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Performance of Golden Jackal Optimization Algorithm for Estimating Parameters of PV Solar Cells Models

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Abstract: Solar radiation is becoming an increasingly popular source of clean energy. Photovoltaic (PV) panels, which house solar cells (SCs), are used in converting solar energy into electric energy. The classification of the current-voltage characteristic for PV models is considered as nonlinear. Because of the absence of information on manufacturers' datasheets for PV models, numerous parameters remain unclear. The precise determination of the inherent properties of SCs is necessary for the accurate design of PV systems. Several algorithms have been put forth to optimize these devices' parameters. Research in this area faces two challenges: identifying a model to distinguish SCs and addressing the lack of accessibility to data on PV cells. While various methods have been implemented in parameters estimation of PV cells, their results normally suffer from inaccuracies. This paper demonstrates the efficiency and precision of the Golden Jackal Optimization (GJO) metaheuristic technique in estimating the parameters of PV SCs different models. Three commonly used SCs models; the single-diode solar cell model (SDSCM), the double-diode solar cell model (DDSCM), and the triple-diode solar cell model (TDSCM) were utilized to showcase the GJO's ability to estimate the values of the parameters of SCs models. The values obtained were compared with those generated by several reliable optimization methods, including the Tunicate Swarm Algorithm (TSA), Osprey Optimization Algorithm (OOA), Harris Hawk's Optimization (HHO), Rime-Ice Algorithm (RIME), Chimp Optimization Algorithm (ChOA), and Grey Wolf Optimization (GWO), using data from the R.T.C France SC. The experimental results and relative analysis show that the GJO exhibited a better level of accuracy in estimating SCs parameters than the other algorithms included in the experiments.

Keywords: *Metaheuristic optimization, Golden Jackal Optimization algorithm, solar energy, renewable energy, photovoltaic models.*

1. Introduction

Renewable energy is energy derived from natural sources that are constantly replenished and produced at a higher rate than they are consumed. Sunlight and wind, for example, are examples of such sources. Because of the fluctuating pricing of fossil fuels, their solid wastes, and pollution, renewable energy (RE) sources have come to be seen as a potential option [1]. Solar energy (SE) is one of the main types of RE sources because of its minimal maintenance requirements, close to traditional production methods, widespread distribution, and noiseless operation [2-6]. A system known as a photovoltaic system (PV) uses solar energy to produce electricity [7]. The primary use of PVs is for satellites [8], water de-salination [9], and heating and cooling [10]. According to the number of connected di-odes, there are various types of solar cells, including the single-diode (SD), double-diode (DD), and triple-diodes (TD) models, as well as their variations [11-13]. To achieve the highest performance, it is crucial to identify parasitic solar cell factors [14]. The model determines how many variables there should be. The improved SD model has six parameters, while the original has five. The updated DD model has eight parameters, while the original has seven. The TD model has nine parameters, while its modified version has ten parameters [15,16]. Iterative approaches and metaheuristic procedures are two types of main solutions that can be used to estimate these parameters.

A Mathematical model for SD is discussed in [17], while improvements to solar cell power are given in [18]. Three locations are used to perform the I-V characteristics in a nonlinear manner [19]. The iterative solution has focused on identifying the PV variables in [20-23], using techniques such as the Lambert W function [20], Newton-Raphson with maximum likelihood [21], the linear least-squares [22] and the Gauss-Seidel [23]. Furthermore, several studies limit the number of parameters that need to be calculated by excluding some variables or by making assumptions to eliminate the number of factors that should be calculated [24–27]. The very clear benefits of metaheuristic techniques have provided applying and confirming different methods for solving complex optimization problems [27-35].

The main issue in this study is to extract PV variables using a novel metaheuristic technique, which is Golden-Jacal Optimization GJO method. The considered problem of this study is examined previously using several algorithms such as artificial bee swarm [12], differential evolution [36], generalized oppositional teaching learning-based optimization [37], Particle Swarm Optimization (PSO) [38], Salp swarm algorithm [39], chaos particle swarm optimization [40], Nelder-mead modified particle swarm

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optimization [41], harmony search [42], Cat Swarm optimization [43], cuckoo search algorithm [44], genetic algorithms [45], simulated annealing [46], improved adaptive differential evolution (IADE) [47], pattern search [48], combining a simplified explicit equation with some intelligent optimization methods [49], sin-cosine algorithm [50] and bacterial foraging algorithm [51].

This work is contributed according to the following items:

- Applying a novel optimization algorithm called Golden Jackal Optimization (GJO) in extracting solar cell models.
- The single-diode solar cell (SDSCM), double-diode solar cell (DDSCM), and triple-diode solar cell (TDSCM) are considered in this study.
- The objective function used in this work is minimizing the root mean square error for the current value.
- Practical comparison between the Golden Jackal Optimization (GJO) technique with another six algorithms such as Tunicate Swarm Algorithm (TSA), Ospery Optimization algorithm (OOA), Harris Hawk's optimization (HHO), Rime-Ice algorithm (RIME), Chimp Optimization Algorithm (ChOA) and Grey Wolf Optimization (GWO) is implemented.
- The statistical analytical results are applied for all the considered optimization methods to measure the performance evaluation of all these techniques over 30 independent runs.
- The convergence and robustness curves are extracted to measure the high reliability and faster algorithm.
- The efficiency of the GJO algorithm is determined according to the absolute error value for power and current between the measured and extracted data.

The organization of this paper is as follows: the analysis of the solar cell mathematical model is produced in section 2. Section 3 discusses the objective function of the problem study. The Golden Jackal Optimization GJO algorithm is analysed in section 4. The results of the estimated identified parameters for SDSCM, DDSCM and TDSC will be discussed in section 5. The conclusion of this work is presented in section 6.

2. Analysis of PV Solar Cell Models

In this study, three solar cell models will be considered; the single-diode solar cell model (SDSCM), the double-diode solar cell model (DDSCM), and the triple-diode solar cell model (TDSCM).

2.1. Mathematical Analysis of PV SDSCM

The SDSCM equivalent circuit is clarified as represented in Fig. 1, while the mathematical model of SDSCM is defined as follows in equations (1) and (2):

$$I = I_{pv} - I_{D1} - I_{sh} \tag{1}$$

$$I = I_{pv} - I_{h1}\left[e^{\frac{q(V+IR_S)}{n_1 KT_C}} - 1\right] - \frac{V+IR_S}{R_{sh}} \tag{2}$$

where I is the SDSCM current output, I_{pv} is the generated light current, I_{sh} is the current of shunt resistor, I_{D1} is the current in the diode, R_s is the series resistance, R_{sh} is the parallel resistance, n_1 is the emission factor of the diode, q is the electron charge, K Boltzmann constant, and T_c the cell temperature.

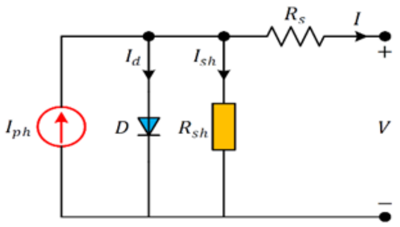

Fig 1. SDSCM Equivalent circuit.

2.2. Mathematical Analysis of PV DDSCM

The DDSCM equivalent circuit is clarified as given in Fig. 2, while the mathematical model of DDSCM is defined as follows in equations (3) and (4):

$$I = I_{pv} - I_{D1} - I_{D2} - I_{sh} \tag{3}$$

$$I = I_{pv} - I_{h1}\left[e^{\frac{q(V+IR_S)}{n_1 KT_C}} - 1\right] - I_{h2}\left[e^{\frac{q(V+IR_S)}{n_2 KT_C}} - 1\right] - \frac{V+IR_S}{R_{sh}} \tag{4}$$

where I_{D2} and n_2 are the current and the emission factor of second diode respectively.

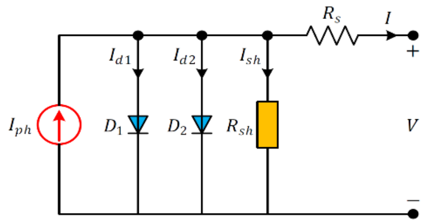

Fig 2. DDSCM Equivalent circuit.

2.3. Mathematical Analysis of PV TDSCM

The TDSCM equivalent circuit is clarified as shown in Fig. 3, while the mathematical model of TDSCM is defined as follows in equations (5) and (6):

$$I = I_{pv} - I_{D1} - I_{D2} - I_{D3} - I_{sh} \tag{5}$$

$$I = I_{pv} - I_{h1}\left[e^{\frac{q(V+IR_S)}{n_1 KT_C}} - 1\right] - I_{h2}\left[e^{\frac{q(V+IR_S)}{n_2 KT_C}} - 1\right] - I_{h3}\left[e^{\frac{q(V+IR_S)}{n_3 KT_C}} - 1\right] - \frac{V+IR_S}{R_{sh}} \tag{6}$$

where I_{D3} and n_3 are the current and the emission factor of third diode respectively.

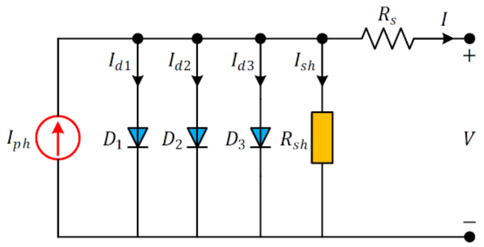

Fig 3. TDSCM Equivalent circuit.

3. Objective Function for Solar Cell Parameters Estimation

Practically, the two primary elements in any problem solved using optimization methods are the limits (or ranges) of the variables involved and the goal (or objective) function. In this paper, the objective function for the solar cell problem is to minimize the root mean square error (RMSE) that is mathematically represented by the as follow s in equations (7) and (8):

$$J(V.I.X) = I_{sim} - I_{exp} \quad (7)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(J(V.I.X)\right)^2} \quad (8)$$

where I_{exp} is the measured recorded current, N is the number of samples and X is the estimated variable parameters of SC model.

The estimated variable parameters of SDSCM are:

$$X = \{(R_s.\ I_{h1}.\ n_1.\ R_{sh}\ and\ I_{pv})\},$$

the DDSCM estimated variables are:

$$X = \{(R_s.\ I_{h1}.n_1\ .\ R_{sh}\ .I_{pv}\ .\ I_{h2}\ and\ n_2)\},$$

and the TDSCM estimated variables are:

$$X = \{(R_s.\ I_{h1}.\ n_1.\ R_{sh}\ .I_{pv}\ .\ I_{h2}\ .n_2\ .I_{h3}\ and\ n_3)\}.$$

The parameters' selection is based on the fact that these variable parameters are not defined in the solar cell datasheet. Table 1 presents the boundary limits of the estimated variable parameters.

Table 1. The variables' lower and upper boundaries of the parameters.

