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COOT OPTIMIZATION ALGORITHM FOR PARAMETER ESTIMATION OF PHOTOVOLTAIC MODEL

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Abstract

Because of the technical and environmental advantages of many solar energy sources, their use has recently been rapidly rising. The extraction of the unknown parameters in photovoltaic models is one of the key challenges in the modeling and simulation of solar energy sources. To satisfy the behavior of the solar photovoltaic (SPV) cells, the Single-Diode Model (SDM) is recommended as a more dependable modeling method. In this study, we applied the recently introduced meta-heuristic optimization method that inspires the behavior of the swarm of birds called Coot. This Coot Algorithm is used to estimate the unknown parameters of a SPV cell/module at 33 ℃. Simulation results of this study were compared with other nine different previous Optimization Algorithms, which are Moth Flame Optimization (MFO), Dragonfly Algorithm (DA), Whale Optimization Algorithm (WOA), Grey Wolf Optimization (GWO), Ant Lion Optimization (ALO), Harris Hawk Optimization (HHO), Hybrid of Particle Swarm Optimization and Grey Wolf Optimization (PSOGWO), Marine Predator Algorithm (MPA), and African Vultures Optimization Algorithm (AVOA). The obtained results of this comparison showed that the Coot algorithm outperformed the previous algorithms in terms of the root mean square error (RMSE) and the degree of convergence between the power versus voltage curve and the current versus voltage curve compared with the measured data. Moreover, the results confirm that the Coot optimization algorithm is favorable in reducing the time and improving the accuracy.

Keywords: *solar photovoltaic, Coot algorithm, parameter estimation, single-diode model, solar energy*

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1 INTRODUCTION

The great demand for energy by the population causes high fuel depletion. This depletion increases global warming and the pollution of the environment. In recent years, renewable energy sources such as solar energy, waves, tides, wind, geothermal, and biomass have received more attention due to the little or fewer effects on the environment (Awan & Khan, 2014; Irmak et al., 2014; Jha et al., 2017; Lau et al., 2012). Solar energy is a promising source of renewable energy due to its usability and cleanliness (Abbassi, 2012; Hanger et al., 2016; Mcelroy & Chen, 2017). Moreover, solar energy is widely used for power generation via photovoltaic (PV) cells (Wu et al., 2015). However, PV cells are vulnerable to external environmental factors such as global temperature and radiations from sunlight which affects the efficiency of SPV cells (Chen et al., 2016).

The SPV cell is the main unit of the photovoltaic system. So, it is important to estimate the unknown parameters to obtain a relative analysis of the performance of the SPV panel, which is comprised of cells. The cell represents an equivalent circuit which is typically classified as a single, double and triple diode model. All of these models are most widely used for parameter identification (AlHajri et al., 2012; Chellaswamy & Ramesh, 2016). The single diode model (SDM) has five unknown parameters, while the double diode model (DDM) has seven unknown parameters, and the triple diode model (TDM) has nine unknown parameters. The literature stated that SDM and DDM diodes are more widely used than a TDM, where different techniques have been used by researchers to estimate these unknown parameters of the SPV model based on three methods which are numerical, analytical, and optimization algorithm techniques (metaheuristic techniques) (Louzazni & Aroudam, 2015; Tao et al., 2020).

For reaching optimum solutions to the SPV parameters estimation problem, several metaheuristic techniques have been developed and utilized, which include among others; Moth Flame Optimization (MFO) (Mirjalili, 2015), Dragonfly Algorithm (DA) (Isa et al., 2020), Whale Optimization Algorithm (WOA) (Xiong et al., 2018), Grey Wolf Optimization (GWO) (Darmansyah & Robandi, 2017), Ant Lion Optimization (ALO) (Kanimozhi & Kumar, 2018), Harris Hawk Optimization (HHO) (Sharma et al., 2021), Hybrid of Particle Swarm Optimization and Grey Wolf Optimization (PSOGWO) (Premkumar et al., 2021), Marine Predator Algorithm (MPA) (Sattar et al., 2021), and African Vultures Optimization Algorithm (AVOA) (Kumar & Mary, 2021). Each one of these techniques has different strategies for achieving a specific main goal, and the power of each technique depends upon the accuracy of the estimated unknown parameters, and computation time with less complexity.

