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Chaos Game Optimization Algorithm for Parameters Identification of Different Models of Photovoltaic Solar Cell and Module

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Abstract

In order to achieve the optimum feasible efficiency, the electrical parameters of the photovoltaic solar cell and module should always be thoroughly researched. In reality, the quality of PV designs can have a significant impact on PV system dynamic modeling and optimization. PV models and calculated parameters, on the other hand, have a major effect on MPPT and production system efficiency. Because a solar cell is represented as the most significant component of a PV system, it should be precisely modeled. For determining the parameters of solar PV modules and cells, the Chaos Game Optimization (CGO) method has been presented for the Single Diode Model (SDM). A set of the measured I-V data has been considered for the studied PV design and applied to model the RTC France cell, and Photowatt-PWP201 module. The objective function in this paper is the Root Mean Square Error (RMSE) between the measured and identified datasets of the proposed algorithm. The optimal results that have been obtained by the CGO algorithm for five electrical parameters of PV cell and model have been compared with published results of various optimization algorithms mentioned in the literature on the same PV systems. The comparison proved that the CGO algorithm was superior.

Keywords: Photovoltaic modelling; Single diode model; Parameter estimation; Chaos game optimization.

1. Introduction

Renewable energies contribution to the global electricity mix has increased at an exponential rate in recent years. This higher-than-conventional energy rise will continue over the next four years, reaching 28 % in 2021[1]. The Kyoto Protocol's dynamic supports renewable energy in the fight against greenhouse gas emissions [2].

It is critical to understand the specific parameters of a solar cell/module in order to operate the PV plant to its greatest potential [3]. The physical properties of a PV cell/module, on the other hand, have a direct impact on the conversion efficiency and overall performance [4]. As a result, reliable assessment of such parameters is constantly necessary, not only for cell performance evaluation but also for improving cell design, fabricating process optimization, and cell quality control [5].

An accurate PV simulator is required to appreciate the features of PV systems and subsequently optimise their design [6]. Since a solar cell is the most significant component of a PV system, it should be precisely modelled. Extracting the characteristics of the equivalent circuit model is the most essential step in building solar cell models, which entails two steps: proposed mathematical design and then precise parameter estimate [7].

According to the lack of data provided by PV manufacturers, the PV module is theoretically approximated using a nonlinear I-V relationship, which includes several unknowns [8]. An analogous circuit and a set of parameters that characterise the electrical answer and functioning of a PV generator are normally included in a model of a PV generator. These characteristics are difficult to determine since they are not included on the PV module's datasheet and their values fluctuate depending on the operating conditions [9].

Because of the reduced number of unknown factors, sufficient accuracy, and simplicity, the Single Diode Model (SDM) is the simplest and most common model of PV solar cells for describing the non-linear performance of solar PV systems [10].

Various metaheuristic algorithms been already used to PV models in the literature, including as: Applied chaotic asexual reproduction optimization (CARO) in [11], Generalized oppositional teaching learning-based optimization (GOTLBO) in [12], Improved JAYA optimization algorithm (IJAYA) in [13], Modified simplified swarm optimization algorithm (MSSO) in [14], Cuckoo search algorithm (CSA) in [15], Hybrid firefly algorithm and pattern search algorithm (FA-PSA) in [16], Biogeography optimization algorithm-based heterogeneous cuckoo search (BBO-HCS) algorithm in [17], Used new Hybrid grey wolf optimizer and cuckoo search (GWO-CS) in [18], Chaotic whale optimization algorithm (CWOA) in [19], Whale optimisation algorithm (WOA) in [20], the hybrid firefly algorithm and pattern search Algorithm (FA-PSA) in [21], Memetic adaptive differential evolution (MADE) in [22], JAYA Algorithm in [23], Improved sine cosine algorithm (ISCA) in [24], Improved teaching-learning-based optimization (ITLBO) in [25], and recently applied tree growth algorithm (TGA) in [10].

Basing on the previous considerations in this paper, a CGO algorithm’s performance is proposed to estimate the parameters of PV models more accurately and reliably. The CGO algorithm applied for PV parameters identification problem has compared them with other algorithms that mentioned in the state-of-the-art.

The rest parts of the paper are written out as follow. Section 2 presented the PV models' problem formulation. In Section 3, the CGO algorithm is briefly discussed. The optimal results and analysis comparisons are reported in Section 4. At least, in Section 5, the paper's conclusions are presented.