Parameters	*Lower bound*	*Upper bound*
I_{pv}	0	1
R_s	0	0.5
$I_{h1}, I_{h2}\ and\ I_{h3}\ (\mu A)$	0	1
$n_1, n_2\ and\ n_3$	1	2
R_{sh}	0	100

Performing a sensitivity analysis on the parameters estimated in the previous table can help determine how changes in input parameters impact the outputs. Sensitivity analysis assesses the robustness of our parameter estimates and their sensitivity to variations. Here's a discussion of sensitivity analysis for the parameters in Table 1:

- *Sensitivity of Photogenerated Current* (I_{pv})*:* We can conduct sensitivity analysis by perturbing the I_{pv} parameter slightly and observing how it affects the RMSE. For instance, calculate the resulting RMSE for each change. If the RMSE remains relatively stable, it suggests that the model is not highly sensitive to variations in I_{pv}.
- *Sensitivity of Current* (I_h): like I_{pv}, perturb the I_h parameter and observe its effect on RMSE. Determine the range of I_h values over which the RMSE remains acceptable. This analysis can provide insights into the sensitivity of the model to changes in I_h.
- *Sensitivity of Ideality Factor* (n_1): Sensitivity of ideality factor n_1 involves varying the ideality factor within a reasonable range (e.g., ±0.1) and recording the corresponding RMSE values. If the RMSE exhibits significant changes with small variations in n_1, it indicates that the parameter has a substantial impact on the model's accuracy.
- *Sensitivity of Series Resistance* (R_s): For series resistance R_s, analysing how variations in R_s affect RMSE. Gradually increase or decrease R_s and record RMSE values. The range over which RMSE remains within an acceptable range provides insights into the sensitivity of the model to R_s.
- *Sensitivity of Shunt Resistance* (R_{sh}): performing sensitivity analysis on R_{sh} is done by varying it within a reasonable range (e.g., ±10\%). Observe the corresponding changes in RMSE. If RMSE remains relatively stable within this range, it suggests that R_{sh} has moderate sensitivity.
- *Sensitivity of RMSE to Model Parameters*:

additionally, we can conduct a global sensitivity analysis by varying all parameters simultaneously within their respective ranges and measuring the impact on RMSE. This type of analysis provides a holistic view of how changes in multiple parameters affect the model's performance.

Interpreting sensitivity analysis for parameters that lead to significant RMSE changes with small variations is considered sensitive and accurate estimation of these parameters is crucial for model accuracy. Parameters with low sensitivity (i.e., RMSE remains stable with variations) are less critical for model accuracy and may have a lower impact on the model's predictive capabilities. Sensitivity analysis helps in identifying which parameters should be prioritized for accurate estimation and may guide further experiments or optimizations.

4. Golden Jackal Optimization (GJO) Algorithm

In this section, we present the source of inspiration and the mathematical model of Golden Jackal Optimization (GJO) [36].

4.1. Inspiration

The Golden Jackal Optimization (GJO) algorithm is a recent novel evolutionary optimization technique inspired by the foraging behavior of golden jackals in the animal kingdom. A medium-sized terrestrial predator in the Canidae family is the golden jackal (Canis aureus). These creatures can be found throughout Southeast North and East Africa, and the Middle, East Asia, Central Asia, and even Europe. They range from sea level in Eritrea to 3,500m in Ethiopia's Bale Mountain range. This algorithm seeks to find optimal solutions within complex search spaces by mimicking the hunting strategies employed by golden jackals. GJO begins with a population of potential solutions, analogous to a pack of jackals. Each solution represents a potential candidate in the search for the optimum.

The core principle of GJO is the dynamic adjustment of individual positions within the population over successive iterations. This adjustment is influenced by the quality of solutions found so far. Similar to how golden jackals adapt their hunting tactics in response to the availability of prey, GJO adapts the positions of solutions based on their fitness values. Promising solutions are given precedence, guiding the search towards regions with potentially higher fitness. Additionally, GJO introduces randomness into the optimization process to simulate the exploratory nature of golden jackals. This randomness ensures that the algorithm can escape local optima and explore the solution space more comprehensively. Through the interplay of these mechanisms, the Golden Jackal Optimization algorithm efficiently converges towards optimal solutions, making it a valuable tool in solving complex optimization problems.

The following are the primary phases of golden jackal pair hunting:

- Searching and proceeding towards the prey.
- Enclosing and irritating the prey until it stops moving.
- Pouncing towards the prey.

This study uses a mathematical model of a golden jackal pair's hunting strategy to create GJO and afterwords perform the optimization process.

4.2. The GJO Algorithm Mathematical Model

The development process of the GJO algorithm, as a practical and straightforward metaheuristic optimization technique, is in details demonstrated in this subsection.

4.2.1. Search Space Formulation

Like many other metaheuristic techniques, the GJO algorithm is a population-based approach, in which the initial solution is randomly dispersed throughout the search space as the first iteration, as shown in equation (9).

$$Y_0 = Y_{min} + rand(Y_{max} - Y_{min}) \tag{9}$$

where *rand* is a uniform random vector with values in the range between 0 and 1 and Y_{min} and Y_{max} are the lower and upper bounds for these variables. The jackal pair is the one of the first and second fittest members of the initialization that generates the initial matrix Prey. Equation (10) displays the given Prey.

$$Y_0 = \begin{bmatrix} Y_{1,1} & Y_{1,2} & \dots & Y_{1,d} \\ Y_{2,1} & Y_{2,2} & \dots & Y_{2,d} \\ \vdots & \vdots & \vdots & \vdots \\ Y_{n,1} & Y_{n,2} & \dots & Y_{n,d} \end{bmatrix} \tag{10}$$

where $Y_{i,j}$ denotes the j^{th} dimension of i^{th} prey. Totally, there is *n* preys and *d* variables. The parameters of a particular solution are referred to as the *prey position*. During optimization, a fitness (objective) function is used to estimate each prey's fitness value. The resulting matrix gathers the fitness values of all the preys, as provided in equation (11).

$$F_{OA} = \begin{bmatrix} f(Y_{1,1}; & Y_{1,2}; & \dots & Y_{1,d}) \\ f(Y_{2,1}; & Y_{2,2}; & \dots & Y_{2,d}) \\ & \vdots & & \\ f(Y_{n,1}; & Y_{n,2}; & \dots & Y_{n,d}) \end{bmatrix} \tag{11}$$

where *n* is the number of the preys, *f* is the objective function, $Y_{i,j}$ indicates the value of the j^{th} dimension of i^{th} prey, and F_{OA} is the matrix for preserving the fitness of each prey. The male jackal is considered as the fittest, while the female jackal will be considered as the second fittest. Afterthought, the pair jackals then acquire the corresponding prey position.

4.2.2. Searching the Prey (Exploration Stage)

in this section, the GJO algorithm's exploration strategy phase is provided . Because of their natural instincts, jackals can detect and track their prey, but infrequently the prey eludes them and would be difficult to catch. The jackals then wait and look for alternative prey as a result. A male jackal leads the hunt, and a female jackal follows it. Equations 12 and 13 compute the revised positions of the male and female jackals.

$$Y_1(t) = Y_M(t) - E.| + Y_M(t) - rl.Prey(t) \tag{12}$$

$$Y_2(t) = Y_{FM}(t) - E.| + Y_{FM}(t) - rl.Prey(t) \tag{13}$$

where the $Prey(t)$, $Y_M(t)$ and $Y_{FM}(t)$ represent the positions of the male and female jackal, $Y_1(t)$ and $Y_2(t)$ are the updated positions of male and female jackal as per to the prey and the Evading Energy E of prey and is calculated as:

$$E = E_1 * E_0 \tag{14}$$

where E_0 represents the prey's initial energy and E_1 represents its decreased energy. Both initial energy E_0 and decreased energy E_1 are calculated as shown in equations (15) and (16).

$$E_0 = 2 * r - 1 \tag{15}$$

$$E_1 = c_1 * \left(1 - (t/T)\right) \tag{16}$$

where *t* is the current iteration, *T* is the maximum number of iterations, *r* is any integer between 0 and 1, and c_1 is a constant value of 1.5. E_1 decreases linearly over iterations from 1.5 to 0. The *Lévy* movement is represented using the vector *rl* (as in equations (12) and (13)), which is based on the Lévy distribution and contains random numbers. Equation (17) is used to calculate *rl*, which simulates the movement of prey in a Lévy fashion [30].

$$rl = 0.05 * LF(Y) \tag{17}$$

such that:

$$LF(Y) = 0.01 * \frac{\mu * \rho}{\left(\left|\upsilon^{\left(\frac{1}{\beta}\right)}\right|\right)}, \quad \rho = \left\{\frac{\Gamma(1+\beta) * sin\,(\frac{\pi\beta}{2})}{\Gamma\left(\frac{1+\beta}{2}\right) * \beta * 2^{(\beta-1)}}\right\}^{1/\beta}$$

where β is the default constant and is set to 1.5, μ and υ are random real numbers in (0, 1) and *LF* is the function of Levy flight. The jackal positions are finally updated, as shown is equation (18), by averaging the two equations (12) and (13).

$$Y(t+1) = \frac{1}{2}\left(Y_1(t) + Y_2(t)\right) \tag{18}$$

4.2.3. Enclosing and Pouncing the Prey (Exploitation Stage)

The mathematical model models the behaviour of the male and female jackal pair hunting together (given in equations (12) and (13)) will be updated as expressed in equations (19) and (20) and proceeds as follows: the prey loses energy in response to the jackals' harassment, and the jackal pair moves to encircle the prey, which they had previously spotted. After the victim is confined, the jackals spring on it and attack it.

$$Y_1(t) = Y_M(t) - E.|\, rl.Y_M(t) - Prey(t) \tag{19}$$

$$Y_2(t) = Y_{FM}(t) - E.|rl.Y_{FM}(t) - Prey(t) \tag{20}$$

where $Y_1(t)$ and $Y_2(t)$ are updated positions of male and female jackals corresponding to the prey respectively and *t* indicates the current iteration and. Afterwords, the Prey's evading energy *E* is calculated as per equation (14) and the jackal positions are finally updated as per equation (18).

In equations (19) and (20), the factor *rl* has the role of providing arbitrary behavior throughout the exploitation stage and favoring exploration and avoiding local optima. The value of *rl* is determined using equation (17). Using the *rl* element aids in avoiding the slowness of local optima, especially in the final iterations. When obstacles are in the way of approaching the prey, it would be beneficial to consider and use the factor *rl*. Some natural problems may usually arise in the jackals' pursuit tracks, impeding their ability to move quickly and suitably in the direction of their prey. This is why *rl* factor is proposed and considered during the exploitation stage.

4.2.4. Exploration Stage to Exploitation Stage Transition

In the GJO method, the transition from exploration to exploitation is accomplished by harnessing the prey's fleeing energy. The prey has a sharp drop in energy during its evasive behaviour. In light of this, the evasive energy E of the prey is modelled as expressed in equation (14). At every time, the initial energy E_0 varies erratically from -1 to 1. The physical waning of the prey is indicated when the E_0 value decreases from 0 to -1. Conversely, an increase in the E_0 value from 0 to 1 signifies an improvement in the prey's strength. As illustrated in Figure 4, the altering evading energy E decreases over the iteration procedure. When $|E| < 1$, GJO attacks and exploits the prey; when $|E| > 1$, the jackal pairs seek prey in different portions. In conclusion, the development of an arbitrary population of prey (possible solutions) marks the start of the search process in GJO. A male and female jackal hunting pair estimates the prey's expected position during iterations. Each candidate in the population modifies how far away it is from the pair of jackals. The emphasis on exploration and exploitation is achieved by reducing the E_1 parameter from

1.5 to 0 correspondingly. When $E > 1$, a hunting pair of golden jackals deviates from the prey, and when $E < 1$, they concentrate near the prey. Finally, the fulfilment of an end criterion completes the GJO algorithm. Figure 4 represents the complete entire design of GJO algorithm's pseudocode.

```
Inputs: The population size N and maximum number of
        iterations T
Outputs: The location of prey and its fitness value
Initialize the random prey population Y_i (i = 1, 2, . . . N)
while (t < T) do
   Calculate the fitness values of Prey
   Y_1 = best prey individual (Male Jackal Position)
   Y_2 = second best prey individual (Female Jackal Position)
   for each prey individual do
      Update the evading energy E using Equations (14), (15)
      and (16)
      Update rl using Equations (17) and (18)
      if (|E| ≥ 1) then
         Exploration phase: Update the prey position using
         Equations (12), (13) and (18)
      end if
      if (|E| < 1) then
         Exploration phase: Update the prey position using
         equations (19), (20), and (18)
       end if
   end for
   t = t + 1
end while
return Y_1
```

Fig 4. Pseudo-code of the GJO algorithm [36].

