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A Novel SDM Discrete Search-Based Parameter Estimation for PV Solar Cells and Modules

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ABSTRACT

The solar cells and photovoltaic (PV) modules are a key to clean electric power production that save the universe from warming contamination. It is fabricated using semiconductors that produce electric current under solar irradiance and metal contacts for system circuitry. The designing of the PV power system plant depends on estimating the parameters that accurately model the solar cells or PV modules. The commonly used model for representing the solar cell or PV module is the single diode model (SDM) because it is simpler than other models, contains only five unknown parameters, and has acceptable accuracy. This paper proposes a novel parameter estimation algorithm based on a discrete search to estimate the SDM parameters, called flexible alternate optimization (FAO). The proposed FAO algorithm performs an exhaustive search for a small set of the estimated parameters (called the decision set (DS)). In contrast, the rest of the parameters are kept fixed. The number of parameters in the decision set flexibly controls the trade-off between algorithm complexity and parameter estimation accuracy to be applicable in wide applications. RTC France solar cell and monocrystalline SM55 module are used to validate the proposed method's effectiveness compared to the literature algorithms. The RMSE reached 9.55E-04 for RTC France solar cell and 0.034 for the PV module by varying the decision set size. A trade-off between the proposed algorithm complexity and the parameter estimation accuracy is presented for wide application uses. Future work is directed to enhance the parameter estimation accuracy and reduce the system complexity.

1. Introduction

Renewable sources are vital to overcoming the shortage of depleted traditional power sources under the increasing demand for electric power. With technological developments, photovoltaic energy produced by PV arrays facing solar irradiation becomes an up-and-coming alternative with the growing power conversion efficiency. However, the theoretical of producing electric current from PV solar cells is described by the Shockley equation; many factors can decrease the overall system efficiency and must be considered in the designing process. The output power of the PV system, which is represented by the $I-V$ characteristic curve, decreased caused of partial shading [1]. Different types of failures in photovoltaic power systems are detected using the artificial neural network ANN by collecting data on power, temperature, and radiation should be detected in less time to enhance the PV system efficiency [2]. Under different conditions of irradiation and temperature, controllers are used to obtaining MPPT accurately to increase the power obtained by the PV system [3].

Models and parameter estimation are very powerful for emulating and studying the multi-nonlinear varying inputs. For connected and coupled systems, parameter estimation and efficient controller design are essential to provide a good performance and an improved system response [4]. Prediction of possible impacts caused by the insertion of a small PV system planet into the utility grid is necessary before real application to avoid the problems that will initiate in the distribution network. The inverters of the PV system can adapt the generated voltage under varying irradiance; hence the power quality is increased [5].Different mathematical equations are formulated for PV solar cell and module models. On the other hand, electrical circuit models are more accessible and widely used as PV solar cell and module models. One electrical circuit model named a single diode model (SDM) has five unknown parameters. It is a low-complex electrical circuit while having an acceptable model efficiency. The double diode model (DDM), and three diode model (TDM), with seven and nine unknown parameters, respectively, and other circuit models are generally more accurate but are more complex as more unknown parameters need to be estimated [6]. The five unknown parameters for the SDM are denoted by I_{PV}, I_S, R_S, R_P, n, where I_{PV} expresses the generated photo-current, I_S diode's reverse saturation current, R_S series resistance, R_P parallel resistance, and n diode ideality index. The circuit and electrical equations are carefully derived in detail in part 3 of this paper.

The model equations are represented by transcendental, complex, and nonlinear equations. Guessing initial values can minimize the model efficiency when solving using analytical methods [6].

The metaheuristic optimization algorithms have been used widely for solving the system equations of model parameter estimation as described in the next part of this paper. They apply algorithms inspired by nature. These algorithms define an objective function (ex. Root mean square error ($RMSE$)), a solution vector of unknown parameters (i.e. $[I_{PV}, I_S, R_S, R_P, n]$) for SDM, and regions of searching for these unknown parameters. Then the algorithms search over the defined regions for a solution

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vector that minimizes the objective function. Many other algorithms have been used as hybrid algorithms [7] or artificial intelligence algorithms [8].

In this paper, a hetero parameter estimation method is proposed. The accuracy and complexity of the parameter optimization algorithms attract researchers and community interests. Moreover, the robustness of the estimated parameters is necessary to be reliable in design considerations. The discrete search methodology is applied for the model's parameter estimation of solar cells and PV modules. The search regions (SR) of the SDM parameters are discretized. Then, an algorithm called flexible alternate optimization (FAO) is used to find the best set of parameters discrete values that minimize the $RMSE$ between the model expected current and the actual measured current for the RTC France solar cell and the monocrystalline SM55 PV module. Moreover, the proposed algorithm's flexibility is represented in its ability to vary the number of parameters on the decision set (DS) during a single iteration of the parameter estimation. So, a trade-off between complexity and model accuracy can be fulfilled to be applicable in a wide range of applications. Real measurements of the RTC France solar cell and a PV module are used in this study to be compared with the estimated currents of the proposed algorithm for the SDM parameter estimation. The results are finally discussed to show the effectiveness of the proposed FAO algorithm in accuracy concerning other methods in the literature. Moreover, a trade-off between the accuracy and the complexity of the proposed FAO algorithm with different decision sets is presented for many applications.

