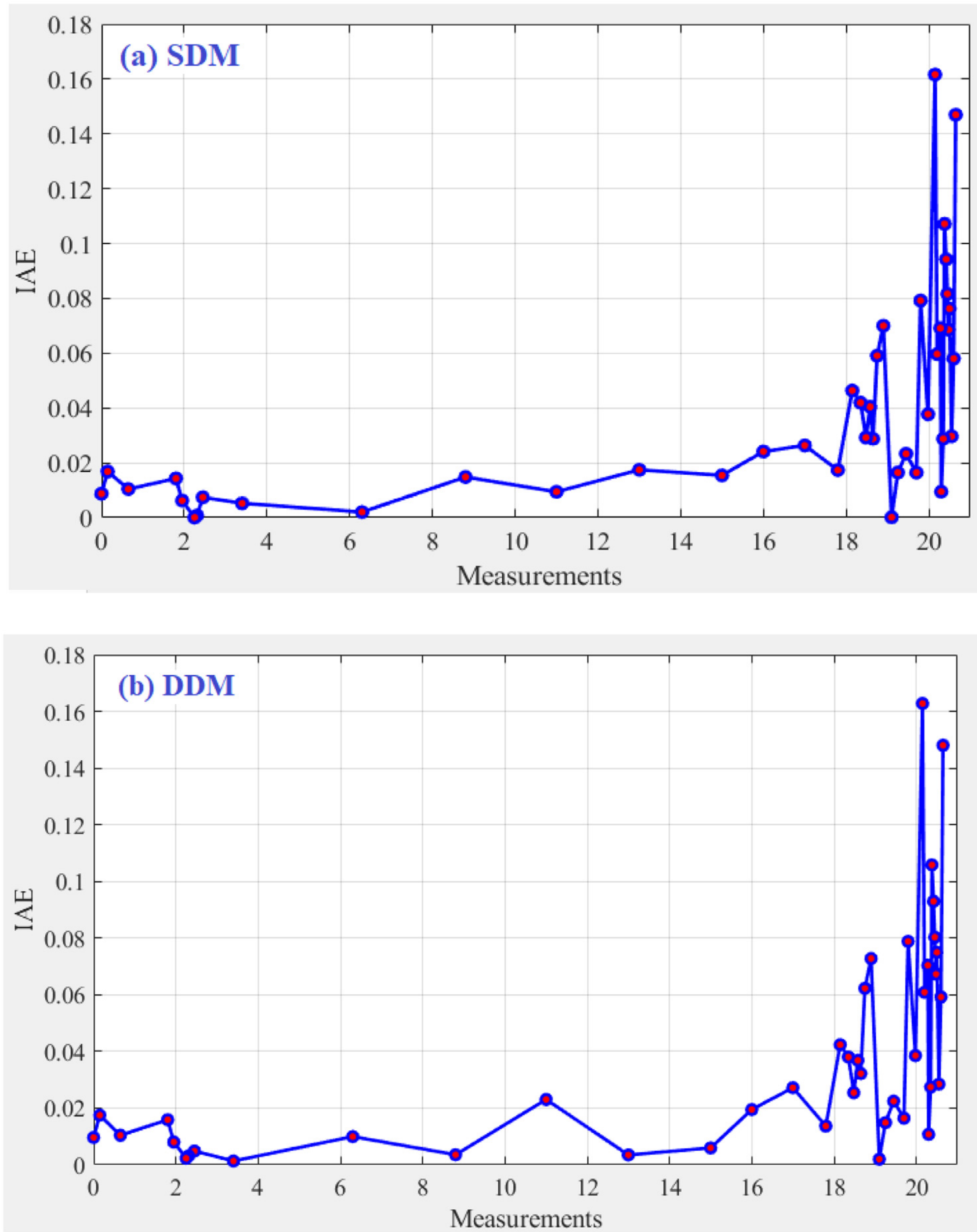

Fig. 15. Absolute error against measured PV module voltage for the ESP-160 PPW PV module using different strategies. (a) SDM and (b) DDM.

of any sort of system, and this has been widely used for the evaluation in different fields. Therefore, to prove the perfectness of the proposed system, this test has been performed and presented in this work to indicate the Excellency of the method.

5.3. Results of the third case study

Based on the experimental dataset on the ESP-160 PPW PV module, the proposed strategy of SFS is used to determine the optimal parameters for both SDM and DDM of the cell. Table 6 presents the maximum and minimum boundaries of each unknown parameter and optimal values of SDM and DDM parameters of the FSM PV solar module using SFS strategy.

For SDM, the values of RMSE and MAE are 0.05422 and 0.039007, respectively, using the SFS strategy. Whereas, for DDM, the values of RMSE and MAE are 0.0540 and 0.0384, respectively. The best coefficient of determination values is 0.999328 and 0.9993, respectively, for SDM and DDM. This is confirmed that there is a perfect agreement between the estimated datasets and the experimental data. Fig. 14 shows the experimental dataset versus the estimated, respectively, for both SDM and DDM.