5. Results and Discussion

This section clarifies the parameters extracted for the SSCM, DDSCM, and TDSCM models using the GJO algorithm. The GJO method is competed with other algorithms such as; Harris Hawk's optimization (HHO) [53], Grey Wolf Optimization (GWO) [54], Tunicate Swarm Algorithm (TSA) [55], Chimp Optimization Algorithm (ChOA) [56], Osprey Optimization algorithm (OOA) [57], and Rime-ice algorithm (RIME) [58]. As a case study, the R.T.C France module is used for comparing all the techniques. The variable setting for all considered methods is shown in Table 2.

Table 2. The variables' lower and upper boundaries of the parameters.

Algorithm	***Parameter Setting***
GJO	c_1 is a constant value equal to 1.5
GWO	E_1 decrease linearly from 1.5 to 0
OOA	*a* decrease linearly from 2 to 0
RIME	$r_{i,j}$ are random numbers belong to the interval [0, 1]
ChOA	$I_{i,j}$ are random numbers belong to the set {1, 2}
TSA	r_1 is a random number belongs to the range (-1,1)
HHO	r_2 is a random number in belongs to the range (0,1)

One key attribute of GJO is its dynamic adaptation mechanism. As GJO iterations progress, solutions with higher fitness values influence the positions of other solutions within the population. This adaptive nature enables GJO to quickly converge towards promising regions of the solution space, exploiting areas where the fitness landscape exhibits convexity. This adaptability is particularly advantageous in scenarios where the optimization landscape contains multiple local optima, as GJO effectively navigates past these suboptimal solutions. Furthermore, GJO's incorporation of randomness through probabilistic jumps adds an element of exploration to the optimization process. While traditional optimization algorithms may get trapped in local optima, GJO's ability to make random jumps introduces the possibility of discovering new, globally optimal regions. This stochasticity is especially beneficial in complex, multi-modal optimization landscapes where deterministic methods may struggle.

Additionally, GJO's inspiration from the golden jackals foraging behavior plays an important role in its performance. In nature, jackals exhibit a combination of focused search and opportunistic exploration when hunting for prey. Similarly, GJO's balance between exploiting known high-value regions (local search) and exploring uncharted areas (random jumps) mirrors this adaptability, allowing it to effectively adapt to varying optimization landscapes.

5.1. Discussion on Assumptions and Limitations

Through this subsection, we address assumptions and limitations in the context of using the Golden Jackal Optimization (GJO) algorithm for PV SC models parameters estimation:

Assumptions:

1. *Model Validity:* One of the primary assumptions in our study is the validity of the chosen PV solar cell model. We assumed that the selected mathematical model accurately represents the behavior of the specific solar cell under consideration. Deviations from the assumed model, due to many factors such as temperature variations or nonuniform illumination, could affect the accuracy of the estimation of the considered parameter.

2. *Homogeneous Conditions:* We assumed that the operating conditions for the photovoltaic solar cell, such as uniform illumination and constant temperature, remain relatively constant throughout the parameter estimation process. In practice, real-world conditions can vary, introducing uncertainties.

3. *Measurement Accuracy:* Our study relies on accurate and precise measurements of the solar cell's electrical characteristics, including current-voltage (I-V) curve data. We assumed that these measurements are free from significant errors or noise, which might not always be the case in practical experiments.

4. *Objective Function Selection:* The choice of the root mean square error (RMSE) between both simulated and experimental current of the solar cell of R.T.C France as the fitness function assumes that minimizing this metric leads to the best parameter estimates.

Limitations:

1. *Local Optima:* Like many optimization algorithms, the GJO algorithm is not immune to getting stuck in local optima. The effectiveness of GJO in finding global optima depends on the objective function landscape. Multiple runs with different initial conditions may be required to mitigate this limitation.

2. *Computational Resources:* GJO can be computationally intensive, especially for complex parameter estimation problems or when using a large population size. Researchers should consider the available computational resources and time constraints.

3. *Sensitivity to Hyperparameters:* The performance of GJO algorithm can be sensitive to the selection of hyperparameters, such as the jumping probability and the range of random jumps. Finding suitable hyperparameters may require experimentation.

4. *Convergence Time:* The convergence time of the GJO algorithm can vary depending on the complexity of the optimization problem. Researchers should be aware of the potential need for longer computation times for challenging parameter estimation tasks.

5. *Generalization:* The optimized parameters obtained using GJO algorithm are specific to the dataset and conditions used during optimization. They may not necessarily generalize well to different experimental setups or environmental conditions. Validation and sensitivity analysis are essential to assess generalizability.

In conclusion, the use of the GJO algorithm for parameter estimation in PV solar cell models holds promise. Acknowledging these factors is critical for interpreting the results accurately, assessing the robustness of the parameter estimates, and understanding the applicability of the method in practical scenarios. Future research may focus on addressing some of these limitations and refining the application of GJO in solar cell modeling and optimization.

5.2. Discussion of SDSCM Results

The results of the identified variable parameters for SDSCM evaluated from the proposed GJO Algorithm and the additional considered techniques at the best RMSE are given in Table 3.

1. *At the level of Photogenerated Current $I_{pv}(A)$:* Among the optimization algorithms, GJO and GWO provide very similar estimates for the photogenerated current $I_{pv}(A)$, with values around 0.760 A. These two algorithms seem to excel in estimating this parameter, as indicated by the lowest RMSE (0.000986022 and 0.001205557, respectively).

2. *At the level of Current at Diode's Ideality Factor $I_{h1}(A)$:* The HHO algorithm produces a notably higher estimate for $I_{h1}(A)$ compared to the other algorithms, with a value of 4.75E-07 A. In contrast, ChOA estimates the lowest $I_{h1}(A)$ at 5.07E-08 A. However, the RMSE values for $I_{h1}(A)$ indicate that the ChOA algorithm has a considerably higher error (0.007640622), suggesting that its estimate for this parameter is less accurate.

3. *At the level of Ideality Factor n_1:* The optimization algorithm HHO estimates the highest ideality factor n_1 at 1.520924087, while ChOA provides the lowest estimate at 1.317375646. This parameter exhibits a significant variation among the algorithms, which is reflected in the RMSE values. The GJO algorithm achieves the lowest RMSE (0.000986022), indicating that it provides the best estimate for n_1.

4. *At the level of Series Resistance $R_s(\Omega)$:* Among the algorithms, the optimization algorithm HHO estimates the lowest series resistance $R_s(\Omega)$ at 0.035030244 Ω, while ChOA estimates the highest at 0.039827959 Ω. The GJO algorithm has the second lowest RMSE (0.001006495) for Rs(Ω), suggesting accurate

parameter estimation.

5. *At the level Shunt Resistance* $R_{sh}(\Omega)$*:* The optimization algorithm ChOA estimates the lowest shunt resistance $R_{sh}(\Omega)$ at 22.22929772 Ω, while HHO provides the highest estimate at 73.06072271 Ω. RIME and TSA also produce notably different estimates for $R_{sh}(\Omega)$. The RMSE values for $R_{sh}(\Omega)$ are relatively high for most algorithms, indicating potential challenges in accurately estimating this parameter.

6. *At the level of Root Mean Square Error RMSE:* The *RMSE* values quantify the goodness of fit between the modeled data and the experimental data. Lower *RMSE* values indicate better model accuracy. The GJO algorithm attains the lowest *RMSE* (0.000986022), implying the best overall fit to the experimental data.

The best method that reaches the optimum value of RMSE is the GJO algorithm. The method ordering according to the best fitness function is RIME, GWO, HHO, OOA, TSA, and ChOA respectively. The SDSCM characteristics based on the optimum estimated variable parameters from the GJO method are used in the simulation of the curves of P-V and I-V as clearly illustrated in Figures 5 and 6 respectively. Also, the absolute error for power and current is analyzed in those two figures. According to the recorded results, the power reaches an absolute error equal to 0.0000019729262562317 and the current reaches an absolute error equal to 0.0000874090632038138.

5.3. Discussion of DDSCM Results

The results of the identified variable parameters for DDSCM evaluated from the proposed GJO Algorithm and the competitive techniques at the best RMSE are outlined in Table 4.

1. *At the level of Photogenerated Current* $I_{pv}(A)$*:* The GJO algorithm yields an estimated photogenerated current $I_{pv}(A)$ of approximately 0.760776216 A, which is very close to the value obtained using the GWO algorithm (0.760389467 *A*). Both GJO and GWO exhibit the lowest *RMSE* values (0.000983088 and 0.001211413, respectively), giving the best fit to the experimental data for $I_{pv}(A)$.

2. *At level of Current at Diode's Ideality Factor* $I_{h1}(A)$*:* Interestingly, the HHO algorithm estimates a value of 0.00E+00 A for $I_{h1}(A)$, indicating that it essentially does not predict current in this diode. On the other hand, GJO and ChOA estimate significantly higher values for $I_{h1}(A)$. The *RMSE* values for $I_{h1}(A)$ are relatively high for several algorithms, indicating the challenge in accurately estimating this parameter.

3. *At level of Ideality Factor* n_1*:* The GJO optimization algorithm estimates an ideality factor n1 of approximately 1.999999999, very close to the ideal value of 2. This suggests that GJO predicts an ideal diode behavior for n_1. The RMSE value for n_1 using GJO is the lowest among the algorithms, indicating an accurate parameter estimation.

4. *At level of Series Resistance* $R_s(\Omega)$*:* The optimization algorithms GJO, GWO, and HHO provide relatively similar estimates for series resistance $R_s(\Omega)$, with values close to 0.036 Ω. The RMSE values for $R_s(\Omega)$ are also relatively low for these three algorithms, indicating accurate parameter estimation.

5. *At level Shunt Resistance* $R_{sh}(\Omega)$*:* The optimization algorithm TSA estimates the highest shunt resistance $R_{sh}(\Omega)$ at 81.11183487 Ω, while ChOA provides the lowest estimate at 11.7834362 Ω. The RMSE values for $R_{sh}(\Omega)$ vary between algorithms, and TSA has the lowest *RMSE*, suggesting accurate parameter estimation.

6. *Current at Diode's Ideality Factor* $I_{h2}(A)$ *and* n_2*:* For the ideality factor $I_{h2}(A)$, it appears that the analysis includes parameters related to a second diode in the DDSCM. Like $I_{h1}(A)$, $I_{h2}(A)$ and n_2 show variations among the optimization algorithms. These parameters have relatively high *RMSE* values, indicating potential challenges in accurate estimation.

Table 3. Identified parameters at the optimal RMSE for SDSCM.

Parameter	*GJO*	*GWO*	*HHO*	*OOA*	*RIME*	*ChOA*	*TSA*
$I_{pv}(A)$	0.760775383	0.760434273	0.760447264	0.757522151	0.761039595	0.761802741	0.757291175
$I_{h1}(A)$	3.23E-07	2.67E-07	4.75E-07	3.86E-07	3.04E-07	5.07E-08	2.89E-07
n_1	1.481186363	1.462178429	1.520924087	1.499554883	1.475297989	1.317375646	1.469506585
$R_s(\Omega)$	0.036377009	0.036825416	0.035030244	0.034982442	0.03654007	0.039827959	0.036480554
$R_{sh}(\Omega)$	53.72093421	50.25003	73.06072271	77.75879679	49.52768507	22.22929772	79.78135609
RMSE	0.000986022	0.001205557	0.001277464	0.00235091	0.001006495	0.007640622	0.002574147

Table 4. Identified parameters at the optimal RMSE for DDSCM.

