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Original research article

Golden Jackal Optimization for Parameters Estimation of Photovoltaic Models

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ABSTRACT

This article presents the determination of PV parameters using the Golden jackal optimization (GJO) method. Photovoltaic (PV) generation systems play a major role in the sustainable use of solar energy. Precise and reliable simulation and optimization techniques for PV systems are urgently needed. A reliable algorithm is needed to determine good PV parameters. GJO is an optimization method based on the behavior of Canis aureus in foraging. This method has three important steps, namely seeking, approaching and attacking prey. The research was conducted using Matlab software. To get the performance of the GJO method, this article presents the whale optimization algorithm (WOA), hunger game search (HGS) and aquilla optimizer (AO) methods for comparison. The benchmark is the root mean square error (RMSE) function. From the simulation results, the GJO method has a better RMSE than the AO method of 77.28%.

Keywords: Golden jackal optimization; Metaheuristic; Optimization algorithm; Parameter estimation; Solar cell

1. Introduction

The decimation of non-renewable natural resources encourages the development of power plants to explore other forms of energy [1, 2]. In addition, the resulting pollution is also a consideration [3, 4]. The use of environmentally friendly energy and emissions is the solution [5]. The latest solution is the application of energy such as wind, solar, tidal waves [6]. Solar is one of the renewable energies that is abundant and can be converted to electricity [7]. Solar requires a process with the help of equipment to be converted into electricity [8]. Solar-based photovoltaic (PV) generators are installed in outdoor locations. A PV is a device that is used as a means of transforming solar energy to electrical energy. The use of an outdoor PV also depends on its maintenance management.

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PV capabilities are often limited by the capabilities of the device, the weather and its location. This results in limited ability to perform transformations. Research that focuses on increasing the accuracy of PV system parameters is becoming popular and interesting. The difficulty of identifying the core parameters is often due to aging and the incompleteness of the instrument.

Various efforts have been made to increase the efficiency of power conversion from solar cells, one of which is the application of new materials. In addition, simulation and optimization of the precise shape of the PV cell model is very important. This is to help the generation system become more efficient and resistant in all weather and temperature conditions. The single diode model (SDM) is one that is often used and popular [9]. The accuracy of the PV cell model plays a major role in obtaining the characteristic analysis (I-V curve). The key issue is the identification of the PV parameter. The value of model parameters that are close to the experimental data has been difficult to obtain. This factor causes the performance of the PV model to be not optimal. PV parameters can be used as a reference in designing solar cells, increasing PV conversion, and tracking maximum power points. Identification of PV parameters with conventional methods requires a basic function by considering several curve spots (I-V) and (P-V). This method has the advantages of low computational cost and easy application. On the other hand, the main drawback of this technique is the application of some assumptions made to reduce the number of unknown parameters. The Newton-Raphson and Gauss-Seidel approaches are applied to break the limitations of the analytical approach. The solution obtained through this approach is highly dependent on the initial conditions of the unknown parameters and easily captures the local optimal solution. The method is not suitable for the extraction of PV model parameters under any environmental conditions.

Computational techniques have begun to be used to get more accurate and reliable optimization. Some researchers have presented several techniques such as strategy by using two nested PSO search loops (NESTPSO) in which the inside loop contains the original objective function, and the outside loop uses PSO. NESTPSO is used for optimization of MPPT and PV energy systems [10]. Particle Swarm Optimization (PSO) is used to find the parameters of the PV [11]. Time varying acceleration coefficients particle swarm optimization (TVACPSO) is used to find the parameters of PV. From the research results, TVACPSO presents more accurate parameters than conventional PSO [12]. The PSO algorithm can determine the model parameters of three industrial silicon solar cell diodes [13].

Coyote Optimization Algorithm (COA) is presented to determine PV cell/module parameters. This method was tested to identify the parameters of PV [14]. The COA method is also used to identify unknown parameters in various solar cell models. The comparison is done by validating the Root Mean Square Error (RMSE). [15]. The COA was also applied to extract parameters with the three-diode model. In addition, two commercial PV models are also used, namely KC200GT and MSX-60 [16].

Enhanced Harris Hawks Optimization is proposed to find out the parameters of the photovoltaic cell. This method is a combination of 2 different learning concepts [17]. An improved Harris hawks optimization is proposed named CCNMHHO to provide efficient simulation of photovoltaic systems and extraction of unknown parameters [18]. Whippy Harris Hawks Optimization (WHHO) was applied to determine the parameters of three commercial modules at different radiation and temperature conditions [19]. Harris

Hawk Optimization is presented to determine the parameters of a three-diode PV (TDPV) model with nine electrical parameters used. Two commercial PV modules are used, namely CS6K-280M and KC200GT [20]. Enhanced Harris Hawk Optimization Algorithm (EHHO) is used to optimize the required parameters of the PV. The improvement is carried out in the exploration phase by fluctuating towards or out of the best optimal solution using the sine and cosine functions [21].