The rest of this paper is written in five parts: in part 2, the related work is notably reviewed. In part 3, the problem is carefully formulated as an equation then an optimization problem is defined for SDM parameter estimation. In part 4, the proposed FAO algorithm of SDM parameter estimation for RTC France solar cells, and SM55 PV module are studied. In part 5, numerical results are carried out for the flexible decision set sizes to show the trade-off between the complexity and the model efficiency for different applications. Finally, the conclusion of this study and future work are presented in part 6.

2. Related work

Analytical methods are formulated with costly multi-nonlinear variables and suffer from low accuracy due to arbitrary chosen initial values [6]. Metaheuristic optimization methods are used instead of analytical methods for accurate parameter estimation for the SDM of the RTC France solar cell and PV modules. Artificial bee colony [9], adaptive differential evolution algorithm [10], cat swarm optimization algorithm [11], a modified simplified swarm optimization algorithm [12], an improved chaotic whale optimization algorithm [13], an improved opposition-based whale optimization algorithm (WOA) [14], an improved cuckoo search algorithm [15], an opposition-based sine cosine approach with local search [16], an improved teaching-learning-based optimization, Coyote optimization algorithm [17], A stochastic slime mould optimization algorithm [18], gray wolf optimizer (GWO) [19], sine cosine algorithm (SCA) [20], ant lion optimizer (ALO) [21], and multiverse optimizer (MVO) [22], are examples of modern metaheuristic optimization algorithms. Although the parameter estimation problem is rich in publications, more attention is forwarded to enhancing the model efficiency and reducing the complexity.

Discrete search has been used in engineering systems. Continuous systems can be converted to discrete systems and vice versa. In [23], discrete search has been used in a telecommunication problem. This paper proposes a novel algorithm based on a discrete search with a flexible decision set named FAO to estimate the five SDM PV solar cell parameters. Complexity and model accuracy (in terms of $RMSE$) are studied under different sizes of the decision set for the searched parameters for different case studies.

3. Photovoltaic model

The datasheets provided by the manufacturers of solar cells and PV modules contain data that are nonlinearly changing with multiple variables such as cell temperature and solar irradiance intensity [6]. For more convenience and reliability, it is required to study the effects of these variables by forming a model for a solar cell so that the impact of changing variables can be analyzed and studied carefully.

SDM is an electrical circuit model of a PV solar cell and modules. It is composed of two semiconductor regions. It acts like a normal diode in the dark and follows the Shockley equation formulated in (1), where I_D is the diode current and V_D is the cell output voltage. The thermal voltage of the diode is defined by (2), where K is the Boltzmann constant, T is the temperature in Kelvin, and q is the electron charge.

In contrast, a current source is added under solar irradiance to represent the generated photo-electric current. Silver nanoparticles and indium oxide are deposited on the surface of the two layers of the semiconductor regions of the solar cell can increase the absorption of the light to increase the power conversion efficiency [24]. Two resistors are added; one is in series to define the metal electrode contact resistances, while the second represents the diode leakage current [25].

Figure 1 shows the complete electrical circuit components of SDM, where estimated current can be derived using Kirchhoff voltage law (KVL) at the node in Figure 1. $I_{est} = I_{PV} - I_D - I_{R_P}$.

The current in the parallel resistor R_P is denoted I_{R_P} and calculated by KVL as in (3), where V is the model output voltage. The model estimated current I_{est} is formulated as in (4), as depicted in [25].

$$I_D = I_S\left[exp\left(\frac{qV_D}{nKT}\right) - 1\right] \tag{1}$$

$$V_t = \frac{KT}{q} \tag{2}$$

$$I_{R_P} = \frac{V + I \times R_S}{R_P} \tag{3}$$

$$I_{est} = I_{PV} - I_S\left[exp\left(\frac{(V + I \times R_S)\, q}{n\, K\, T}\right) - 1\right] - \frac{V + I \times R_S}{R_P} \tag{4}$$

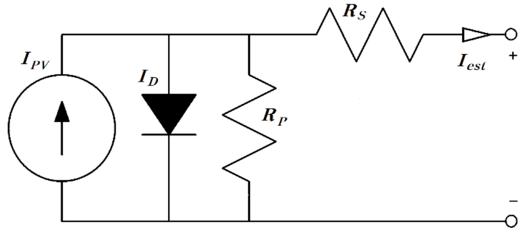

Figure 1: Single diode model of PV solar cell or module

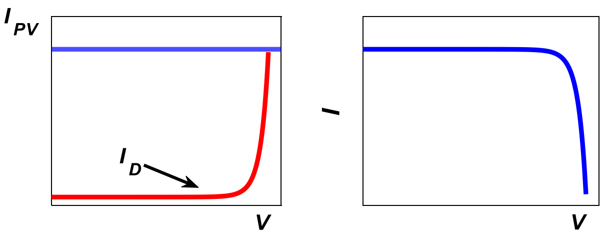

Figure 2: Composition of PV cell $I - V$ curve by superposition of I_{PV} and I_D

In (4), five unknown parameters are defined as a solution vector X for the SDM and formulated in (5).

$$X = [I_{PV},\ I_S,\ R_S,\ R_P,\ n] \tag{5}$$

From Figure 1, the superposition theorem can be applied to form the characteristics $I - V$ curve from I_{PV} and I_D as shown in Figure 2.