In this study, a Coot optimization algorithm (Naruei & Keynia, 2021) has been studied to identify the unknown parameters of SPV cells. The Coot represents a new promising metaheuristic optimizer which mainly represents the Coot bird movement to determine the precise unknown parameters for the SPV model. It constitutes a powerful and vast multidimensional exploration. It can adapt its performance and easily transfer from one stage to another depending upon the surrounding conditions. The benchmarking commercial RTC France solar module is studied and analyzed to evaluate its performance under specific loading and operating conditions.

2 PROBLEM FORMULATION

2.1 Single diode model

The SDM has described the properties of SPV cells most likely better than other models. Fig. 1 illustrates the structure of the equivalent circuit diagram of the SDM, which consists of the generator of photocurrent (I_{ph}), diode current (I_d), shunt (R_{sh}) and series resistor (R_s). Moreover, the output current of the SDM is given by:

$$I_L = I_{ph} - I_d - I_{sh} \quad (1)$$

Where I_L represents the output current, I_{ph} represents the photocurrent, and the I_d is the diode current that can be obtained according to Shockley's equation as in equation (2). I_{sh} is the current passing through the shunt resistor which is expressed as shown by equation (3):

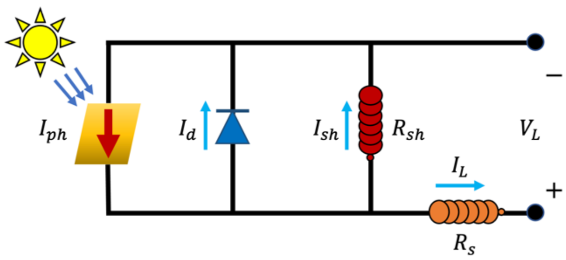

Fig. 1 Equivalent circuit diagram of SDM

$$I_d = I_{sd} \times \left[exp\left(\frac{q \times (V_L + R_s \times I_L)}{n \times k \times T}\right) - 1\right] \quad (2)$$

$$I_{sh} = \frac{V_L + R_s \times I_L}{R_{sh}} \quad (3)$$

The voltage V_L in Fig. 1 represents the output voltage, and I_{sd} represents the reverse saturation current of the SDM, *n* is the ideal diode factor, *k* is the Boltzmann constant $(1.380649 \times 10^{-23} J\ K^{-1})$, *q* is the charge of the electron $(1.60217663 \times 10^{-19} C)$, and *T* is the temperature in degrees Kelvin. So, equation (1) can be converted into the following conveient formula:

$$I_L = I_{ph} - I_{sd} \times \left[exp\left(\frac{q \times (V_L + R_s \times I_L)}{n \times k \times T}\right) - 1\right] - \frac{V_L + R_s \times I_L}{R_{sh}} \quad (4)$$

According to equation (4), SDM contains five parameters $(I_{ph}, I_{sd}, R_s, R_{sh}, n)$.

2.2 Objective function

A comparison has been made between the calculated data of this study and the measured data, which were obtained previously by experiment (Easwarakhanthan et al., 1986). The purpose of this comparison is to figure out the suitable algorithm for the objective function. This algorithm is going to obtain the solutions that produce the best fit for the measured data. Obtaining the best fit is by reducing the root mean square error (RMSE) where this way represents the most common method for minimizing the difference between calculated and the measured data. This RMSE is expressed in the following form:

$$RMSE(X) = \sqrt{\frac{1}{M} \sum_{i=1}^{N} f(V_L, L_L, X)^2} \quad (5)$$

Where *X* represents the solution vector of the *N* unknown parameters. Therefore, this study is focused on finding the value of vector *X* that enables RMSE to reach the minimum value, and *M* represents the number of measured data. Thus, the objective function of the SDM can be written in the following form:

$$f(V_L, I_L, X) = I_{ph} - I_{sd} \times \left[exp\left(\frac{q \times (V_L + R_s \times I_L)}{n \times k \times T}\right) - 1\right] - \frac{V_L + R_s \times I_L}{R_{sh}} \quad (6)$$