Parameter	*GJO*	*GWO*	*HHO*	*OOA*	*RIME*	*ChOA*	*TSA*
$I_{pv}(A)$	0.760776216	0.760389467	0.759490081	0.783324753	0.761041387	0.781287797	0.757932623
$I_{h1}(A)$	4.75E-07	6.73E-07	0.00E+00	2.22E-07	7.75E-08	4.37E-07	3.09E-07
n_1	1.999999999	1.989170397	1.883260056	1.535863568	1.547775056	1.513054471	1.477327384
$R_s(\Omega)$	0.036575654	0.037380965	0.03639245	0.060063011	0.036465979	0.031746146	0.03587831
$R_{sh}(\Omega)$	55.00082774	64.56911816	74.00899105	59.64729661	52.44891214	11.7834362	81.11183487
$I_{h2}(A)$	2.61E-07	2.15E-07	3.19E-07	1.40E-07	2.57E-07	1.65E-08	5.92E-08
n_2	1.463131859	1.445883058	1.479518801	1.44667356	1.471833056	2	1.876476881
RMSE	0.000983088	0.001211413	0.00137838	0.045497895	0.001011992	0.01422437	0.002177321

Table 5. Identified parameters at the optimal RMSE for TDSCM.

Parameter	*GJO*	*GWO*	*HHO*	*OOA*	*RIME*	*ChOA*	*TSA*
$I_{pv}(A)$	0.760782337	7.62E-01	7.61E-01	0.780305804	0.760804506	7.54E-01	0.76289745
$I_{h1}(A)$	9.79E-07	3.71E-07	8.67E-07	4.43E-07	9.99E-07	0.00E+00	9.54E-08
n_1	1.999808073	1.50E+00	1.62E+00	1.572350975	1.918323113	1.87E+00	2
$R_s(\Omega)$	0.036890353	0.035956271	0.030529716	0.047125371	0.036470919	0	0.034134898
$R_{sh}(\Omega)$	56.39602373	49.46459462	85.32287663	46.88655892	64.78240147	9.656121549	47.57256276
$I_{h2}(A)$	1.93E-07	0.00E+00	6.42E-08	8.21E-07	9.90E-07	9.88E-07	6.47E-08
n_2	1.438065187	1.654724006	1.608373649	1.695538571	1.996078954	1.619963479	2
$I_{h3}(A)$	7.31E-08	1.24E-09	1.97E-07	1.72E-07	1.17E-07	0.00E+00	5.32E-07
n_3	1.998081004	1.813499871	1.609161597	1.825298084	1.40275812	1.98461433	1.53501469
RMSE	0.000983227	0.001232716	0.002780114	0.030275843	0.001132313	0.039555218	0.002394933

7. *At level of Root Mean Square Error RMSE:* The *RMSE* values quantify the good-ness-of-fit between the modelled data and the experimental data. Lower *RMSE* values indicate better model accuracy. The GJO algorithm achieves the lowest *RMSE* (0.000983088), implying the best overall fit to the experimental data.

The best method to achieve the optimum value of RMSE is the GJO algorithms. The order of the other methods according to the best fitness function is RIME, GWO, HHO, TSA, ChOA, and OOA respectively. The DDSCM characteristics based on the optimum estimated variable from the GJO method are used in the simulation of the curves of P-V and I-V as clearly shown in Figures 7 and 8 respectively. Also, the absolute error for power and current is analyzed in those two figures. According to the recorded results, the power reaches an absolute error equal to 1.81332614118679E-06 and the current reaches an absolute error equal to 8.81539203301252E-06.

5.4. Discussion of TDSCM Results

The results of the identified variable parameters for TDSCM evaluated from the proposed GJO Algorithm and the additional relative techniques at the best RMSE are outlined in Table 5. The best method that reaches the optimum value of RMSE is the GJO technique. The order of the other methods according to the best fitness function is RIME, GWO, TSA, HHO, OOA, and ChOA respectively. The TDSCM characteristics based on the optimum estimated variable parameters from the GJO algorithm are used in the simulation of the curves of P-V and I-V as represented in Figures 9 and 10 respectively. Also, the absolute error for power and current is analyzed in those two figures. According to the recorded results, the power reaches an absolute error equal to 1.80929475575384E-06 and the current reaches an absolute error equal to

0.0000687911957745202.

5.5. Analysis of Statistical Data for the Three Models

Based on 30 separate experimental runs, the statistical data of all the considered methods is fulfilled to compute the maximum, minimum, standard deviation, and mean of the objective function. The minimum and standard deviation values of RMSE, respectively, determine the reliability and accuracy of the mentioned methods. Tables 6, 7, and 8 conclude the reported statistical data for the different three solar cell models SDSCM, DDSCM, and TDSCM, respectively. From these three tables, it is clear that the GJO algorithm achieves the optimum value of minimum RMSE for the three models SDSCM, DDSCM and TDSCM. Furthermore, the optimum standard deviation value for the three models SDSCM, DDSCM and TDSCM is achieved by the GJO algorithm. So that, the proposed GJO technique is the best method on all comparator ones since it achieves high accuracy and reliability. The robustness curves of the three models SDSCM, DDSCM and TDSCM are clarified in Figures 11, 12, and 13 respectively. The convergence curves of the three models SDSCM, DDSCM, and TDSCM are clarified in Figures 14, 15, and 16 respectively. According to these figures; it is recognizable that the GJO method converges to the global optimal solution faster that all other techniques. Moreover, compared to all other methods included in the practical experiment, the GJO method also achieves excellent robustness and reliability to the optimal solution.

Table 6. Statistical Results of SDSCM.

Algorithm	***Min***	***Mean***	***Max***	***STDV***
GJO	0.000986	0.00102	0.001438	1.15E-04
GWO	0.001206	0.009907	0.045697	0.013118
HHO	0.001277	0.024428	0.097538	0.026126
OOA	0.002351	0.14808	0.289284	0.074319
RIME	0.001006	0.001972	0.007048	0.001186
ChOA	0.007641	0.12125	0.22287	0.086321
TSA	0.002574	0.009278	0.038364	0.011741

Table 7. Statistical Results of DDSCM.

Algorithm	***Min***	***Mean***	***Max***	***STDV***
GJO	0.000983	0.001061	0.001438	0.000145
GWO	0.001211	0.006315	0.038353	0.008856
HHO	0.001378	0.010028	0.032096	0.007534
OOA	0.045498	0.153379	0.292036	0.075031
RIME	0.001012	0.002079	0.00399	0.000939
ChOA	0.014224	0.120425	0.222875	0.081475
TSA	0.002177	0.006585	0.0378	0.008298

Table 8. Statistical Results of TDSCM.

Algorithm	***Min***	***Mean***	***Max***	***STDV***
GJO	0.000983	0.0011	0.001438	0.000171
GWO	0.001233	0.008177	0.037379	0.010241
HHO	0.00278	0.044284	0.300537	0.088492
OOA	0.030276	0.176115	0.310742	0.079704
RIME	0.001132	0.002467	0.003725	0.000796
ChOA	0.039555	0.169171	0.2229	0.077667
TSA	0.002395	0.004801	0.012679	0.001935

Additionally, regarding the minimum fitness (Objective) function, the GJO method (besides the 6 algorithms included in this experimental study; HHO, GWO, TSA, ChOA, OOA, and RIME) is compared with other algorithms such as: weighted mean of vectors (INFO) [29], moth–flame optimizer (MFO) [35], sine—cosine algorithm (SCA) [50], tunicate swarm algorithm (TSA) [55], Runge–Kutta optimization (RUN) [59], Gradient-Based Optimizer (GBO) [60] and cuckoo search algorithm (CSA) [61]. Results on the minimum fitness (Objective) function are represented in Table 9. The data of the INFO, MFO, SCA, TSA, RUN, GBO, and CSA were expressed in [2,3].

Table 9. Minimum Fitness (Objective) Function Statistical results for the three photovoltaic models.

Algorithm	***SDSCM***	***DDSCM***	***DDSCM***
GJO	0.000986022	0.000986022	0.000986022
GWO	0.001205557	0.001205557	0.001205557
HHO	0.001277464	0.001277464	0.001277464
OOA	0.002350910	0.002350910	0.002350910
RIME	0.001006495	0.001006495	0.001006495
ChOA	0.007640622	0.007640622	0.007640622
TSA	0.002574147	0.002574147	0.002574147
INFO	0.000986022	0.000986022	0.000986022
MFO	0.001211865	0.001211865	0.001211865
SCA	0.013427050	0.013427050	0.013427050
TSA	0.002027996	0.002027996	0.002027996
RUN	0.001024176	0.001024176	0.001024176
GBO	0.000986020	0.000986020	0.000986020
CSA	0.000991184	0.000991184	0.000991184

6. Conclusion and Future Work

This research has investigated the application of a recent optimization metaheuristic technique, which is the Golden Jackal Optimization (GJO) algorithm, in estimating the variable parameters of different three PV solar cells models: single-diode solar cell model (SDSCM), double-diode solar cell model (DDSCM), and triple-diode (TDSCM). The main idea of this work is to efficiently evaluate the performance of GJO algorithm in the proper estimation of the three PV solar cells models parameters. Due to the manufacturer's lack of data, the SDSCM was classified as a non-linear equation between current and voltage five unknown variable parameters. Additionally, the DDSCM and TDSCM work similarly to the SDSCM with the exception that the DDSCM had seven unknown variable parameters, while the TDSCM has nine. Minimizing the root mean square error between the simulated current and the experimental current of the R.T.C. France solar cell was the goal of the derived parameters in the three PV solar cell models. Minimizing the root mean square error between the simulated current and the experimental current of the R.T.C. France solar cell was the goal of the estimated parameters in the three PV solar cell models. Minimizing the objective (fitness) function of parameter extraction of the three PV solar cells models SDSCM, DDSCM, and TDSCM is the primary role of using GJO algorithm. Many benefits were achieved of the GJO algorithm such as its fast convergence between analysis and exploitation, balance, and accurate solutions. Compared to other six rival algorithms that were examined in the study, the GJO produced more accurate results.

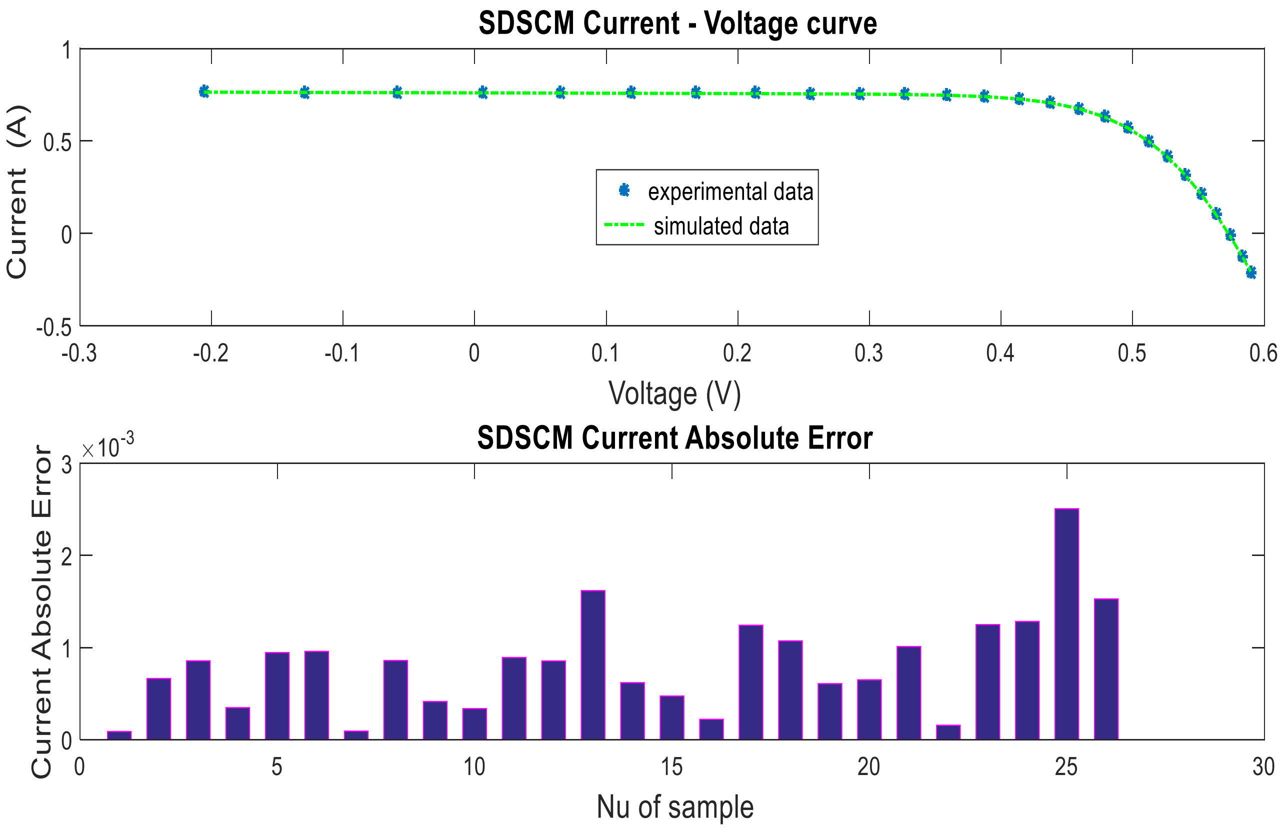

Fig 5. The I-V curve of SDSCM based on the GJO algorithm.