4. Problem formulation

The accuracy improvement of solar system components leads to minimizing and optimizing the number and size of the installed components and decreases the cost of the PV system. The model of PV solar cells or PV arrays is essential in designing and operating processes. Parameter estimation of these models helps in properly controlling the power electronic circuits of pulse width modulation PWM inverters under varying conditions.

The parameter estimation of the PV models should be simple, accurate, and reliable. In metaheuristic optimization algorithms, the solution vector is defined as $X = [I_{PV},\ I_S,\ R_S,\ R_P,\ n]$ for SDM unknown parameters. In addition, an objective function is defined as minimizing $RMSE$ of (10) between the estimated current and the measured current. Furthermore, the search regions are chosen to search for the best parameter values. SR for SDM parameters for the RTC France solar cells and the monocrystalline SM55 PV modules are shown in Table 1, as depicted in [26].

Table 1: SDM Parameters searched regions

Parameters	RTC France solar cell		Monocrystalline SM55 PV module	
	LL	*UL*	*LL*	*UL*
SR_1 for I_{PV}	0.5	0.8	1.2	4
SR_2 for I_S	0.2E-06	0.4E-06	1.5E-07	6.0E-06
SR_3 for R_s	0.03	0.05	0.1	0.5
SR_4 for R_p	50	60	100	500
SR_5 for n	1	5	1.3	2

In [26], the absolute error is used to find the deviation at an individual point between measured and estimated current values as depicted in (6). Mean absolute error (MAE) in (7) calculates the average of (AE) for N individual data. Relative error (RE) and mean relative error (MRE) are other forms of error metrics as derived in (8) and (9) respectively.

$RMSE$ as an accuracy metric is used in this paper between the values of the estimated current in (4) for the SDM and the measured values in [27] which is more accurate as an error metric and formulated in (10), as described in [26].

$$Absolute\ Error\ (AE_i) = |I_i - I_{i,est}| \tag{6}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N} AE_i \tag{7}$$

$$Relative\ Error\ (RE_i) = \frac{|I_i - I_{i,est}|}{I_i} \tag{8}$$

$$MRE = \frac{1}{N}\sum_{i=1}^{N} RE_i \tag{9}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}\left(I_i - I_{i,est}\right)^2}{N}} \tag{10}$$

In this paper, the parameters of the SDM of the RTC France solar cell and PV modules are considered as two study cases. The principles of applying metaheuristic optimization algorithm are applied to search the discrete best parameters values. The parameters' searched regions are discretized into discrete values. The vector $N = [N_1, N_2, N_3, N_4, N_5]$ is defined to determine the number of discrete values for the SDM parameters $P_i\ \forall\ i = \{1, \cdots, 5\}$. The FAO tries all combinations of discrete parameters and determines the best parameters with the lowest $RMSE$. A trade-off between accuracy and complexity is studied for different decision set sizes of the proposed FAO algorithm for parameter estimation of SDM for the study cases to be applicable in a wide range of applications.

5. Proposed method

The optimum discrete search is usually used to search for values in the discrete domain. Applying the optimum search in the parameter estimation problem for the SDM of PV solar cells and modules gains complexity because the search is carried out for every combination of all discrete values. The complexity of this method is related to the number of discrete values to be searched. The number of possible combinations is exponentially increasing with the number of discrete numbers of the SDM parameters.

5.1. The proposed FAO algorithm

In this paper, a flexible search method is proposed. A search is defined in a small set of the regions of the predefined parameter while fixing the other remaining parameters. The set of parameters to be searched is named the decision set, where it can 2, and 1 for the five parameters of the SDM. The decision set equal to 5 is equivalent to the optimum search. The remaining decision set values FAO tries all combinations of the decision set and keeps the remaining parameters fixed at their updated values in the successive iterations of the FAO proposed algorithm. Figure. 3 show the possibilities diagram for the parameters' discrete values with different decision set.