Grasshopper Optimization Algorithm (GOA) was applied to determine the parameter with the three diode model. In addition, two commercial PV modules are used namely the Kyocera KC200GT and Solarex MSX-60 [22]. An improved Levy flight based grasshopper optimization algorithm (LGOA) was used to identify PV parameters under different irradiation and temperature operating conditions [23]. The Grasshopper Optimization Algorithm (GOA) was applied to estimate the optimal parameters of the photovoltaic (PV) module single diode (SDM) model from experimental data. Researchers validated the proposed method using 2 comparison methods [24]. An improved grasshopper optimization algorithm (IGOA) by adding chaos initialization to improve the quality of the initial population as an optimization of determining PV parameters. In addition, differential evolutionary strategies are used to guard population diversity through the processes of mutation, crossover and selection. This is to avoid local optimization and search for better solutions in GOA [25]. The Flower Pollination Algorithm (FPA) is presented to extract optimal parameters from single diode and dual diode models. Tests were carried out using three different data sources. [26]. The new hybrid bee pollination algorithm flower pollination (BPFPA) was used to determine the PV parameters. The BPFPA method was tested using PV for single diodes and dual diodes. In addition, testing is also in different environmental conditions [27]. Nelder-mead simplex method and general opposition-based learning mechanism into the basic flower pollination algorithm framework applied to the problem of pv system parameter estimation [28]

However, optimization to obtain better PV parameters still is a popular and interesting field. This article presents a PV parameter optimization approach using the Golden jackal optimization (GJO). GJO imitates the behavior of the golden wolf in nature [29]. GJO performs well in difficult and unidentified search spaces. The contributions of this article are:

- PV parameter optimization approach with golden jackal optimization method.
- The performance of the GJO method is compared to the whale optimization algorithm, Aquilla Optimizer and hunger games search.

The structure of this paper is the second part regarding GJO method and PV model. The third part is the results and discussion. The last part is to draw conclusions.

2. Materials and Methods

2.1 Golden Jackal Optimization

Golden jackal optimization (GJO) is an algorithm inspired by Canis aureus in foraging. They are medium-sized land predators and belong to the Canidae family.

2.1.1 Search space formulation

GJO is a population-based algorithm that is like other metaheuristic methods. GJO in the first phase, which is looking for a search space, can be modeled mathematically as follows:

$$X_0 = X_{\min} + rand\left(X_{\max} - X_{\min}\right), \tag{2.1}$$

$$P = \begin{bmatrix} X_{11} & X_{12} & \cdots & X_{1n} \\ X_{21} & X_{22} & \cdots & X_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ X_{m1} & X_{m1} & \cdots & X_{mn} \end{bmatrix}, \tag{2.2}$$

where $rand$ is a uniform random vector with a range from 0 to 1. X_{ij} denotes the jth dimension of the ith prey. There are a total of m prey, and a n variable. The position of the prey refers to a certain solution parameter.

$$F = \begin{bmatrix} f\left(X_{11} : X_{12} : \cdots : X_{1d}\right) \\ f\left(X_{21} : X_{22} : \cdots : X_{2d}\right) \\ f\left(X_{n1} : X_{n2} : \cdots : X_{nd}\right) \end{bmatrix}, \quad (2.3)$$

where n is the amount of prey. F is a matrix to store the fitness of each prey. The male wolf is symbolized as the fittest one and the female wolf is symbolized as the second fittest. The pair of wolves acquires a suitable prey position.

2.1.2 Searching the prey

Jackals have a strategy in hunting prey. This is a foraging instinct. Jackals know how to spot and follow prey so they don't run away. The male jackal is the leader and the female jackal is a follower:

$$X_1(t) = X_m - A \cdot \left|X_m(t) - rl \cdot P(t)\right|, \quad (2.4)$$

$$X_2(t) = X_f - A \cdot \left|X_f(t) - rl \cdot P(t)\right|, \quad (2.5)$$

$$A = A_1 \times A_0, \quad (2.6)$$

$$A_0 = 2 \times b - 1, \quad (2.7)$$

$$A_1 = c_1 \times \left(1 - \frac{t}{T}\right), \quad (2.8)$$

$$rl = 0.05 \times LF(y), \quad (2.9)$$

$$LF(y) = \frac{0.01 \times (\mu \times \sigma)}{\left(|\, v^{(1/\beta)} \,|\right)}, \quad (2.10)$$