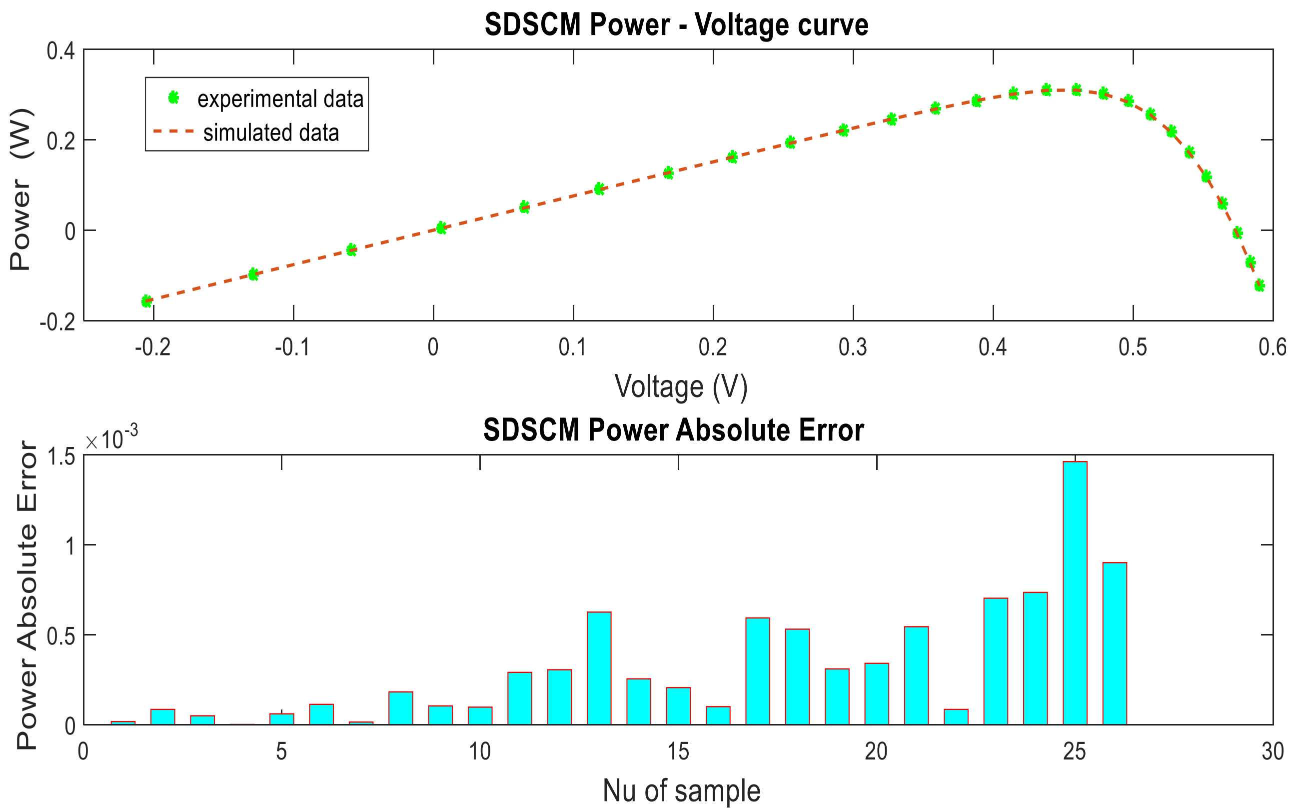

Fig 6. The P-V curve of SDSCM based on the GJO algorithm.

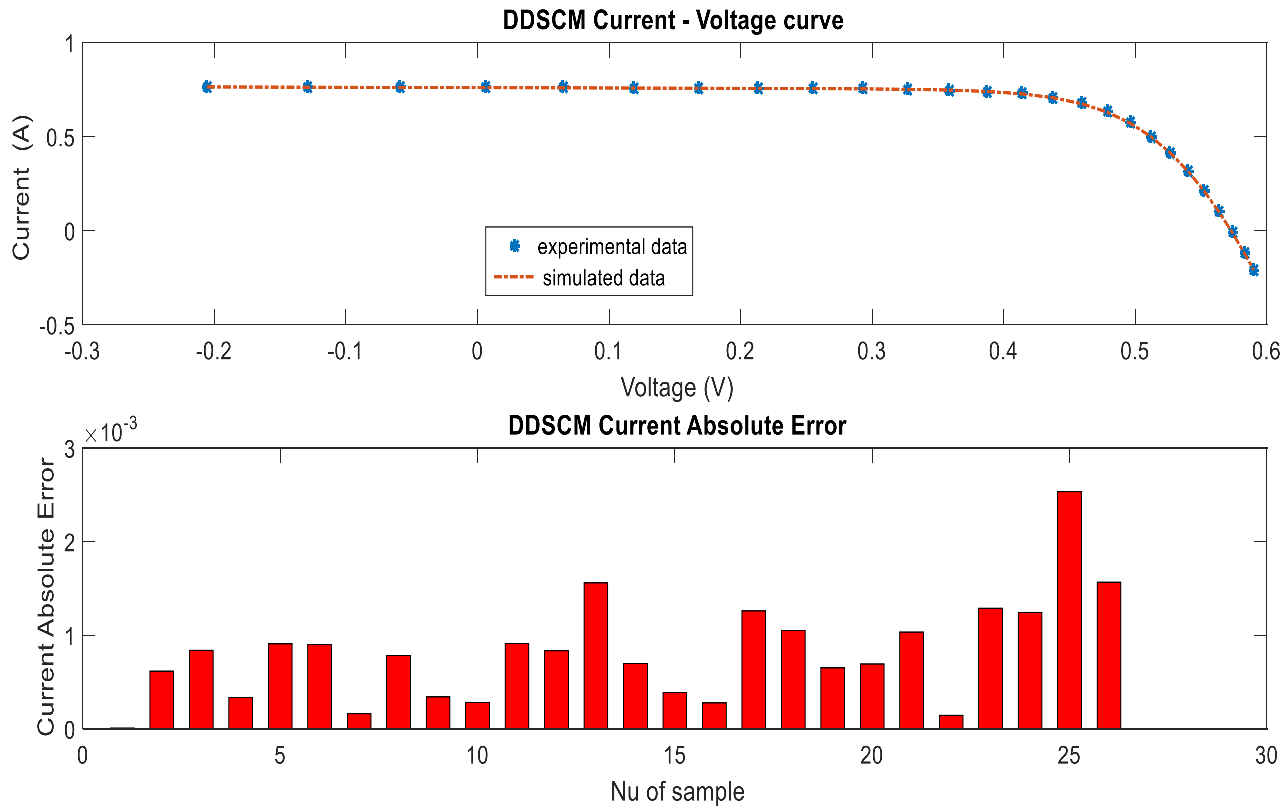

Fig 7. The I-V curve of DDSCM based on the GJO algorithm.

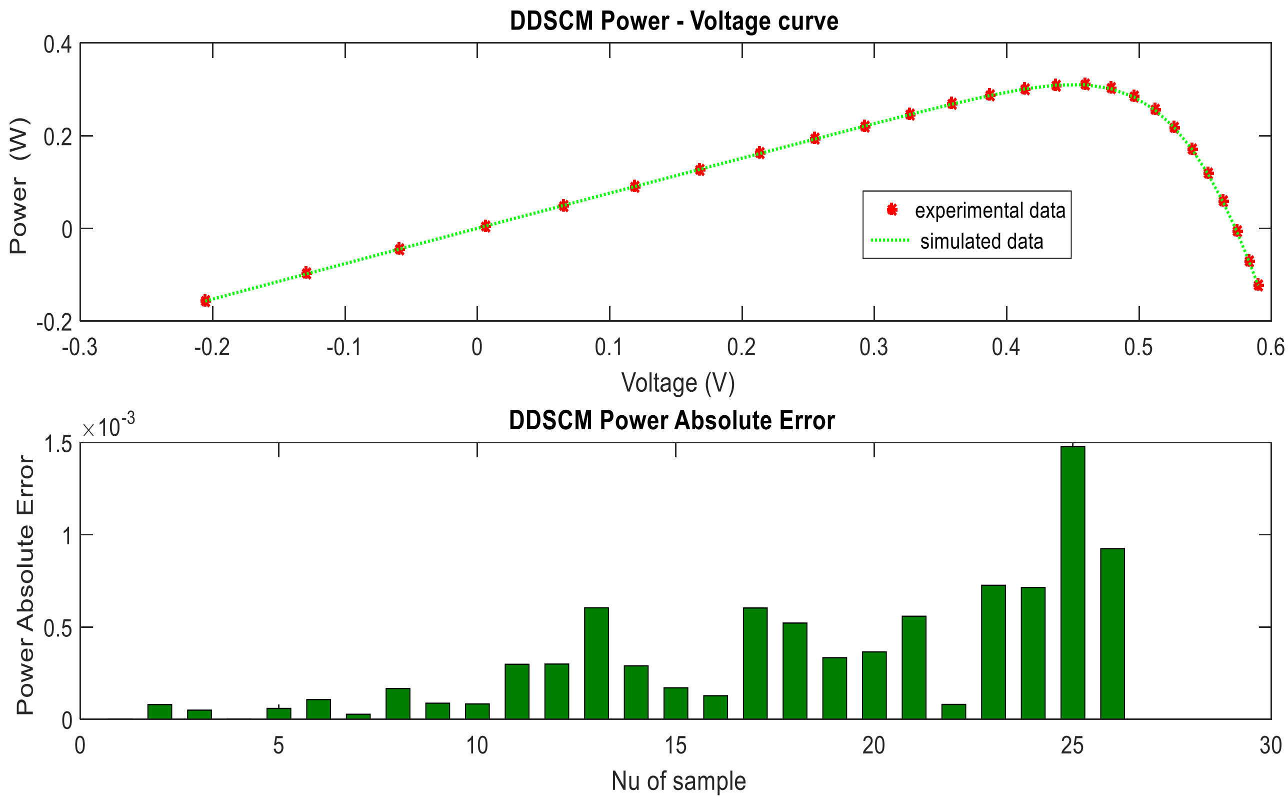

Fig 8. The P-V curve of DDSCM based on the GJO algorithm.