2. Mathematical PV Modelling

In this section, a mathematical formulation of a single diode solar PV system is detailed.

2.1 Single Diode Model (SDM)

Figure 1 shows the PV solar cell circuit architecture in SDM model [8-11].

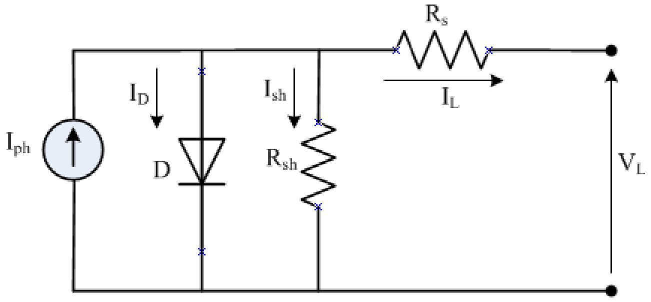


Fig. 1. Equivalent circuit of the SDM.

When Kirchhoff's current low is applied to the circuit in Figure 1, the output current I_L is defined as follows [8-11], [26]:

$$I_L = I_{ph} - I_D - I_{sh} \tag{1}$$

Furthermore, the diode current I_D may be calculated using the well-known Shockley equation:

$$I_D = I_{sd} \cdot \left[\exp\left(\frac{V_L + R_s.I_L}{n.V_t} \right) - 1 \right] \tag{2}$$

The voltage V_t is calculated using the following formula:

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

The next equation represents the current that passes in the shunt resistor:

$$I_{sh} = \frac{V_L + R_s.I_L}{R_{sh}} \tag{4}$$

Based the equations (2) to (4), the load current I_L is designated as,

$$I_L = I_{ph} - I_{sd}.\left[\exp\left(\frac{V_L + R_s.I_L}{n.V_t}\right) - 1\right] - \frac{V_L + R_s.I_L}{R_{sh}} \tag{5}$$

As a result, in the application of SDM, the variable five parameters that must be optimised are (I_{ph}, I_{sd} , Rs, R_{sh} and n).

2.2 PV Module Model

Figure 2 illustrates a standard solar PV module based on a single diode. The model incorporates many solar cells connected in series and/or parallel [10, 27].

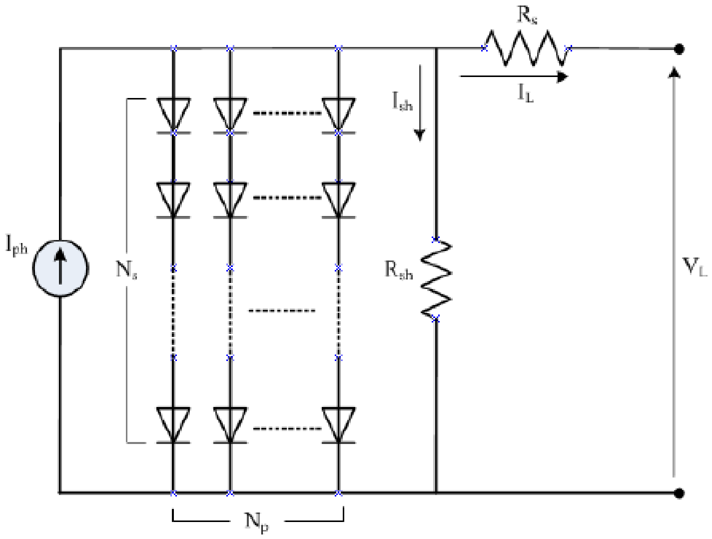


Fig. 2. Equivalent circuit of solar PV module model.

The following mathematical expression, as shown in the next equation, is used to compute the load current output from the PV module [8-20], [27]:

$$I_L = N_p.\left\{ I_{ph} - I_{sd}.\left[\exp\left(\frac{\frac{V_L}{N_s} + \frac{R_s.I_L}{N_p}}{n.V_t}\right) - 1\right] - \frac{\frac{V_L}{N_s} + \frac{R_s.I_L}{N_p}}{R_{sh}} \right\} \tag{6}$$

The module model has five parameters that must be assessed, same like the SDM model.