$$X = \{I_{ph}, I_{sd}, R_s, R_{sh}, n\}$$

3 COOT OPTIMIZATION ALGORITHM

Previous studies figure out different algorithms for finding the optimum values of unknown parameters (Darmansyah & Robandi, 2017). This study has selected specifically the Coot optimization algorithm for the purpose of finding the value of unknown parameters. Coot optimization algorithm is built on different movement behaviors of coot groups that are moving on the water surface. The coots are small water birds that have many different group behaviors on the surface of the water, the final destination of these water birds being achieved through moving mainly towards food or a specific location. Thus, the movement of these birds on the surface of water generates four different types of movements such as chain movement, leader movement, random movement, and adjustment of position according to the leader (Naruei & Keynia, 2021). Equation (7) and Equation (8) implement the specific procedure of the Coot algorithm (Naruei & Keynia, 2021):

Equation (7) builds the random initialization of the population:

$$cootpos(i) = rand(1, d) \times (ub - lb) + lb \quad (7)$$

Where *cootpos(i)* represents the coot position, *d* is the number of variables or dimensions of the problem, *ub* and *lb* represent the upper and the lower bound of the search space respectively.

In equation (8), the *ub* and *lb* may be different from the ones which are stated in equation (7).

$$lb = [lb_1, lb_2, \dots, lb_d], ub = [ub_1, ub_2, \dots, ub_d] \quad (8)$$

After the random initialization of the population is being initialized, and determining the position of each coot, the fitness of calculated data to the measured data is being solved by using the objective function. For doing that *NL* is the number of coots as group leaders where the group leaders have been chosen randomly. Accordingly, the four movements on the water surface by coots will be implemented.

3.1 Random movement

Equation (9) limits the search space of the random position of the coots which are moving towards the random position that is suggested as a search space:

$$Q = rand(1, d) \times (ub - lb) + lb \quad (9)$$

According to the movement of the coots, it can explore different parts of the search space making a possibility for the algorithm to be stuck at local optimal. In this case, the algorithm escaped from this local by this movement, and equation (10) will be used to calculate the new position of the coot.

$$cootpos(i) = cootpos(i) + A \times R2 \times (Q - cootpos(i)) \quad (10)$$

Where *R2* represents a random number in the interval [0, 1] and *A* is calculated according to the following equation:

$$A = 1 - L \times \left(\frac{1}{Iter}\right) \quad (11)$$

L represents the current iteration and *Iter* represents the maximum number of iterations.

3.2 Chain movement

There are two ways of calculating the chain movement for two coots; one of them is the average position, and the second one is the distance vector. By the two ways, one coot is moving toward another coot which is equal to the half distance between the two coots. In this study, the mathematical average position has been used to calculate the new position of the coot as depicted in equation (12):

$$cootpos(i) = 0.5 \times (cootpos(i-1) + cootpos(i)) \quad (12)$$

Where *cootpos(i-1)* represents the location of the second coot.

3.3 Adjustment of the position

In this movement, the coot moves toward the group leader, and accordingly, there are many possibilities to move each coot behind many leaders that have different positions. Therefore, it is difficult to calculate the movement of one coot towards many leaders, and to solve this problem; an average position of many leaders has to be considered to limit the position of those leaders. Where *L* represents the current iteration and *Iter* represents the maximum iteration.

In summary, the Coot algorithm has implemented the general problem, as depicted by the flowchart in Fig. 2.

Therefore, each coot can change its position based on the average position and by applying equation (13), the leader can be selected.

$$K = 1 + (i \ MOD \ NL) \quad (13)$$

According to equation (13), the current coot is represented as i and the number of leaders is represented as *NL* where *K* is represented as the number of the leader index. So, *coot(i)* has to change its position according to the leader's *k*. Based on the selected leader the next position of the *coot(i)* can be calculated and equation (14) will be applied:

$$cootpos(i) = leaderpos(k) + 2 \times R1 \times cos(2R\pi) \times (leaderpos(k) - cootpos(i)) \quad (14)$$

Where *cootpos(i)* represents the current position of the coot, *leaderpos(k)* represents the selected leader position, *R1* represents a random number between the interval [0, 1] and *R* represents a random number between the interval [–1, 1].