5.2. The proposed FAO method complexity

For optimum search, the total number of possible combinations $T_P(opt)$ is formed in (11), where N_i is the number of discrete values of parameter $P_i\ \forall\ i = \{1, \cdots, 5\}$ for SDM five parameters.

$$T_P(opt) = N_1 \times N_2 \times N_3 \times N_4 \times N_5 \tag{11}$$

For a decision set equal to 1, the total number of possible combinations $T_P(1)$ is formed in (12), where I_τ is the number of iterations till convergence.

$$T_P(1) = (N_1 + N_2 + N_3 + N_4 + N_5) \times I_\tau \tag{12}$$

For a decision set equal to 2, the total number of possible combinations $T_P(2)$ is formed in (13).

$$T_P(2) = [(N_1 \times N_2) + (N_3 \times N_4) + (N_5)] \times I_\tau \tag{13}$$

For a decision set equal to 3, the total number of possible combinations $T_P(3)$ is formed in (14).

$$T_P(3) = [(N_1 \times N_2 \times N_3) + (N_4 \times N_5)] \times I_\tau \tag{14}$$

For a decision set equal to 4, the total number of possible combinations $T_P(4)$ is formed in (15).

$$T_P(4) = [(N_1 \times N_2 \times N_3 \times N_4) + (N_5)] \times I_\tau \tag{15}$$

In this study, we consider the discrete values $[N_1, N_2, N_3, N_4, N_5]$. The number of iterations is considered fixed at two iterations. A comparison is carried out on the different decision set sizes concerning the complexity and the accuracy of the parameter estimation of the SDM for the RTC France solar cell and SM55 monocrystalline PV module.

The following steps summarize the proposed FAO algorithm for SDM parameter estimation:

Step 1:

Define k as the no. of parameters that need to be estimated.

Define DS as the size of the decision set.

Step 2:

Quantize parameters $P_i\ \forall\ i = 1, \cdots, k$ into N_i values.

Step 3:

Try all N_i possible discrete combinations in the decision set $\forall\ i = 1, \cdots, DS$, while the rest $k - DS$ parameters are kept fixed.

equal 5, 4, 3,

Step 4:

Find the optimal value of **Step 3** which achieves the minimum $RMSE$ as:

$$P_i^* = \arg \min_{i \in \{1, \ldots, DS\}} \{|I - I_{est}(P_i)|\} \tag{16}$$

Step 5:

Estimate the rest of the $k - DS$ parameters as in **Step 3 & Step 4.**

Step 6: Repeat **Steps 3-5** I_τ times till convergence.

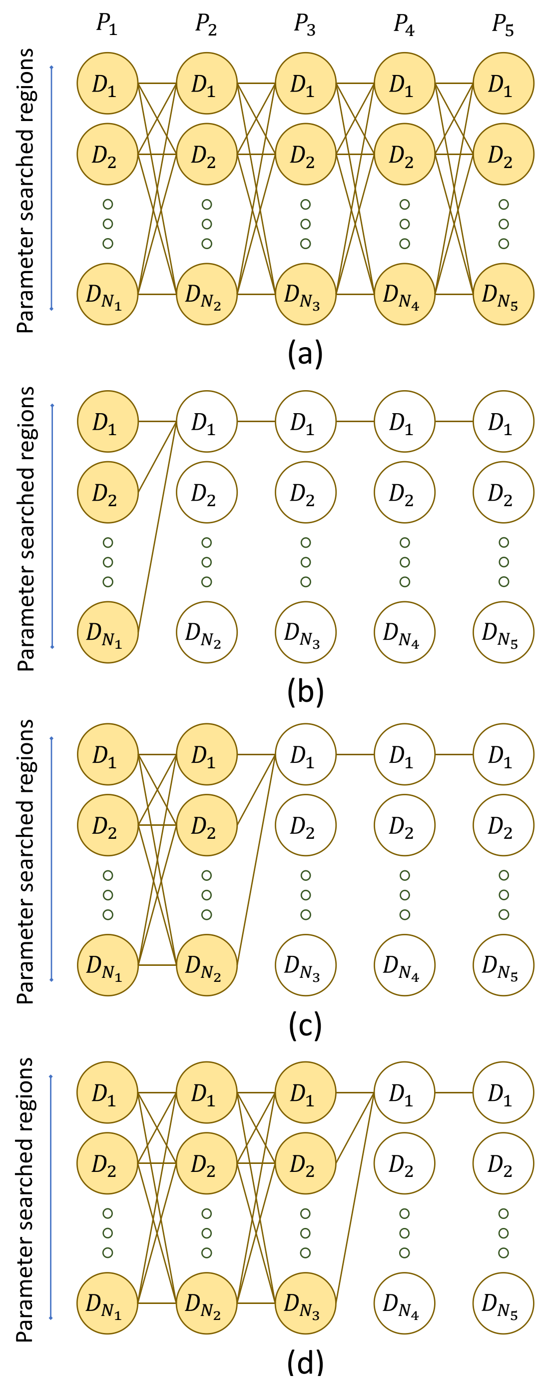

Figure 3: Search methodology (a) Optimum search (b) FAO with a decision set equal to 1 (c) FAO with a decision set equal to 2 (d) FAO with a decision set equal to 3

The flowchart in Figure 4 shows the process of applying the proposed FAO algorithm for the parameter estimation of the SDM for PV solar cells and modules.