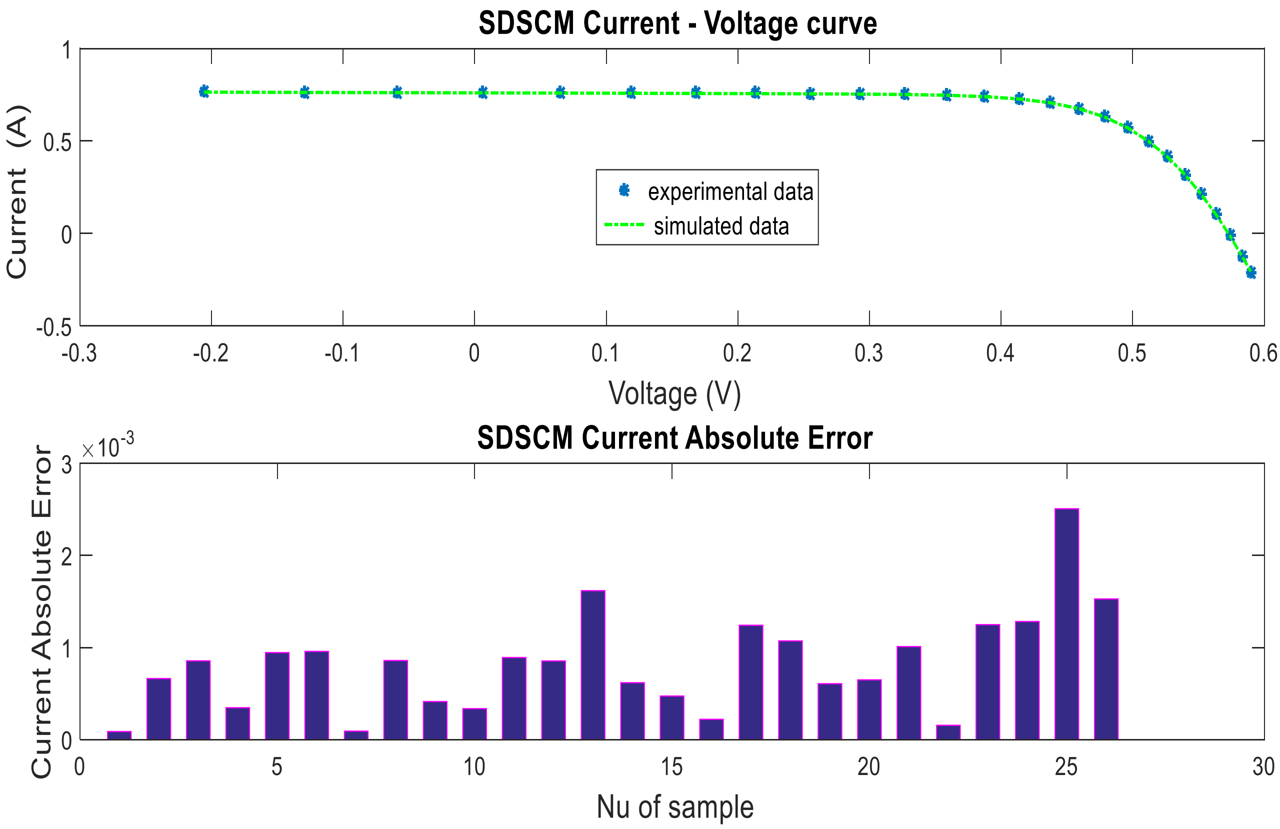

Fig 9. The I-V curve of TDSCM based on the GJO algorithm.

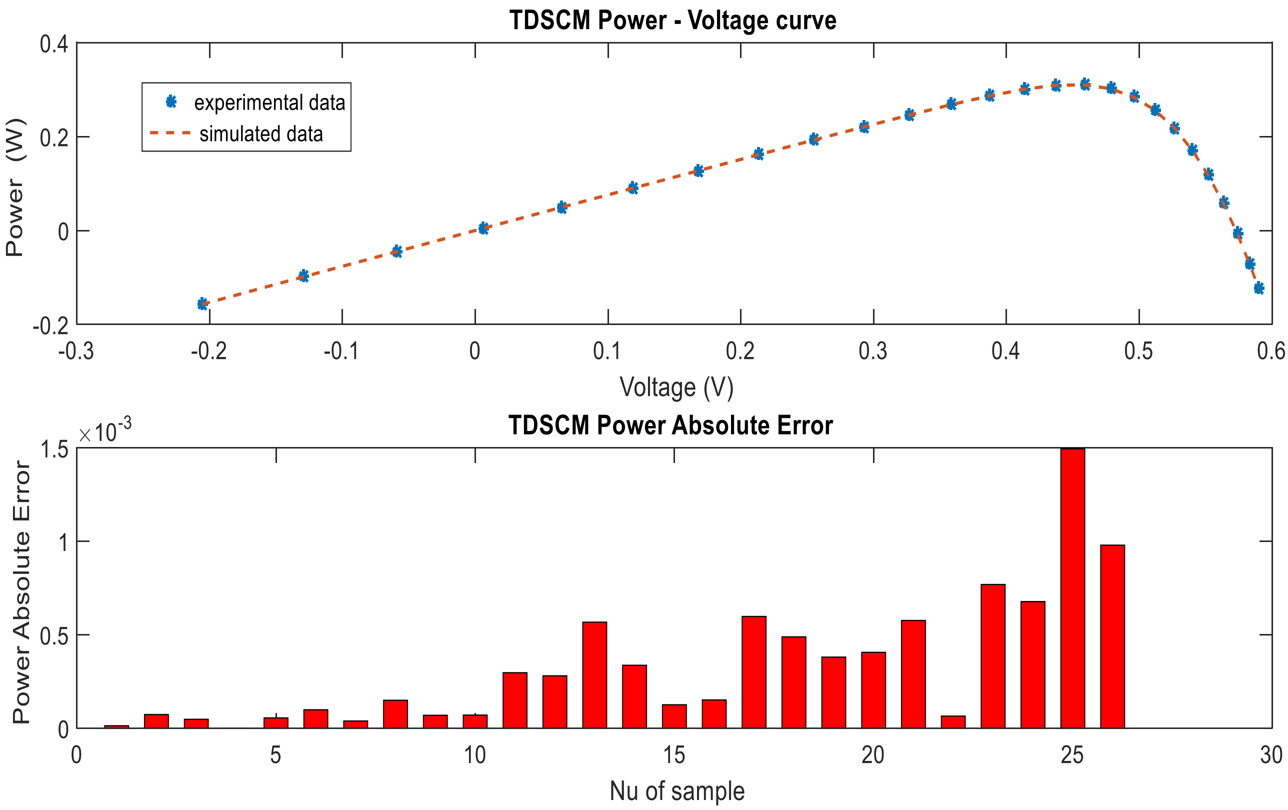

Fig 10. The P-V curve of TDSCM based on the GJO algorithm.

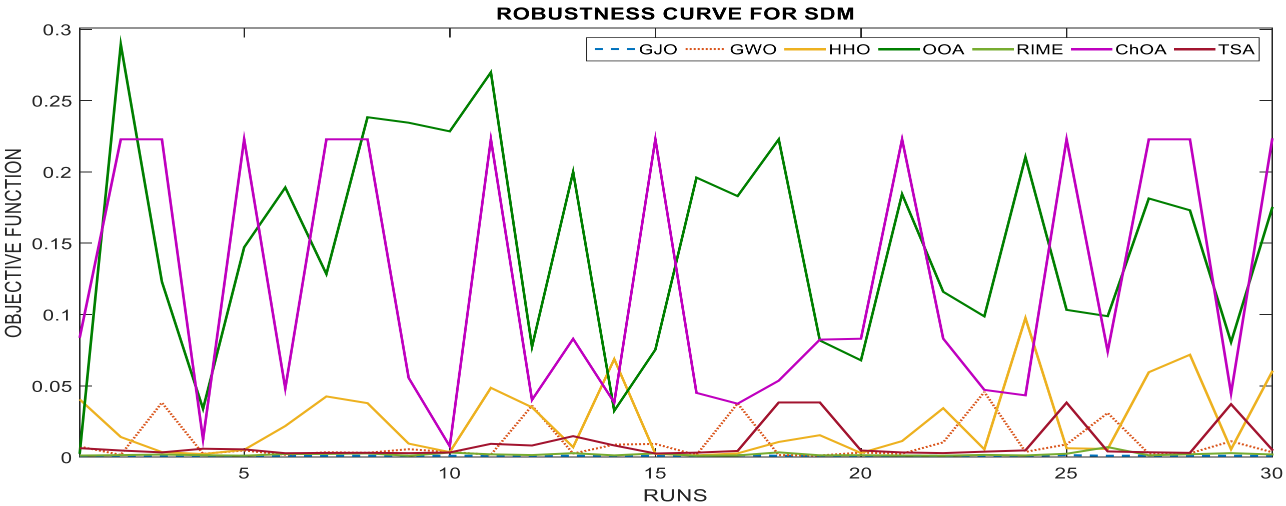

Fig 11. The robustness curve of SDSCM.

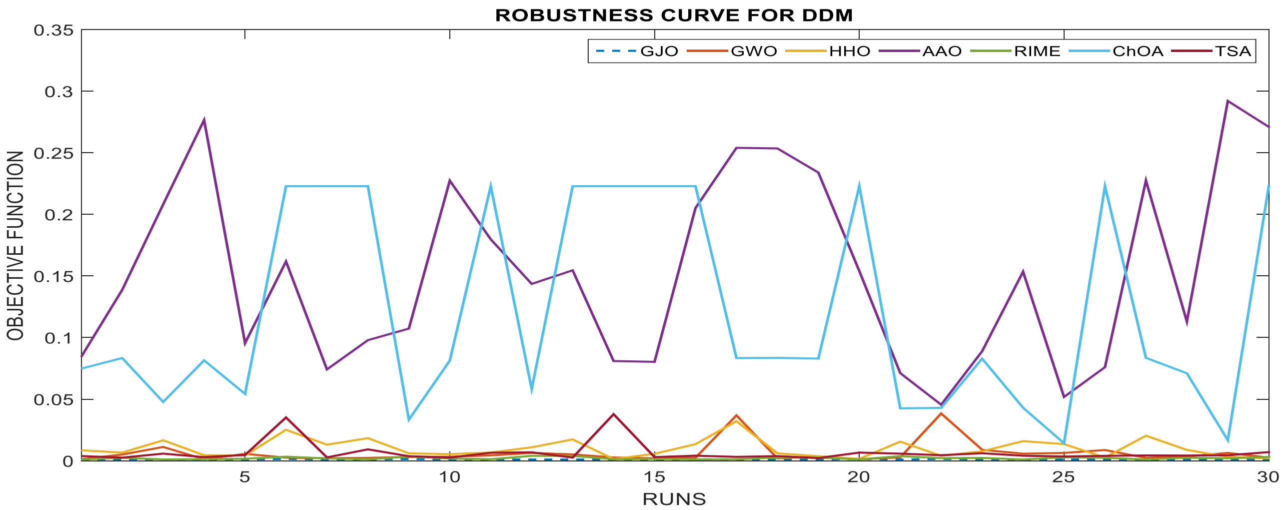

Fig 12. The robustness curve of DDSCM.