2.3 The Objectif Function and Constraints

The decision variables (D) are the unknown parameters of such models in this PV parameter identification issue:

$$D = \left[I_{ph}, I_{sd}, n, R_s, R_{sh}\right] \tag{7}$$

The fundamental Objective Function (OF) of the model is to minimise the differentiation between measured data from the actual PV source and the simulated sources by means of the electrical equivalent circuit of the model which based on the Root Mean Square Error (RMSE) [10-19].

$$OF = \min\left(RMSE\right) = \frac{1}{N}\sum_{w=1}^{N}\left(I_{Measured} - I_{Estimate.}\right)^2 \tag{8}$$

Subject to,

$$I_{ph}^{\min} \leq I_{ph} \leq I_{ph}^{\max} \tag{9}$$

$$I_{sd}^{\min} \leq I_{sd} \leq I_{sd}^{\max} \tag{10}$$

$$n^{\min} \leq n \leq n^{\max} \tag{11}$$

$$R_{s}^{\min} \leq R_{s} \leq R_{s}^{\max} \tag{12}$$

$$R_{sh}^{\min} \leq R_{sh} \leq R_{sh}^{\max} \tag{13}$$

Where, $I_{Estimate}$ is the current value estimated by the model at hand is calculated by equation (5).

Table 1. Principal parameters of PV models.

PV Type	N_s x N_p	G (W/m^2)	T (°C)
RTC France Cell	1 X 1	1000	33
Photowatt PWP201 Module	36 X 1	1000	45

Table 2. Limit of PV models' parameters.

Parameters	RTC France Cell		Photowatt-PWP201 Module	
	LB	*UB*	*LB*	*UB*
I_{ph} (A)	0	1	0	2
I_{sd} (µA)	0	1	0	50
R_s (Ω)	0	0.5	0	2
R_{sh} (Ω)	0	100	0	2000
n	1	2	1	50

3. Chaos Game Optimization (CGO) Algorithm

The applied CGO algorithm is based on the chaos theory ideas provided. In this case, the number of solutions X represents some suitable spots inside a Sierpinski triangle. Where, each X_i comprises of some $x_{i,j}$ that refer to the position of these eligible points inside a triangle [28].

The CGO algorithm considers *S* in this purpose which represents some eligible seeds inside a triangle [29] is shows in Figure 3.

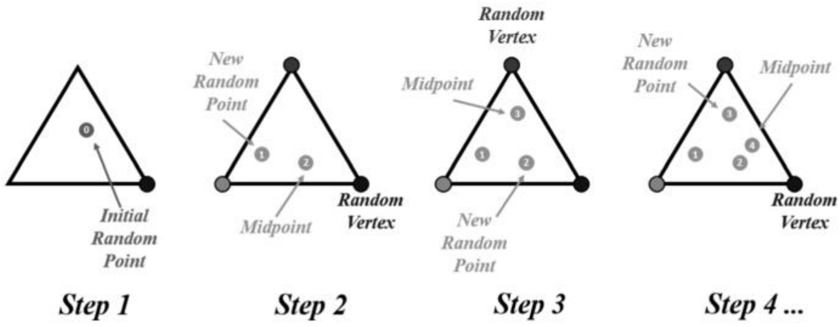


Fig. 3. The Sierpinski triangle [28].

The following equation is a mathematical representation of these aspects [28, 29]:

$$X = \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_i \\ \vdots \\ X_n \end{bmatrix} = \begin{bmatrix} x_1^1 & x_1^2 & \cdots & x_1^j & \cdots & x_1^d \\ x_2^1 & x_2^2 & \cdots & x_2^j & \cdots & x_2^d \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ x_i^1 & x_i^2 & \cdots & x_i^j & \cdots & x_i^d \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ x_n^1 & x_n^2 & \cdots & x_n^j & \cdots & x_n^d \end{bmatrix}, \begin{cases} i = 1, 2, ..., n \\ j = 1, 2, ..., d \end{cases} \tag{14}$$

The starting locations of the regarded eligible points in the search area are selected at random:

$$x_i^j(0) = x_{i,\min}^j + rand.\left(x_{i,\max}^j - x_{i,\min}^j\right) \tag{15}$$

For the first seed, a schematic representation of the stated procedure is shown below, while the mathematical representation is as follows:

$$Seed_i^1 = X_i + \alpha_i \times \left(\beta_i + GB - \gamma_i \times MG_i\right) \tag{16}$$

The mathematical presentation of the second seed, whereas the mathematical presentation of the first seed:

$$Seed_i^2 = GB + \alpha_i \times \left(\beta_i \times X_i - \gamma_i \times MG_i\right) \tag{17}$$