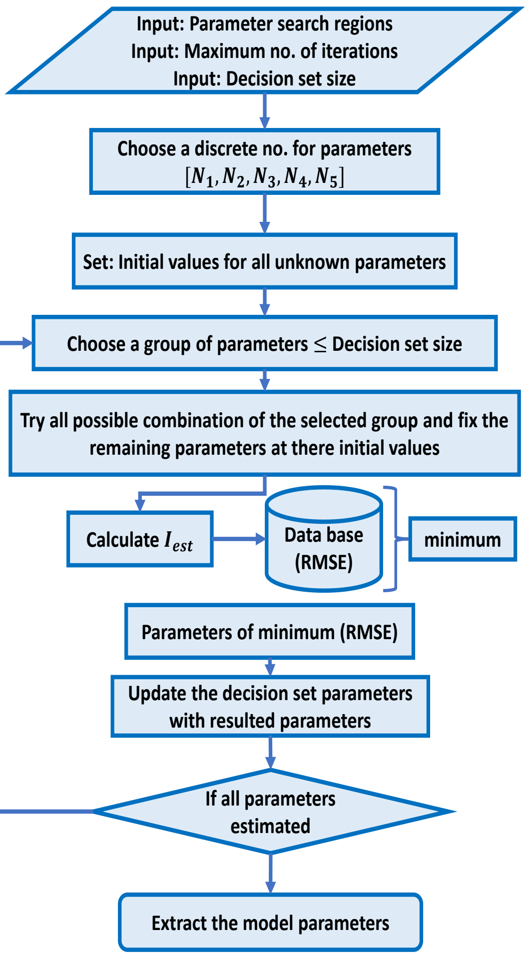

Figure 4: Proposed FAO algorithm flowchart for SDM parameter estimation

6. Numerical Results

Real measurements for RTC France solar cells and SM55 monocrystalline PV modules are considered in this study as two study cases. The accuracy of the proposed FAO algorithm is compared with the most accurate optimization algorithms in the literature. Furthermore, a trade-off between the accuracy and the complexity of different decision set sizes of the proposed FAO algorithm for SDM parameter estimation is discussed and explained.

6.1. RTC France solar cell

RTC France solar cell is considered a single solar cell. The measured data are given in [27]. The search regions for the parameters of the SDM are considered in Table 1 for RTC France solar cell. The discrete values N for the SDM parameters are chosen, such as [100 90 70 70 100]. The number of iterations of the proposed FAO algorithm is equal to 2 iterations. The results of accuracy measurements are tabulated in Table 2 and Table 3 for different decision set sizes (i.e., $DS = 1$, and $DS = 3$).

From Table 3, the $RMSE$ of the proposed FAO algorithm with $DS = 1$ is equal to 0.0059 which is better than SCA and WOA in terms of parameter estimation accuracy of the SDM for the RTC France solar cell. By applying a $DS = 3$ of the proposed FAO algorithm the $RMSE$ is equal to $9.5514E-4$ which is better than the literature metaheuristic algorithms.

The estimated data of currents for the SDM of the RTC France solar cell are plotted in $I-V$ and $P-V$ characteristic curves with real measured data, as shown in Figure 5. It shows a perfect matching of estimated results and real measurements.

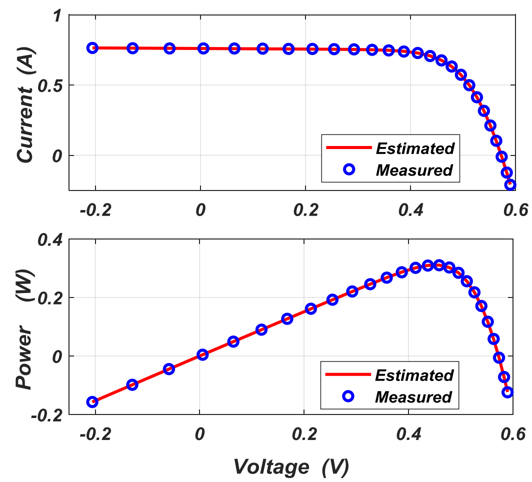

Figure 5: Characteristics curves for RTC France solar cell

In Table 2, the complexities of the proposed FAO with $DS = 1$, and $DS = 3$ are calculated from (12) and (14) respectively. There is a clear trade-off between model accuracy and algorithm complexity which can be used in a wide range of applications.

Table 2: Accuracy and complexity results of SDM for RTC France solar cell.

DS	$RMSE$	Iterations	Complexity
1	0.0059	2	2,580
3	9.5514E-4	2	1,274,000

6.2. SM55 monocrystalline PV module

SM55 monocrystalline is considered a PV module containing 36 solar cells in series. The measured data for this PV module are given experimentally for different irradiation intensities. The search regions for the parameters of the SDM are considered as in Table 1 for the monocrystalline PV module. The discrete values N for the SDM parameters are chosen, such as [100 90 70 70 100]. The number of iterations of the proposed FAO algorithm is set to 2 iterations. The results of accuracy measurements are tabulated in Table 4 and Table 5 for different decision set sizes (i.e., $DS = 2$, and $DS = 3$).