The absolute error against measured PV module voltage for both SDM and DDM using SFS strategy is presented in Fig. 15. Approximately, the maximum absolute error is 0.161 for both SDM and DDM.

The variation cost function during parameter estimation of STP6 120/36 PV panel using SFS strategy for both SDM and DDM is presented in Fig. 16. It is noted that for both models, approximately 25 iterations are required to catch the best solution. The best solution values are 0.05422 and 0.0540 for SDM and DDM, respectively.

The results of the whiteness test for STP6 120/36 PV panel using the STS strategy for both SDM and DDM are shown in Fig. 17. The RCAF values range from −1 to +1 for both strategies.

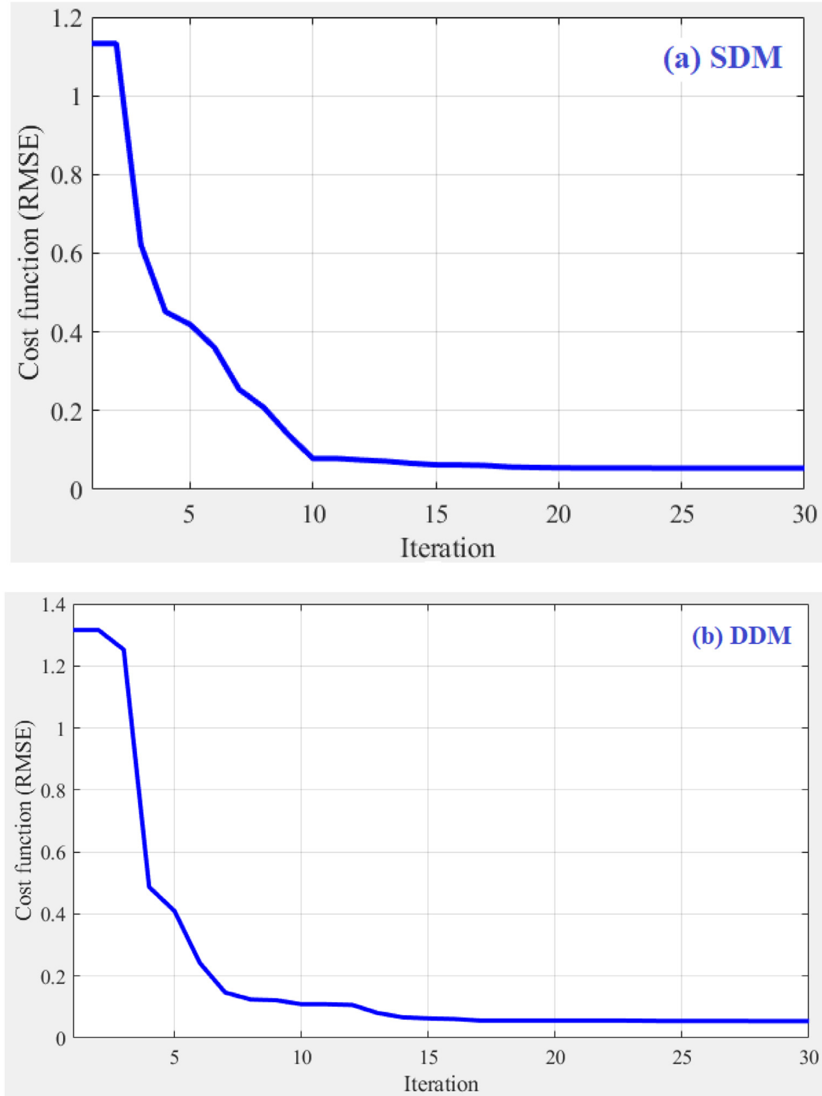

Fig. 16. The variation cost function during parameter estimation of ESP-160 PPW PV module using SFS strategy. (a) SDM and (b) DDM.

Table 6
Boundaries and optimal values of SDM and DDM parameters of ESP-160 PPW PV module using proposed SFS strategy.

Parameter	Boundary		Optimal parameters	
	Min.	Max.	SDM	DDM
I_{sc} (A)	1	10	5.534	5.537
I_{o1} (A)	1e−8	1e−4	5.859e−7	3.9167e−07
I_{o2} (A)	1e−8	1e−4	na	3.5697e−07
n_1	0.1	3	0.6518	0.63614
n_2	0.1	3	na	1.0887
R_s (Ω)	0.05	0.5	0.2175	0.2226
R_p (Ω)	10	1000	77.962	70.211
RMSE			0.05422	0.0540
MAE			0.039007	0.0384
R^2			0.999328	0.99930