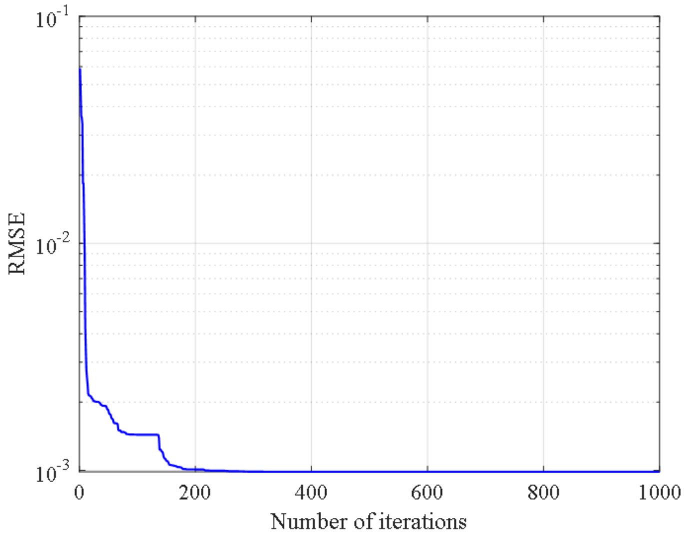
The following is a schematic representation of seeds third and fourth:

$$Seed_i^3 = MG_i + \alpha_i \times \left(\beta_i \times X_i - \gamma_i \times GB\right) \tag{18}$$

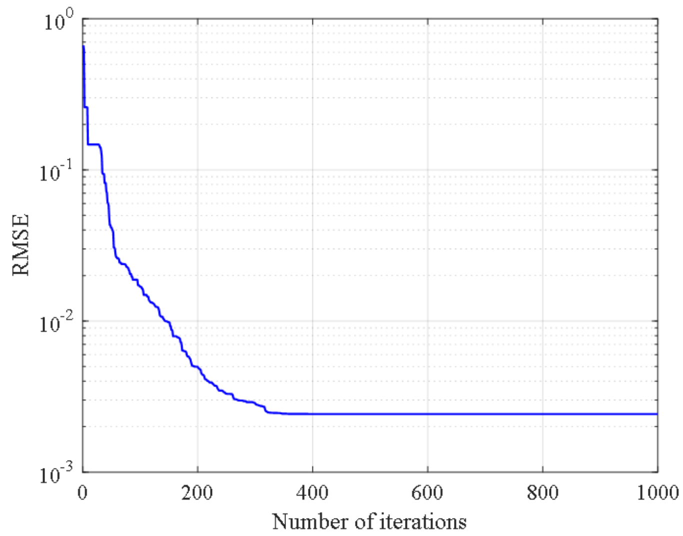
$$Seed_i^4 = X_i\left(x_i^k = x_i^k + R\right), \quad k = [1, 2, ..., d] \tag{19}$$

4. Results, Comparison, and Discussion

To assess the CGO algorithm's optimization performance, tests of parameter identification on single diodes and PV modules are compared to the performance of other optimization techniques. The proposed CGO algorithm is validated on various types of PV cell and module. The convergence curve of applied algorithm for two test PV models are presented in Figure 4.



(a)

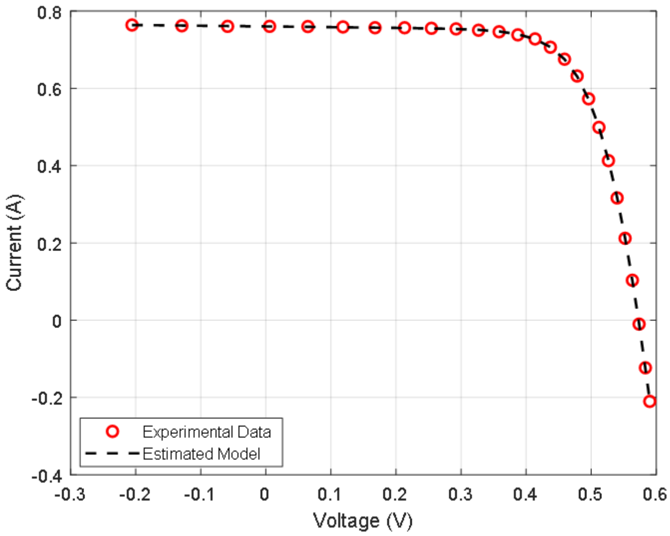


(b)