From Table 4, the $RMSE$ of the proposed FAO algorithm with $DS = 2$ is equal to 0.04670 which is better than WOA in terms of parameter estimation accuracy for the SDM of the SM55 monocrystalline PV module. By applying a $DS = 3$ of the proposed FAO algorithm the $RMSE$ is equal to 0.03422, which is better than WOA and $FAO_{DS=2}$ in terms of model accuracy.

Table 3: Results of different optimization algorithms compared with the proposed FAO algorithm for SDM parameter estimation of RTC France solar cell.

Algorithm	Estimated parameters					$RMSE$
	I_{PV}	I_{S1}	R_s	R_p	n_1	
$FAO_{DS=3}$	**0.7606**	**2.2247 E-7**	**0.0382**	**50.0000**	**1.4444**	**9.5514E-4**
$FAO_{DS=1}$	**0.7576**	**2.1573 E-7**	**0.0390**	**50.0000**	**1.4444**	**0.0059**
ALO [21]	0.7601	2.4432 E-7	0.0375	57.2379	1.4534	0.0010
SCA [16]	0.7515	2.5606 E-7	0.0372	54.2298	1.4593	0.0072
MVO [22]	0.7630	3.9989 E-7	0.0377	56.3258	1.5027	0.0031
GWO [19]	0.7606	2.2496 E-7	0.0385	54.6069	1.4455	0.0011
WOA [14]	0.7641	2.8588 E-7	0.0484	59.9940	1.4702	0.0132

Table 4: Results of different optimization algorithms compared with the proposed FAO algorithm for SDM parameter estimation of SM55 monocrystalline PV module.

Algorithm	Estimated parameters					$RMSE$
	I_{PV}	I_{S1}	R_s	R_p	n_1	
$FAO_{DS=3}$	**2.8404**	**1.5000 E-7**	**0.2739**	**105.7971**	**1.3848**	**0.03422**
$FAO_{DS=2}$	**2.8687**	**1.5000 E-7**	**0.3145**	**100.0000**	**1.3848**	**0.04670**
MVO [22]	3.5035	5.5002 E-6	0.4723	458.6703	1.7827	0.0239
GWO [19]	3.4843	8.2134 E-7	0.2290	277.7882	1.5390	0.0156
WOA [14]	3.5174	4.8375 E-6	0.3226	236.1436	1.7563	0.0643

The estimated data of currents for the SDM of the SM55 monocrystalline PV module are plotted in $I-V$ and $P-V$ characteristic curves with real measured data as shown in Figure 6. It shows a perfect matching of estimated results and real measurements.

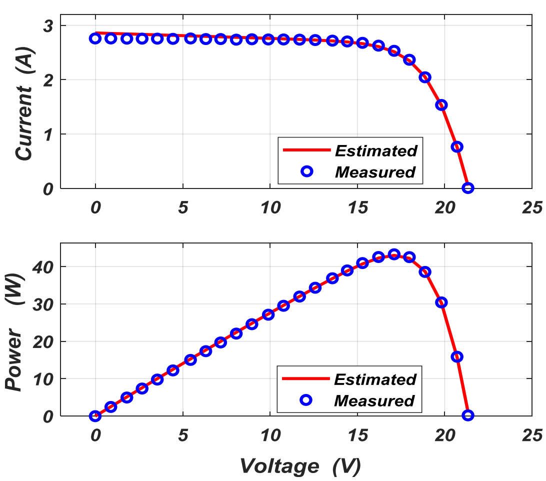

Figure 6: Characteristics curves for SM55 monocrystalline PV module

Table 5: Accuracy and complexity results of SM55 monocrystalline PV module

DS	$RMSE$	Iterations	Complexity
2	0.04670	2	28,000
3	0.03422	2	1,274,000

In Table 5, the complexities of the proposed FAO with $DS = 2$, and $DS = 3$ are calculated from (13) and (14) respectively. There is a clear trade-off between model accuracy and algorithm complexity which can be used in a wide range of applications.

From the previous two study cases, the FAO algorithm is valid for applying parameter estimation for PV solar cells and PV modules with good accuracy for estimated model parameters.

It should be noted here that the proposed method depends on a combination of parallel and series executions. Every iteration is executed sequentially depending on the previous iteration's best parameters. At the same time, concurrent executions are carried out in a single iteration, and the best-estimated parameters are extracted that minimize the $RMSE$. These series and concurrent computing can greatly reduce the complexity of the proposed algorithms when big computing processors are used for parameter estimations. From the results of accuracy and complexity for the RTC France solar cell and SM55 monocrystalline PV module in Table 2 and Table 5, and the previous discussion. The trade-off between model accuracy and algorithm complexity is valid depending on the platform and processors of PV systems.

7. Conclusion and Future work

FAO is a discrete search-based algorithm proposed to model the RTC France solar cell and SM55 PV module using SDM. The proposed algorithm flexibly chooses the decision set size for the searching process. The discrete numbers for the SDM parameters are chosen, and the proposed FAO algorithm estimates the best

SDM parameters that minimize the $RMSE$. The proposed FAO algorithm is compared to the literature algorithms regarding the $RMSE$. A trade-off between accuracy and complexity is discussed for different decision set sizes. The numerical results show that the proposed FAO algorithm is competitive with the literature in terms of $RMSE$ for RTC France solar cells and PV modules. Furthermore, a trade-off between model accuracy and algorithm complexity is valid for SDM parameter estimation for the RTC France solar cell and SM55 monocrystalline PV module. In the future, the proposed FAO algorithm can be extended to estimate the DDM and TDM parameters, and discrete variant algorithms can upgrade for different solar cells and PV modules models parameters estimations.