$$\sigma = \left(\frac{\Gamma(1+\beta) \times \sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(\frac{1+\beta}{2}\right) \times \beta \times \left(2 \frac{\beta - 1}{2}\right)} \right)^{\frac{1}{\beta}}, \quad (2.11)$$

$$X(t) = \frac{X_1(t) - X_2(t)}{2}, \quad (2.12)$$

where $P(t)$ is the prey position vector, and t represents the current iteration $X_m(t)$ and $X_f(t)$ represents the position of the agent. A is the avoidance power of the prey. A_1 indicates a decrease in the prey's energy and A_0 indicates its initial energy state. Where r is an random value [0, 1]. T indicates the maximum number of iterations, c_1 is a constant value. A_1 decreases linearly from 1.5 to 0 throughout the iteration. rl is a vector of random value. This value encourages avoidance of the local optima trap, especially in the closing iteration $LF(y)$ is the levy flight function. v is a random value inside (0, 1). β is the default value (1.5).

2.1.3 Approaching and attacking prey

The hunting behavior of male and female jackals that surround, pounce and devour them in this phase is mathematically modeled as follows:

$$X_1(t) = X_m - A \cdot \left|X_m(t) - rl \cdot P(t)\right|, \quad (2.13)$$

$$X_2(t) = X_f - A \cdot \left|X_f(t) - rl \cdot P(t)\right|. \quad (2.14)$$

2.1.4 Phase change from exploration to exploitation

In this phase, the prey's ability to escape drops significantly. This ability is used to move from exploration to exploitation. This phase is modeled mathematically in Eq. (2.6). A_0 which has a value of -1 deviates to 1 in each iteration. When $|A| > 1$, jackal pairs look for unexplored spots to find prey and when $|A| < 1$. Jackal exploits by attacking prey.

2.2 Solar PV modeling

In analyzing, it is necessary to mathematically model the PV cells. This study uses a PV modeling approach with a single diode solar PV model system. This model has the advantage that it has good accuracy and is simple. Solar PV is assumed as the source. An illustration of an equivalence circuit diagram can be seen in Fig. 1. This type of model is suitable for PV systems that require low production costs and fast response. The mathematical equations for the SDM system are as follows:

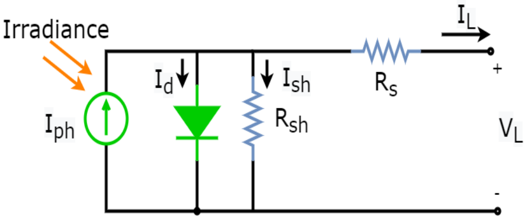


Fig. 1. Single diode circuit of PV [30].

$$I_L = I_{ph} - I_d - I_{sh}, \tag{2.15}$$

$$I_d = I_{sd}\left[\exp\left(\frac{\left(V_L + R_{sI_L}\right)}{V_t}\right) - 1\right], \tag{2.16}$$

$$I_{sh} = \frac{V_L + R_{sI_L}}{R_{sh}}, \tag{2.17}$$

$$V_t = \frac{\alpha KT}{q}, \tag{2.18}$$

where α represents the ideality factor of the diode, $q = 1.6027646 \times 10^{-19} C$ represents the electron charge, $q = 1.3806503 \times 10^{-23} J/K$. From Eq. (2.15), it is seen that the parameters $\left(I_{ph}, I_{sd}, R_s, R_{sh}, \alpha\right)$ need to be estimated correctly in SDM.

2.3 Newton-Raphson technique

To obtain the roots of nonlinear equations, a popular technique is Newton-Raphson (NR). The NR technique is stated as follows:

$$I_{L(m+1)} = I_{L(m)} - \frac{f\left(I_{L_{(m)}}\right)}{f'\left(I_{L_{(m)}}\right)}, m \geq 0, \tag{2.19}$$

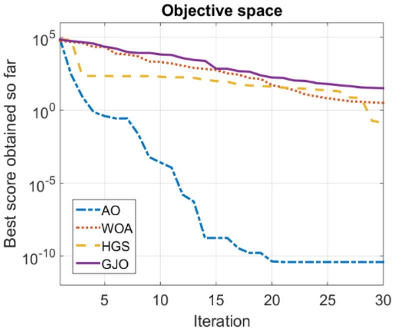
$$f\left(I_{L(m)}\right) = I_{L(m)} - I_{ph} + I_{sd}\left[\exp\left(\frac{V_L + R_{sI_L}}{V_t}\right) - 1\right] + \frac{V_L + R_{sI_L}}{R_s} = 0, \tag{2.20}$$

$$f'\left(I_{L(m)}\right) = 1 + \frac{I_{sd} R_s}{V_t}\left[\exp\left(\frac{V_L + R_{sI_L}}{V_t}\right) - 1\right] + \frac{R_s}{R_{sh}} = 0. \tag{2.21}$$