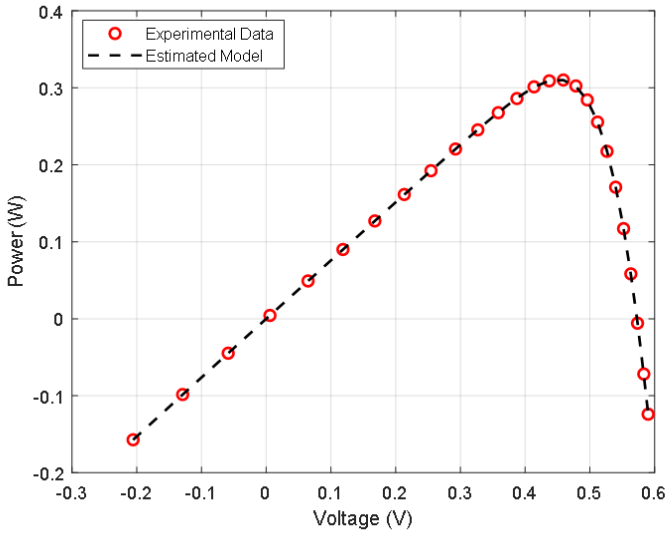
Fig. 4. Convergence curve of CGO for various PV models:

a). RTC France cell, b). Photowatt-PWP201 module.

Figure 5 represented the comparisons PV characteristic curves (I-V and P-V) between the measured (experimental) data and estimated data acquired by proposed CGO algorithm for RTC France cell model.



(a)

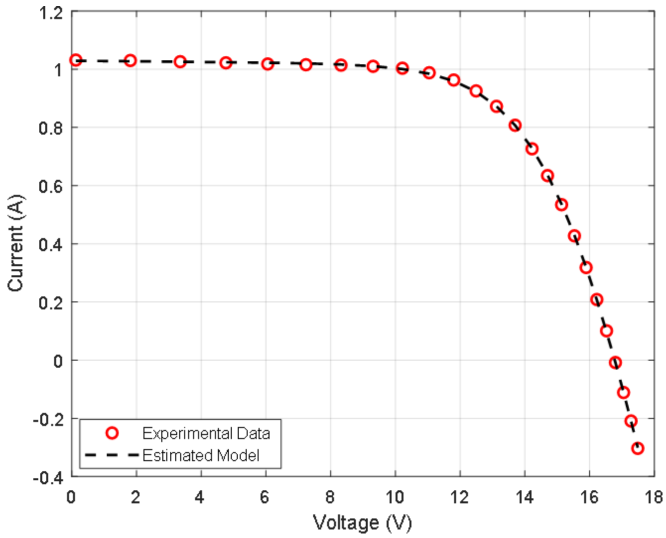


(b)

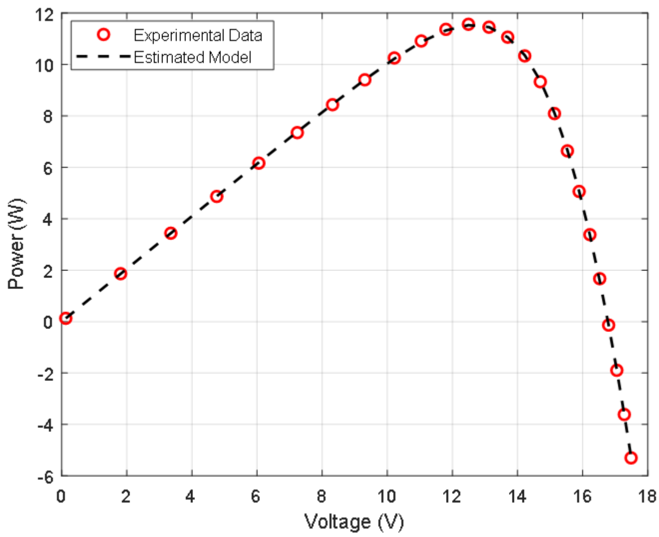
Fig. 5. Comparisons between the measured and estimated data obtained by CGO for RTC France cell model: a). I-V characteristic, b). P-V characteristic.

The I-V and P-V curves of the simulated data obtained by the CGO method are immensely compatible with the real measured data, as shown in Figure 5. In each example, the figures also show the regression plot, which indicates the degree of fit between the fuel cell's real data and the desired data. The I–V and P–V curves in Figure 8 indicate that the simulated data accurately reproduces the real data, demonstrating the agreement of the optimum solution generated by the CGO algorithm.