Conflict of Interest

The authors declare no conflict of interest.

References

[1] A. M. Mohamed, A.-H. M. El-Sayed, Y. S. Mohamed, and H. A. Ramadan, "ENHANCEMENT OF PHOTOVOLTAIC SYSTEM PERFORMANCE BASED ON DIFFERENT ARRAY TOPOLOGIES UNDER PARTIAL SHADING CONDITIONS," *Journal of Advanced Engineering Trends,* vol. 40, no. 1, pp. 49-62, 2021. 10.21608/JAET.2021.82192

[2] M. R. Aboelmagd, A. A. Z. Diab, and G. M. Dousoky, "Failure Analysis in Photovoltaic Power Systems Using an Artificial Neural Network," *Journal of Advanced Engineering Trends,* vol. 41, no. 2, pp. 205-218, 2021. 10.21608/JAET.2021.49408.1069

[3] I. Y. Fawzy, Y. Mohamad, E. Shehata, and M. Abd El Sattar, "A modified perturb and observe technique for MPPt of intgrated PV system using DC-DC boost converter," *Journal of Advanced Engineering Trends,* vol. 40, no. 1, pp. 63-77, 2021. 10.21608/JAET.2021.82231

[4] M. G Stohy, H. S Abbas, A.-H. M El-Sayed, and A. G Abo El-maged, "Parameter estimation and PI control for a water coupled tank system," *Journal of Advanced Engineering Trends,* vol. 38, no. 2, pp. 147-159, 2020. 10.21608/JAET.2020.73062

[5] H. Abobakr, A. Diab, Y. B. Hassan, and A. A. Khalaf, "Performance Analysis of a Small-Scale Grid-Connected Photovoltaic System: A Real Case Study in Egypt," *Journal of Advanced Engineering Trends,* vol. 40, no. 1, pp. 79-96, 2021. 10.21608/JAET.2021.82

[6] A. R. Jordehi, "Parameter estimation of solar photovoltaic (PV) cells: A review," *Renewable and Sustainable Energy Reviews,* vol. 61, pp. 354-371, 2016. https://doi.org/10.1016/j.rser.2016.03.049

[7] N. Rawat and P. Thakur, "Comparative analysis of hybrid and metaheuristic parameter estimation methods of solar PV," *Materials Today: Proceedings,* 2022. https://doi.org/10.1016/j.matpr.2022.06.426

[8] M. Zamen, A. Baghban, S. M. Pourkiaei, and M. H. Ahmadi, "Optimization methods using artificial intelligence algorithms to estimate thermal efficiency of PV/T system," *Energy Science & Engineering,* vol. 7, no. 3, pp. 821-834, 2019. https://doi.org/10.1002/ese3.312

[9] D. Oliva, E. Cuevas, and G. Pajares, "Parameter identification of solar cells using artificial bee colony optimization," *Energy,* vol. 72, pp. 93-102, 2014. https://doi.org/10.1016/j.energy.2014.05.011

[10] C. Chellaswamy and R. Ramesh, "Parameter extraction of solar cell models based on adaptive differential evolution algorithm," *Renewable Energy,* vol. 97, pp. 823-837, 2016. https://doi.org/10.1016/j.renene.2016.06.024

[11] L. Guo, Z. Meng, Y. Sun, and L. Wang, "Parameter identification and sensitivity analysis of solar cell models with cat swarm optimization algorithm," *Energy conversion and management,* vol. 108, pp. 520-528, 2016. https://doi.org/10.1016/j.enconman.2015.11.041

[12] P. Lin, S. Cheng, W. Yeh, Z. Chen, and L. Wu, "Parameters extraction of solar cell models using a modified simplified swarm optimization algorithm," *Solar Energy,* vol. 144, pp. 594-603, 2017. https://doi.org/10.1016/j.solener.2017.01.064

[13] D. Oliva, M. Abd El Aziz, and A. E. Hassanien, "Parameter estimation of photovoltaic cells using an improved chaotic whale optimization algorithm," *Applied energy,* vol. 200, pp. 141-154, 2017. https://doi.org/10.1016/j.apenergy.2017.05.029

[14] M. Abd Elaziz and D. Oliva, "Parameter estimation of solar cells diode models by an improved opposition-based whale optimization algorithm," *Energy conversion and management,* vol. 171, pp. 1843-1859, 2018. https://doi.org/10.1016/j.enconman.2018.05.062

[15] T. Kang, J. Yao, M. Jin, S. Yang, and T. Duong, "A novel improved cuckoo search algorithm for parameter estimation of photovoltaic (PV) models," *Energies,* vol. 11, no. 5, p. 1060, 2018. https://doi.org/10.3390/en11051060