6. Conclusion

In this paper, a novel algorithm named stochastic fractal search (SFS) is used for the first time to improve the estimation of the parameters of PV cells/models. This algorithm has been applied to solve the parameter estimation problem of SDM and DDM for both single solar cells and PV modules. With the successful implementation of the algorithm under three different test cases and by comparing the simulated results with experimental results

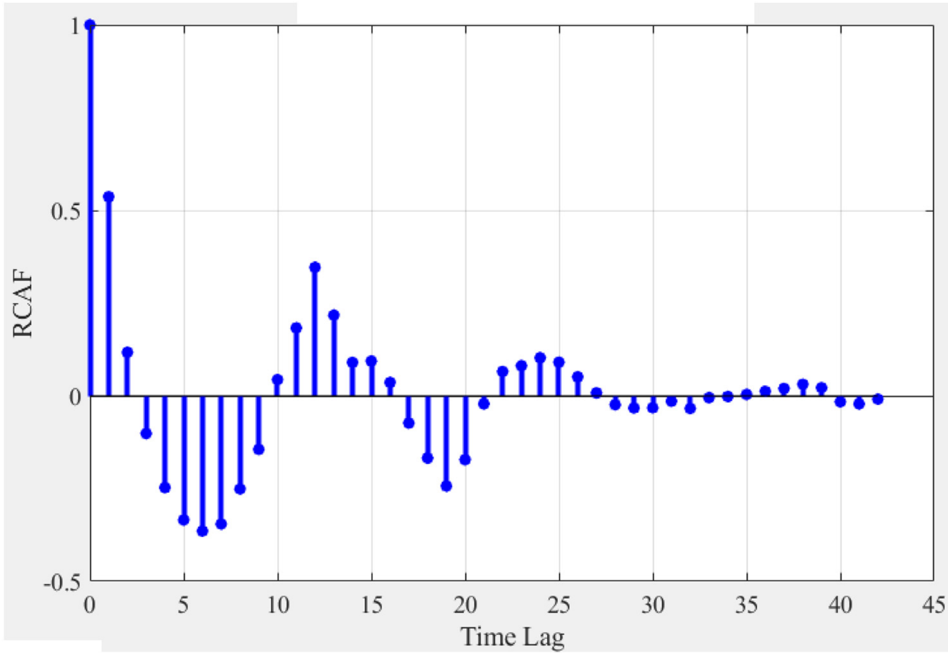

Fig. 17. RCAF results for SDM of ESP-160 PPW PV module using SFS strategy.

Table A.1
The measurements'' V-I data of ESP-160 PPW PV module in the experiments work.

No	*V* (V)	*I* (A)	no	*V* (V)	*I* (A)	no	*V* (V)	*I* (A)
1	20.65	0.05	**16**	19.7	1.78	**31**	13	5.3
2	20.6	0.07	**17**	19.45	2.2	**32**	11	5.38
3	20.55	0.09	**18**	19.25	2.5	**33**	8.8	5.39
4	20.5	0.15	**19**	19.1	2.7	**34**	6.3	5.44
5	20.48	0.2	**20**	18.9	2.9	**35**	3.4	5.47
6	20.45	0.25	**21**	18.75	3.1	**36**	2.45	5.48
7	20.42	0.3	**22**	18.65	3.25	**37**	2.31	5.49
8	20.38	0.37	**23**	18.58	3.4	**38**	2.25	5.49
9	20.35	0.51	**24**	18.48	3.5	**39**	1.95	5.5
10	20.3	0.65	**25**	18.35	3.65	**40**	1.8	5.51
11	20.28	0.75	**26**	18.15	3.85	**41**	0.65	5.5
12	20.2	0.9	**27**	17.8	4.12	**42**	0.15	5.5
13	20.15	1.1	**28**	17	4.58	**43**	0	5.51
14	19.98	1.3	**29**	16	4.95			
15	19.8	1.51	**30**	15	5.15			

that have been taken from the real-time setup established in the university campus, the following conclusions were made. From the examined three cases, it can be understood that exploitation and exploration capability in SFS have a solid effect in avoiding premature convergence. The obtained parameters via SFS were closely matched with the experimental data set, which indicates the perfectness of the method; this can be observed in all three test cases. Besides, other performance study RCAF shows the accuracy of the method, also, from the presented convergence plots it can observe that the proposed algorithm take less number of iterations than other methods mentioned in the literature. From the achieved notable merits, the involvement of less complexity, it is worth mentioning that, the proposed SFS method can be recommended as a high valued optimization technique for the estimation of solar PV parameters under any test conditions. Future work will be focused on the modeling of the triple diode model due to the involvement of more parameters which increases the complexity of optimization techniques.

CRediT authorship contribution statement

Hegazy Rezk: Conceptualization, Methodology, Software. **Thanikanti Sudhakar Babu:** Data curation, Writing - original draft preparation. **Mujahed Al-Dhaifallah:** Visualization, Investigation. **Hamdy A. Ziedan:** Supervision, Validation, Writing - reviewing and editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

See Table A.1.

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