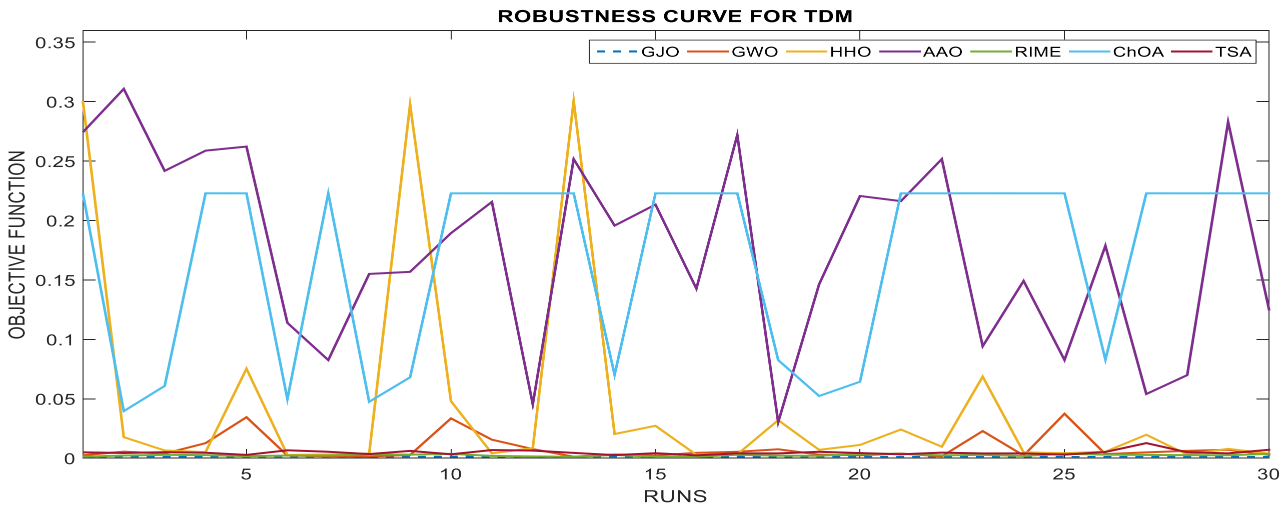

Fig 13. The robustness curve of TDSCM.

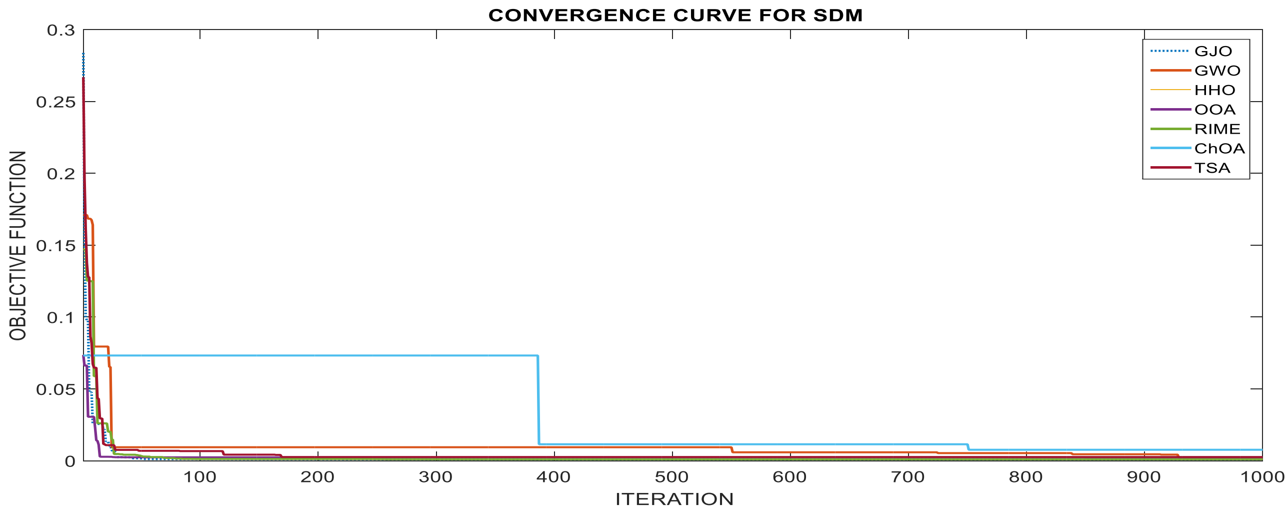

Fig 14. The convergence curve of SDSCM.

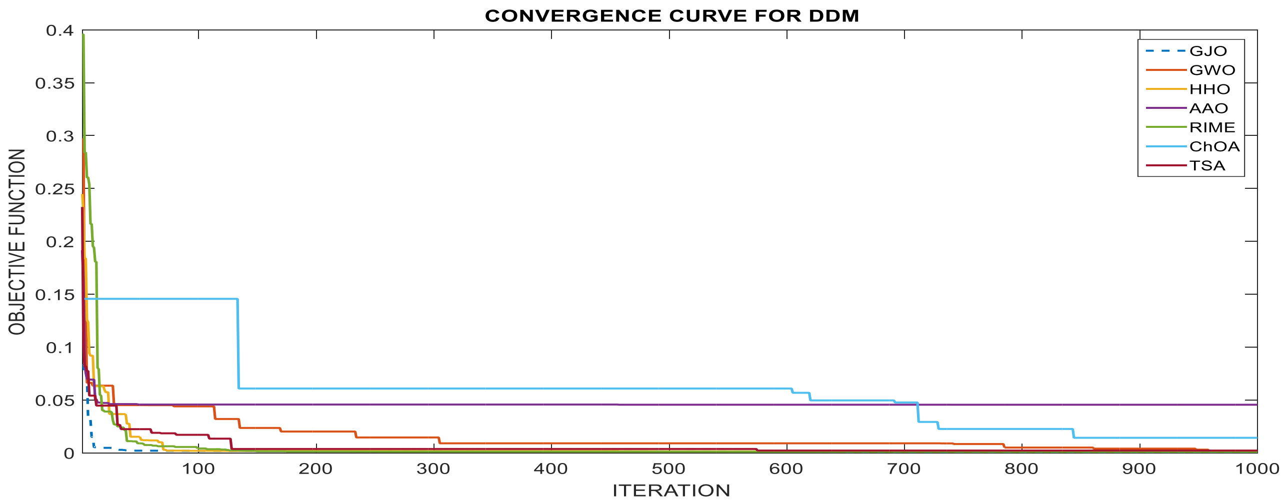

Fig 15. The convergence curve of DDSCM.

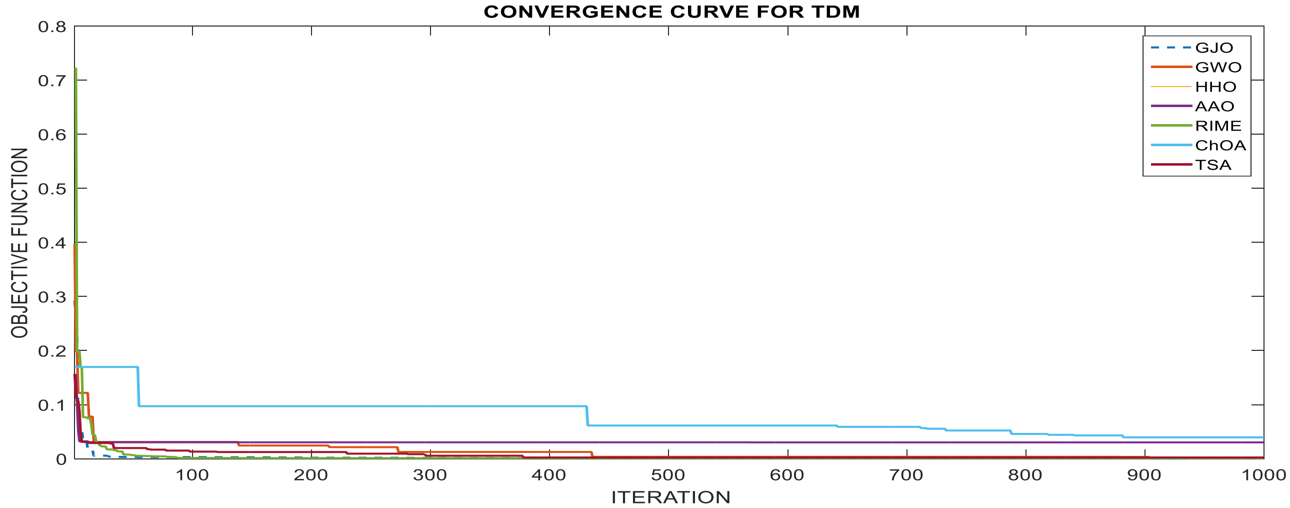

Fig 16. The convergence curve of TDSCM.

An important finding to emerge in this study is that the GJO is a strong alternative technique to resolve PV solar cell systems optimization problems. In the future, further research should be applied using the GJO to compute the current-voltage characteristics of multi-diode diodes and models, as well as to determine the PV parameters of multidimensional diodes and models.

Conflicts of interest

The author declares no conflicts of interest.

References

[1] R. Chenouard and R. A. El-Sehiemy, "An interval branch and bound global optimization algorithm for parameter estimation of three photovoltaic models", *Energy Conversion and Management*, vol. 205, 112400, 2020.

[2] A. A. K. Ismaeel, E. H. Houssein, D. Oliva and M. Said, "Gradient-based optimizer for parameter extraction in photovoltaic models", *IEEE Access*, vol. 9, pp. 13403–13416, 2021.

[3] A. Y. Hassan, A. A. K. Ismaeel, M. Said and R. Ghoniem, "Evaluation of Weighted Mean of Vectors Algorithm for Identification of Solar Cell Parameters", *Processes*, vol. 16, no. 10, 1072 , 2022.

[4] A. A. K. Ismaeel, E. H. Houssein, A. Y. Hassan and M. Said, "Performance of gradient-based optimizer for optimum wind cube design", *CMC-Computers, Materials & Continua*, vol. 71, no. 1, pp. 339-353, 2022.

[5] H. Shaban, E. H. Houssein, M. Pérez-Cisneros, D. Oliv, A. Y. Hassan, A. A. K. Ismaeel, D. S. AbdElminaam, S. Deb and M. Said, "Identification of Parameters in Photovoltaic Models through a Runge Kutta Optimizer", *Mathematics*, vol. 9, 2313, 2021.

[6] D. Yousri, M. Abd Elaziz, D. Oliva, L. Abualigah, M. A. Al-qaness and A. A. Ewees, "Reliable applied objective for identifying simple and detailed photovoltaic models using modern metaheuristics: Comparative study", *Energy Conversion and Management*, vol. 223, 113279, 2020.

[7] A. R. Jordehi, "Enhanced leader particle swarm optimization (ELPSO): An efficient algorithm for parameter estimation of photovoltaic (PV) cells and modules", *Solar Energy*, vol. 159, pp. 78-87, 2018.

[8] M. El-Negamy, M. Eteiba and G. El-Bayoumi, "Modeling and simulation of Egyptsat-1 satellite system powered by photovoltaic module", *The Journal of American Science*, vol. 9, no. 1, pp. 110-116, 2013.

[9] M. Mostafa, H. M. Abdullah and M. A. Mohamed, "Modeling and experimental investigation of solar stills for enhancing water desalination process", *IEEE Access*, vol. 8, pp. 219457-219472, 2020.

[10] S. Mahdavi, F. Sarhaddi and M. Hedayatizadeh, "Energy/exergy based evaluation of heating/cooling potential of PV/T and earth-air heat exchanger integration into a solar greenhouse", *Applied Thermal Engineering*, vol. 149, pp. 996-1007, 2019.

[11] M. Said, A. M. Shaheen, A. R. Ginidi, R. A. El-Sehiemy, K. Mahmoud, M. Lehtonen and M. M. Darwish, "Estimating Parameters of Photovoltaic Models Using Accurate Turbulent Flow of Water Optimizer", *Processes*, vol. 9, 627, 2021.

[12] A. Askarzadeh and A. Rezazadeh, "Artificial bee swarm optimization algorithm for parameters identification of solar cell models", *Applied Energy*, vol. 102, pp. 943-949, 2013.

[13] D. S. Abdelminaam, M. Said, and E. H. Houssein, "Turbulent flow of water-based optimization using new objective function for parameter extraction of six photovoltaic models", *IEEE Access*, vol. 9, pp. 35382-35398, 2021.

[14] W. Ahmad, D. Liu, J. Wu, W. Ahmed, Y. Wang, P. Zhang, T. Zhang, H. Zheng, L. Chen, Z. D. Chen and S. Li, "Enhanced Electrons Extraction of Lithium-Doped SnO_2 Nanoparticles for Efficient Planar Perovskite Solar Cells", *IEEE Journal of Photovoltaics*, vol. 9, no. 5, pp. 1273-1279, 2019.