[16] H. Chen, S. Jiao, A. A. Heidari, M. Wang, X. Chen, and X. Zhao, "An opposition-based sine cosine approach with local search for parameter estimation of photovoltaic models," *Energy Conversion and Management,* vol. 195, pp. 927-942, 2019. https://doi.org/10.1016/j.enconman.2019.05.057

[17] A. A. Z. Diab, H. M. Sultan, T. D. Do, O. M. Kamel, and M. A. Mossa, "Coyote optimization algorithm for parameters estimation of various models of solar cells and PV modules," *Ieee Access,* vol. 8, pp. 111102-111140, 2020. 111102-111140. 10.1109/ACCESS.2020.3000770

[18] C. Kumar, T. D. Raj, M. Premkumar, and T. D. Raj, "A new stochastic slime mould optimization algorithm for the estimation of solar photovoltaic cell parameters," *Optik,* vol. 223, p. 165277, 2020. https://doi.org/10.1016/j.ijleo.2020.165277

[19] S. Mirjalili, S. M. Mirjalili, and A. Lewis, "Grey wolf optimizer," *Advances in engineering software,* vol. 69, pp. 46-61, 2014. https://doi.org/10.1016/j.advengsoft.2013.12.007

[20] S. Mirjalili, "SCA: a sine cosine algorithm for solving optimization problems," *Knowledge-based systems,* vol. 96, pp. 120-133, 2016. https://doi.org/10.1016/j.knosys.2015.12.022

[21] S. Mirjalili, "The ant lion optimizer," *Advances in engineering software,* vol. 83, pp. 80-98, 2015. https://doi.org/10.1016/j.advengsoft.2015.01.010

[22] S. Mirjalili, S. M. Mirjalili, and A. Hatamlou, "Multi-verse optimizer: a nature-inspired algorithm for global optimization," *Neural Computing and Applications,* vol. 27, no. 2, pp. 495-513, 2016. 10.1007/s00521-015-1870-7

[23] I. Al-Nahhal, O. A. Dobre, E. Basar, T. M. Ngatched, and S. Ikki, "Reconfigurable intelligent surface optimization for uplink sparse code multiple access," *IEEE Communications Letters,* vol. 26, no. 1, pp. 133-137, 2021. 10.1109/LCOMM.2021.3120560

[24] A. Khalaf and M. Gaballa, "DIRECTING THE ABSORPTION PEAKS OF PLASMOINC SOLAR CELL," *Journal of Advanced Engineering Trends*, vol. 41, no. 1, pp. 27-32, 2022. 10.21608/JAET.2020.38070.1028

[25] V. J. Chin, Z. Salam, and K. Ishaque, "Cell modelling and model parameters estimation techniques for photovoltaic simulator application: A review," *Applied Energy*, vol. 154, pp. 500-519, 2015. https://doi.org/10.1016/j.apenergy.2015.05.03

[26] E. H. Houssein, G. N. Zaki, A. A. Z. Diab, and E. M. Younis, "An efficient Manta Ray Foraging Optimization algorithm for parameter extraction of three-diode photovoltaic model," *Computers & Electrical Engineering*, vol. 94, p. 107304, 2021. https://doi.org/10.1016/j.compeleceng.2021.107304

[27] T. Easwarakhanthan, J. Bottin, I. Bouhouch, and C. Boutrit, "Nonlinear minimization algorithm for determining the solar cell parameters with microcomputers," *International journal of solar energy*, vol. 4, no. 1, pp. 1-12, 1986. https://doi.org/10.1080/01425918608909835

Abbreviation and symbols

PV	**Photovoltaic**
SDM	**Single Diode Model**
DDM	**Double Diode Model**
TDM	**Three Diode Model**
FAO	**Flexible Alternate Optimization**
ANN	**Artificial Neural Network**
I_{PV}	**Model generated photo-current**
I_S	**Model Diode's reverse saturation current**
R_S	**Model series resistance**
R_P	**Model parallel resistance**
n	**Model diode ideality index**
$RMSE$	**Root Mean Square Error**
KVL	**Kirchhoff Voltage Law**
SR	**The parameter searched region**
LL	**Lower limit of the search region**
UL	**Upper limit of the search region**
P_i	**Parameter number**
N_i	**The number of discrete values of parameter** P_i
I_τ	**The proposed method iterations number**
DS	**The decision set.**
k	**The number of parameters.**
I	**Measured current**
I_{est}	**Estimated current**
V	**Measured voltage**
V_D	**Diode voltage**
K	**Boltzmann constant**
T	**Temperature in Kelvin**
q	**Electron charge**
P_i^*	**Parameter optimal value**
WOA	**Whale Optimization Algorithm**
GWO	**Gray Wolf Optimizer**
SCA	**Sine Cosine Algorithm**
ALO	**Ant Lion Optimizer**
MVO	**Multiverse Optimizer**
AE	**Absolute Error**
MAE	**Mean Absolute Error**
RE	**Relative Error**
MRE	**Mean Relative Error**