Figure 6 represented the comparisons PV characteristic curves (I-V and P-V) between the measured data and estimated data acquired by proposed CGO algorithm for Photowatt-PWP201 module model.



(a)

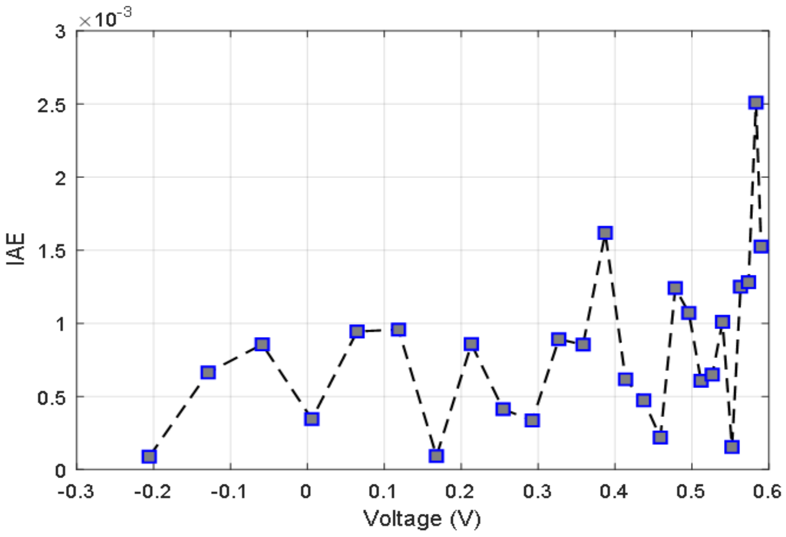


(b)

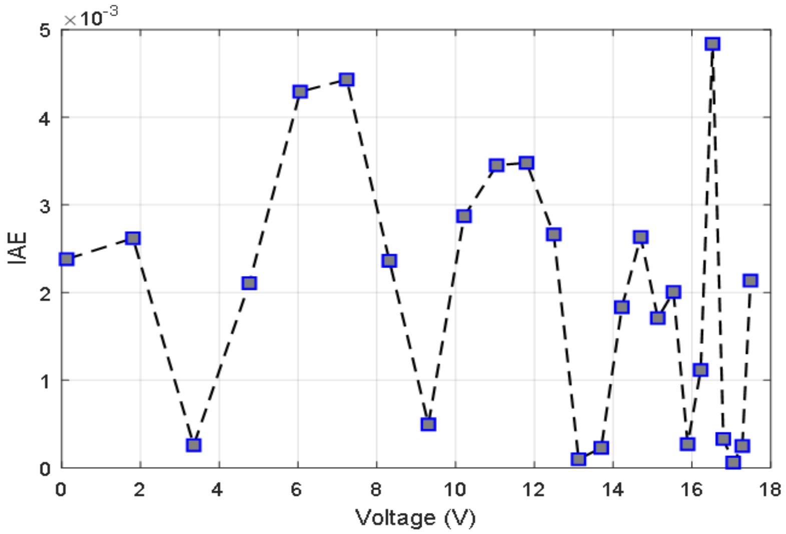
Fig. 6. Comparisons between the measured and estimated data obtained by CGO for Photowatt-PWP201 module model: a). I-V characteristic, b). P-V characteristic.

The I–V and P–V curves in Figure 6 further support the high quality of the best solution discovered using the CGO method. Figure 6 shows that the simulated and measured data for both the I–V and P–V curves are extremely consistent, confirming the excellent quality of the optimum solution generated by the CGO algorithm for the Photowatt-PWP201 module model.

Figures 7.a and 7.b are presents the Individual Absolute Errors (IAE) for current between estimated and the measured data for RTC France cell, and Photowatt-PWP201 module, respectively.



(a)



(b)

Fig. 7. The IAE value for PV model:

a). RTC France cell, b). Photowatt-PWP201 module.

From Figure 7, it is clear that all IAE values of current are small compared to 2.501E-03 and 4.531E-03 for RTC France cell, and Photowatt-PWP201 module, respectively. Demonstrating the high identified effectiveness of applied CGO algorithm. The applied CGO algorithm ideal results are very compatible with the experimental data.