3.4 The leading movement to the optimal area

In this movement, the coots have to update their positions to the main position that the leaders are located in, and in the same situation, the leaders are changing their positions trying to find the optimal position where the coots are following the leaders. Accordingly, equation (15) will be applied to find the optimal position of leaders:

$$leaderpos(i) = \begin{cases} B \times R3 \times \cos(2R\pi) \times (gBest - leaderpos(i) + gBest) & R4 < 0.5 \\ = B \times R3 \times \cos(2R\pi) \times (gBest - leaderpos(i) - gBest) & R4 \geq 0.5 \end{cases} \quad (15)$$

Where *gBest* represents the best position ever found, *R3* and *R4* represent random numbers in the interval [0, 1], *R* represents a random number in the interval [– 1, 1], and *B* is calculated according to equation (16):

$$B = 2 - L \times \left(\frac{1}{Iter}\right) \quad (16)$$

4 RESULTS AND DISCUSSION

The results that have been obtained, revealed the implementation of the Coot algorithm which was verified for parameter estimation of the SPV model. The results of the SPV model have been calculated for SDM. The measured data of SDM were obtained from (Easwarakhanthan et al., 1986), where it is carried out on a 57 mm diameter commercial silicon RTC France solar cell ($1000\ W\ m^{-2}, 33\ °C$). A comparison has been made between the results of the algorithm of this study and the other nine algorithms. It is important to confirm that the following input data of all algorithms are the same in terms of, boundary, number of iterations, and population size, as shown in Table 1, through 30 independent runs. In addition, all algorithms are implemented in Matlab 2021b on a Laptop with an Intel Core i9-9980HK processor @ 2.40 GHz, 16GB RAM, under the Windows10 64-bit OS.