[15] D. S. Abdelminaam, M. Said and E. H. Houssein, "Turbulent flow of water-based optimization using new objective function for parameter extraction of six photovoltaic models", *IEEE Access*, vol. 9, pp. 35382-35398, 2021.

[16] D. S. AbdElminaam, E. H. Houssein, M. Said, D. Oliva and A. Nabil, "An Efficient Heap-Based Optimizer for Parameters Identification of Modified Photovoltaic Models", *Ain Shams Engineering Journal*, vol. 13, 101728, 2022.

[17] M. G. Villalva, J. R. Gazoli and E. R. Filho, "Comprehensive Approach to Modeling and Simulation of Photovoltaic Arrays", *IEEE Transactions on Power Electronics*, vol. 24, no. 5, pp. 1198-1208, 2009.

[18] S. A. Arefifar, F. Paz and M. Ordonez, "Improving Solar Power PV Plants Using Multivariate Design Optimization", *IEEE Journal of Emerging and Selected Topics in Power Electronics*, vol. 5, no. 2, pp. 638-650, 2017.

[19] N. Kumar, T. K. Saha and J. Dey, "Sliding-Mode Control of PWM Dual Inverter-Based Grid-Connected PV System: Modeling and Performance Analysis",

IEEE Journal of Emerging and Selected Topics in Power Electronics, vol. 4, no. 2, pp. 435-444, 2016.

[20] S. Lun, S. Wang, G. Yang and T. Guo, "A new explicit double-diode modeling method based on Lambert W-function for photovoltaic arrays", *Solar Energy*, vol. 116, pp. 69–82, 2015.

[21] A. Ayang, R. Wamkeue, M. Ouhrouche, N. Djongyang, N. E. Salomé, J. K. Pombe and G. Ekemb, "Maximum likelihood parameters estimation of single-diode model of photovoltaic generator", *Renewable Energy*, vol. 130, pp. 111–121, 2019.

[22] F. J. Toledo, J. M. Blanes and V. Galiano, "Two-Step Linear Least-Squares Method for Photovoltaic Single-Diode Model Parameters Extraction", *IEEE Transactions on Industrial Electronics*, vol. 65, pp. 6301–6308, 2018.

[23] K. Et-Torabi, I. Nassar-eddine, A. Obbadi, Y. Errami, R. Rmaily, S. Sahnoun, A. El Fajri and M. Agunaou, "Parameters estimation of the single and double diode photovoltaic models using a Gauss–Seidel algorithm and analytical method: A comparative study", *Energy Conversion and Management*, vol. 148, pp. 1041–1054, 2017.

[24] X. Ma, W.-H. Huang, E. Schnabel, M. Köhl, J. Brynjarsdóttir, J. L. Braid and R. H. French, "Data-Driven II–VV Feature Extraction for Photovoltaic Modules", *IEEE Journal of Photovoltaic*, vol. 9, no. 5, pp. 1405-1412, 2019.

[25] H. Saleem and S. Karmalkar, "An Analytical Method to Extract the Physical Parameters of a Solar Cell from Four Points on the Illuminated I-V Curve", *IEEE Electron Device Letters*, vol. 30, no. 4, 349-352, 2009.

[26] A. H. Soeriyadi, L. Wang, B. Conrad, D. Li, A. Lochtefeld, A. Gerger, A. Barnett and I. Perez-Wurfl, "Extraction of Essential Solar Cell Parameters of Subcells in a Tandem Structure with a Novel Three-Terminal Measurement Technique", *IEEE Journal of Photovoltaics*, vol. 8, no. 1, pp. 327-332, 2018.

[27] E. H. Houssein, S. Deb, D. Oliva, H. Rezk, H. Alhumade and M. Said, "Performance of gradient-based optimizer on charging station placement problem", *Mathematics*, vol. 9, no. 21, 2821, 2021.

[28] A. A. K. Ismaeel, I. A. Elshaarawy, E. H. Houssein, F. H. Ismail and A. Hassanien, "Enhanced Elephant Herding Optimization for Global Optimization", *IEEE Access*, vol. 7, pp. 34738-34752, 2019.

[29] I. Ahmadianfar, A. A. Heidari, S. Noshadian, H. Chen and A. H. Gandomi, "INFO: An efficient optimization algorithm based on weighted mean of vectors", *Expert Systems with Application*, vol. 195, 116516, 2022.

[30] A. Faramarzi, M. Heidarinejad, S. Mirjalili, and A. H. Gandomi, "Marine predators algorithm: A nature-inspired Metaheuristic", *Expert Systems with Applications*, vol. 152, Art. no. 113377, 2020,

[31] M. Said, A. M. El-Rifaie, M. A. Tolba, E. H. Houssein and S. Deb, "An efficient chameleon swarm algorithm for economic load dispatch problem", *Mathematics*, vol. 9, no. 21, pp. 2770, 2021.

[32] E. H. Houssein, B. E. D. Helmy, H. Rezk, A. M. Nassef, "An enhanced Archimedes optimization algorithm based on Local escaping operator and Orthogonal learning for PEM fuel cell parameter identification", *Engineering Applications of Artificial Intelligence*, vol. 103, 104309, 2021.

[33] M. Said, E. H. Houssein, S. Deb, A. A. Alhussan and R. M. Ghoniem, "A Novel Gradient Based Optimizer for Solving Unit Commitment Problem", *IEEE Access*, vol. 10, pp. 18081-18092, 2022.

[34] S. Deb, D. S. Abdelminaam, M. Said and E. H. Houssein, "Recent methodology-based gradient-based optimizer for economic load dispatch problem", *IEEE Access*, vol. 9, pp. 44322-44338, 2021.

[35] S. Mirjalili, "Moth-flame optimization algorithm: A novel nature-inspired heuristic paradigm", *Knowledge-Based Systems*, vol. 89, pp. 228–249, 2015.

[36] M. A. Abido and K. M. Sheraz, "Seven-parameter PV model estimation using differential evolution", *Electrical Engineering*, vol. 100, no. 2, pp. 971-981, 2018.

[37] X. Chen, K. Yu, W. Du, W. Zhao and G. Liu, "Parameters identification of solar cell models using generalized oppositional teaching learning based optimization", *Energy*, vol. 99, pp. 170-180, 2016.

[38] M. A. Mughal, Q. Ma and C. Xiao, "Photovoltaic cell parameter estimation using hybrid particle swarm optimization and simulated annealing", *Energies*, vol. 10, no. 8, 1213, 2017.

[39] S. Mirjalili, A. H. Gandomi, S. Z. Mirjalili, S. Saremi, H. Faris and S. M. Mirjalili, "Salp Swarm Algorithm: A bio-inspired optimizer for engineering design problems", *Advances in Engineering Software*, vol. 114, pp. 163-191, 2017.

[40] A. T. Kiani, M. F. Nadeem, A. Ahmed, I. A. Sajjad, A. Raza and I. A. Khan, "Chaotic inertia weight particle swarm optimization (CIWPSO): An efficient technique for solar cell parameter estimation", in *Proc. iCoMET*, Sukkur, Pakistan, 2020, pp. 1-6.

[41] N. F. A. Hamid, N. A. Rahim and J. Selvaraj, "Solar cell parameters identification using hybrid Nelder-

Mead and modified particle swarm optimization", *Journal of Renewable and Sustainable Energy*, vol. 8, no. 1, 015502, 2016.

[42] M. Derick, C. Rani, M. Rajesh, M. E. Farrag, Y. Wang and K. Busawon, "An improved optimization technique for estimation of solar photovoltaic parameters", *Solar Energy*, vol. 157, pp. 116-124, 2017.

[43] 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.

[44] J. Ma, T. O. Ting, K. L. Man, N. Zhang, S.-U. Guan and P. W. H. Wong, "Parameter estimation of photovoltaic models via cuckoo search", *Journal of Applied Mathematics*, vol. 2013, pp. 1-8, 2013.

[45] J. A. Jervase, H. Bourdoucen and A. Al-Lawati, "Solar cell parameter extraction using genetic algorithms", *Measurement Science and Technology*, vol. 12, no. 11, pp. 1922-1925, 2001.

[46] K. M. El-Naggar, M. R. AlRashidi, M. F. AlHajri and A. K. Al-Othman, "Simulated annealing algorithm for photovoltaic parameters identification", *Solar Energy*, vol. 86, no. 1, pp. 266-274, 2012.

[47] W. Gong and Z. Cai, "Parameter extraction of solar cell models using repaired adaptive differential evolution", *Solar Energy*, vol. 94, pp. 209-220, 2013.

[48] M. AlHajri, K. El-Naggar, M. R. AlRashidi and A. K. Al-Othman, "Optimal extraction of solar cell parameters using pattern search", *Renewable Energy*, vol. 44, pp. 238-245, 2012.

[49] J. Li, C. Qin, C. Yang, B. Ai and Y. Zhou, "Extraction of Single Diode Model Parameters of Solar Cells and PV Modules by Combining an Intelligent Optimization Algorithm with Simplified Explicit Equation Based on Lambert W Function", *Energies*, vol. 16, issue 14, pp. 5425, 2023.

[50] S. Mirjalili, "SCA: A sine cosine algorithm for solving optimization problems", *Knowledge-Based Systems*, vol. 96, pp. 120–133, 2016.

[51] N. Rajasekar, N. K. Kumar and R. Venugopalan, "Bacterial foraging algorithm based solar PV parameter estimation," *Solar Energy*, vol. 97, pp. 255-265, 2013.

[52] N. Chopra, and M. M. Ansari, "Golden jackal optimization: A novel nature-inspired optimizer for engineering applications", *Expert Systems with Applications*, vol. 198, pp. 116924, 2022.

[53] A. A. Heidari, S. Mirjalili, H. Faris, I. Aljarah, M. Mafarja and H. Chen, "Harris hawks optimization: Algorithm and applications", *Future Generation Computer Systems*, vol. 97, pp. 849–872, 2019.

[54] S. Mirjalili, S. M. Mirjalili and A. Lewis, "Grey wolf optimizer", *Advances in engineering software*, vol. 69, pp. 46-61, 2014.

[55] S. Kaur, L. K. Awasthi, A. L.Sangal and G. Dhiman, "Tunicate Swarm Algorithm: A new bio-inspired based metaheuristic paradigm for global optimization", *Engineering Applications of Artificial Intelligence*, vol. 90, 103541, 2020.

[56] M. Khishe and M. R. Mosavi, "Chimp optimization algorithm", *Expert Systems with Applications*, vol. 149, pp. 1–26, 2020.

[57] M. Dehghani and P. Trojovsky, "Osprey optimization algorithm: A new bio-inspired metaheuristic algorithm for solving engineering optimization problems", *Frontiers in Mechanical Engineering*, vol. 8, 1126450, 2023.

[58] H. Su, D. Zhao, A. A. Heidari, L. Liu, X. Zhang, M. Mafarja and H. Chen, "RIME: A physics-based optimization", *Neurocomputing*, vol. 532, pp. 183-214, 2023.

[59] I. Ahmadianfar, A. A. Heidari, A. H. Gandomi, X. Chu, H. Chen, "RUN beyond the metaphor: An efficient optimization algorithm based on Runge Kutta method", *Expert Systems with Applications*, vol. 181, pp. 115079, 2021.

[60] I. Ahmadianfar, O. Bozorg-Haddad and X. Chu, "Gradient-based optimizer: A new metaheuristic optimization algorithm", *Information Sciences*, vol. 540, pp. 131-159, 2020.

[61] A. S. Joshi, O. Kulkarni, G. M. Kakandikar, V. M. Nandedkar, "Cuckoo Search Optimization - A Review", *Materials Today: Proceedings*, vol. 4, no. 8, pp. 7262-7269, 2017.