The algorithms compared with applied CGO algorithm are CARO [11], GOTLBO [12], IJAYA [13], MSSO [14], CSA [15], FA [16], Hybrid BBO-HCS [17], and hybrid GWO-CS [18] is tabulated in Table 3 for RTC France cell.

Table 3. Results comparison for RTC France cell.

Algorithm	I_{ph} **(A)**	I_{sd} **(μA)**	***N***	R_{sh} **(Ω)**	R_s **(Ω)**	***RMSE***
CARO [11]	0.760790	0.31724	1.48168	53.0893	0.03644	9.866500E−04
GOTLBO [12]	0.760780	0.331552	1.483820	54.115426	0.036265	9.874400E−04
IJAYA [13]	0.76080	0.32280	1.4811	53.7595	0.0364	9.860300E−04
MSSO [14]	0.760777	0.323564	1.481244	53.742465	0.036370	9.860700E−04
CSA [15]	0.760777	0.323564	1.481244	53.742465	0.03637	9.860230E−04
FA [16]	0.760872	0.258459	1.45907	48.3069	0.037247	10.72900E−04
BBO-HCS [17]	0.760780	0.32302	1.48118	53.71852	0.036380	9.860220E−04
GWO-CS [18]	0.760773	0.32192	1.480800	53.6320	0.036390	9.860700E−04
Proposed CGO	0.760776	0.323021	1.481185	53.7185852	0.036377	9.860219E−04

For Photowatt-PWP201 module the results comparison is represented in Table 2. Comparison proposed CGO algorithm with previous algorithms: CWOA [19], WOA [20], hybrid HA-PSA [21], MADE [22], JAYA [23], ISCA [24], ITLBO [25], and TGA [10] is represented in Table 4 for Photowatt-PWP201 module.

Table 4. Results comparison for Photowatt-PWP201 module.

Algorithm	I_{ph} **(A)**	I_{sd} **(μA)**	***n***	R_{sh} **(Ω)**	R_s **(Ω)**	***RMSE***
CWOA [19]	1.029962	3.847725	49.023217	1172.121142	1.201407	2.64170E−03
WOA [20]	1.0294212	3.8525	49.030662	1179.944288	1.190630	2.44905E−03
HA-PSA [21]	1.0305	3.4842	48.6449	984.2813	1.2013	2.42510E−03
MADE [22]	1.0305	3.4823	48.6428	981.9823	1.2013	2.42510E−03
JAYA [23]	1.0302	3.4931	48.6531	1022.50	1.2014	2.42780E−03
ISCA [24]	1.0305142	3.482262	48.64283	981.9966	1.201271	2.42510E−03
ITLBO [25]	1.0305143	3.4823	48.642834	981.982192	1.201271	2.425075E−03
TGA [10]	1.0263	9.5710	1.5255	6842.00	0.029800	3.819491E−03
Proposed CGO	1.030514	3.482263	1.351191	27.277278	0.033369	2.425074E−03

From table 3 which contains the results of the RTC France cell, the RMSE value obtained by the proposed CGO algorithm is 9.860219E−04, Also by comparing algorithms, the BBO-HCS algorithm has an RMSE equal to 9.860220E−04 which is the minimum value obtained among all compared algorithms from the literature, the worst RMSE value is 10.72900E−04 was registered and obtained by FA algorithm. From table 4, the best RMSE in case of Photowatt-PWP201 is 2.425074E−03 which also recorded by CGO algorithm, according to the same table the best RMSE among the compared algorithms is 2.425075E−03 which was obtained by ITLBO while the worst value is 3.819491E−03 that provided by TGA algorithm.

5. Conclusion

The CGO algorithm performance is used to extract and identify the parameters of various solar PV cells and module models under static operating conditions. The extensive experimental results demonstrate that the CGO algorithm is a promising candidate approach for obtaining the parameters of the RTC France solar cell and Photowatt-PWP201 module.

In order, the applied CGO algorithm findings were compared to those achieved by various optimisation algorithms mentioned in the literature. Consequently, the CGO algorithm optimum solution for each of the PV parameter extraction issues was shown to be as accurate as or more accurate than the other algorithms solutions. The results reveal that the proposed CGO algorithm shows higher performance compared to the rest of the proposed optimization algorithms in terms of error and precision.

In future work, proposed hybrid CGO algorithm for identified the PV parameters model at different irradiance and temperature levels. Also, will be interesting and favorable to apply the CGO algorithm to solve real power system problems and maximum power point tracking with partial shading conditions.

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