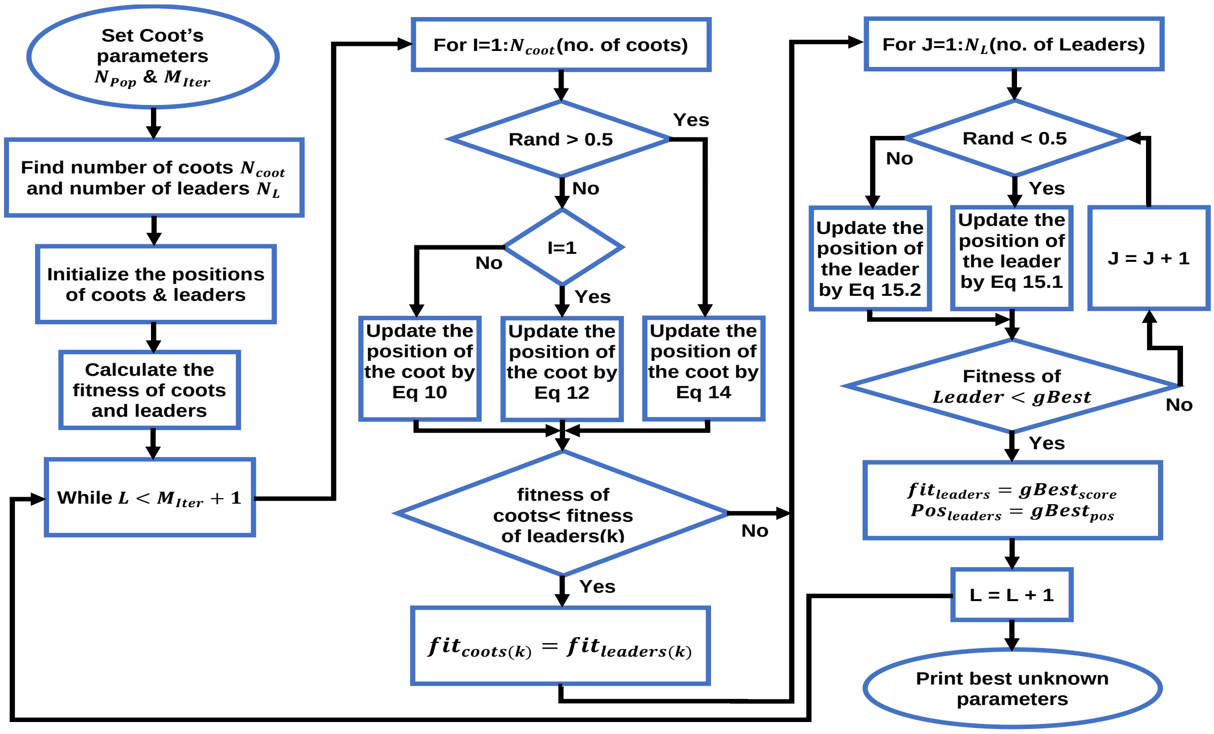

Fig. 2 Flowchart of Coot optimization algorithm

Table 1: Input Data for SPV Model

Parameter Boundaries	RTC France Solar Cell	
	LowerBound	UpperBound
$I_{ph}(A)$	0	1
$I_d(\mu A)$	0	1
$R_{sh}(\Omega)$	0	100
$R_S(\Omega)$	0	0.5
n	1	2
Population size	50	
Number of iterations	1000	

4.1 Results for RTC France solar cell

The results of a 57 mm-diameter RTC France solar cell, which was utilized for SPV parameter estimation. Coot algorithm is compared with (MFO), (DA), (WOA), (GWO), (ALO), (HHO), (PSOGWO), (MPA), and (AVOA) algorithms and the data of this comparison are shown in Table 2.

Table 2 reveals the optimal values of the control variables, which are related to the best run of all algorithms. Also, from Table 2, the Coot algorithm obtains the minimum RMSE of 0.00098602 and less computation time compared with the others. The measured and calculated values of current and the corresponding values of the absolute error (IAE) for 26 chosen voltage values are given in Table 3. Fig. 3 describes the convergence curves of all algorithms and illustrates what has been explained above.

The results obtained from Table 3 reveal the fitness of the P-V and I-V characteristic curves between the calculated and measured data as described in Fig. 4 and Fig. 5 respectively. Also, these figures illustrate the good agreement between the extracted curves based on the Coot algorithm and the experimentally measured data.

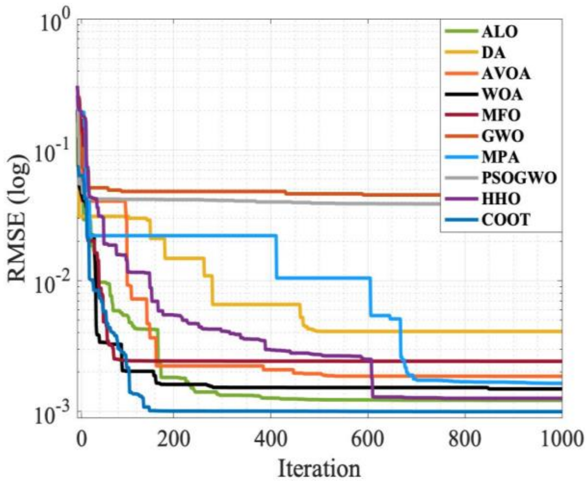

Fig. 3 The Convergence curve of ten algorithms for RTC France solar cell

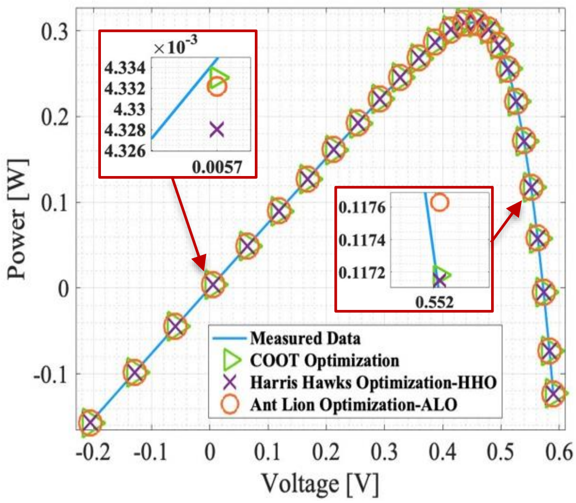

Fig. 4 P–V characteristic curve for RTC France solar cell

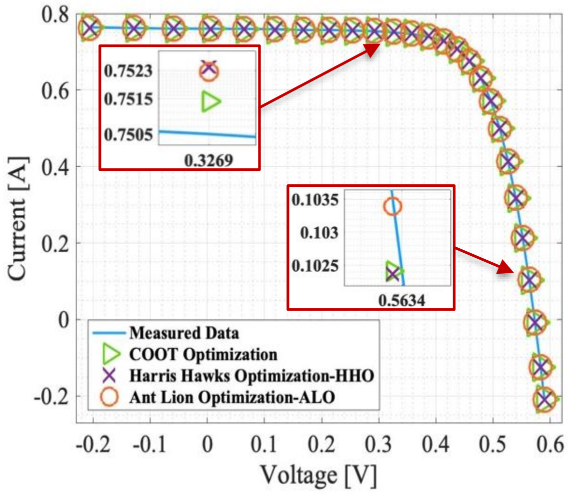

Fig. 5 I–V characteristic curve for RTC France solar cell

Table 2: Parameter estimated for the SDM of the RTC France solar cell

METHOD	$I_{ph}(A)$	$I_d(\mu A)$	$R_{sh}(\Omega)$	$R_s(\Omega)$	n	$RMSE$	$Time(sec)$
COOT	0.7608	0.3233	53.7450	0.0364	1.4813	9.8602E-4	2.498
ALO	0.7605	0.4682	69.0897	0.0349	1.5195	0.0012	9.339
DA	0.7583	0.0732	56.2543	0.0432	1.3448	0.0041	28.523
AVOA	0.7610	0.7113	74.2244	0.0329	1.5653	0.0019	2.732
WOA	0.7605	0.5593	80.2149	0.0344	1.5385	0.0015	3.166
MFO	0.7608	0.9879	100	0.0314	1.6031	0.0024	5.920
GWO	0.7378	1	40.3325	0	1.6145	0.0445	2.634
MPA	0.7607	0.6349	76.0585	0.0335	1.5525	0.0016	5.175
PSOGWO	0.7651	1	7.3537	0	1.6208	0.0382	3.206
HHO	0.7597	0.4006	82.2163	0.0357	1.5029	0.0013	6.209

Table 3: I–V values and individual absolute error (IAE) for the single-diode RTC France solar cell

ITEM	VOLTAGE (V)	MEASURED I (A)	CALCULATED I (A)	IAE
1	–0.2057	0.7640	0.764110	0.00011
2	–0.1291	0.7620	0.762686	0.00068
3	–0.0588	0.7605	0.761379	0.00087
4	0.0057	0.7605	0.760178	0.00032
5	0.0646	0.7600	0.759080	0.00091
6	0.1185	0.7590	0.758067	0.00093
7	0.1678	0.7570	0.757117	0.00011
8	0.2132	0.7570	0.756167	0.00083
9	0.2545	0.7555	0.755113	0.00038
10	0.2924	0.7540	0.753690	0.00030
11	0.3269	0.7505	0.751416	0.00091
12	0.3585	0.7465	0.747378	0.00087
13	0.3873	0.7385	0.740139	0.0016
14	0.4137	0.7280	0.727399	0.00060
15	0.4373	0.7065	0.706984	0.00048
16	0.4590	0.6755	0.675285	0.00021
17	0.4784	0.6320	0.630758	0.0012
18	0.4960	0.5730	0.571926	0.0011
19	0.5119	0.4990	0.499609	0.00060
20	0.5265	0.4130	0.413667	0.00066
21	0.5398	0.3165	0.317558	0.0011
22	0.5521	0.2120	0.212250	0.00025
23	0.5633	0.1035	0.102410	0.0011
24	0.5736	–0.0100	–0.008475	0.0015
25	0.5833	–0.1230	–0.125165	0.0022
26	0.5900	–0.2100	–0.208045	0.0020

5 CONCLUSIONS

The study has shown that the Coot optimization algorithm has revealed the best results for calculating the optimal values of estimated SPV parameters of the RTC France solar cell module at 33 ^{O}C. This conclusion has been drawn according to the comparison of the obtained results by applying the Coot algorithm and the other nine optimization algorithms, where the fitness has been obtained between the calculated data and measured data. This good fitness is due to the minimization of the objective function defined in terms of the RMSE and the reduction in execution time. The results have been observed from the P-V and I-V curves which indicate that the use of the Coot algorithm is interesting in how to generate the optimal value of the estimated parameters for all SPV modules compared to other algorithms.

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