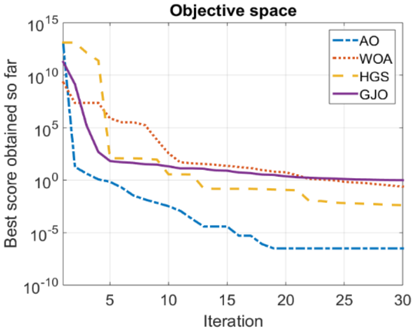
NR technique has the advantage of fast and simple convergence. However, the NR method has drawbacks. The NR method turned out to be inappropriate for estimating a large number of unknown variables. Estimating the initial value for starting this method for a large number of unknown variables is a big challenge. Incorrect initial values can lead to incorrect estimates.

3. Results and Discussion

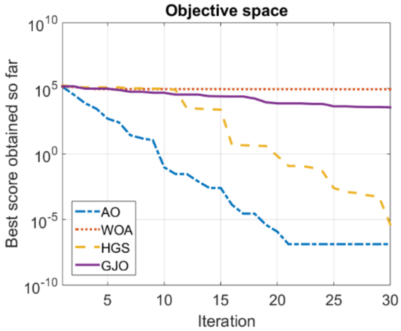
GJO performance was measured and validated with the global optima function and applied to obtain Solar PV parameters with the SDM model. The results were compared with the WOA, AO, and HGS methods. The simulation is carried out using Matlab/Simulink on a laptop with specifications AMD A9-9425 (3.1Ghz) with 4 GB of memory. By considering and comparing 20 global optimal functions. Each function has its own character. Functions F1-F7 are unimodal functions. This function has one global optimal and no local optimal. This function can be seen in Figs. 2(a)-(g). F8-F13 is a multimodal function. This function plays a role in reducing the local optimal position of the algorithm. This function can be seen in Figs. 2(h)-(m). F14-F20 are composite functions. This function is a combination of multi-modal test function. This function can be seen in Figs. 2(n)-(t).


Objective space
Best score obtained so far
10^{5}
10^{0}
10^{-5}
10^{-10}
5 10 15 20 25 30
Iteration
AO
WOA
HGS
GJO

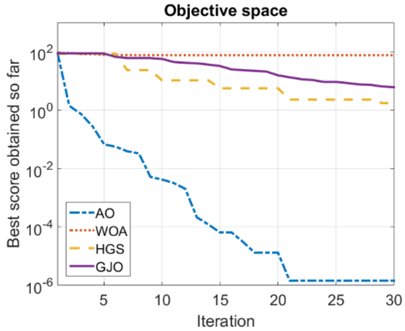
(a)


Objective space
Best score obtained so far
10^{15}
10^{10}
10^{5}
10^{0}
10^{-5}
10^{-10}
5 10 15 20 25 30
Iteration
AO
WOA
HGS
GJO

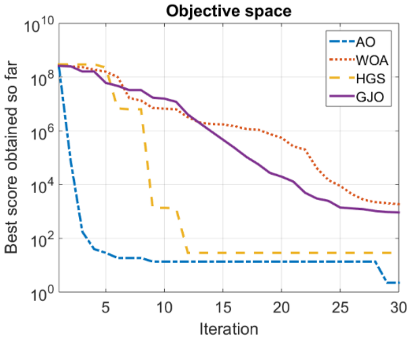
(b)


Objective space
Best score obtained so far
10^{10}
10^{5}
10^{0}
10^{-5}
10^{-10}
5 10 15 20 25 30
Iteration
AO
WOA
HGS
GJO

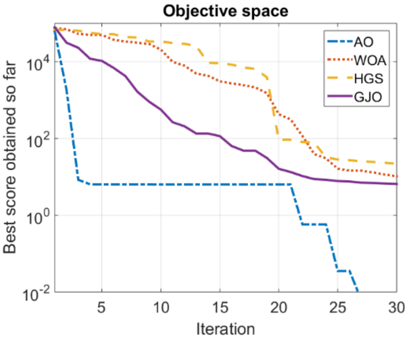
(c)


Objective space
Best score obtained so far
10^{2}
10^{0}
10^{-2}
10^{-4}
10^{-6}
5 10 15 20 25 30
Iteration
AO
WOA
HGS
GJO

(d)


Objective space
Best score obtained so far
10^{10}
10^{8}
10^{6}
10^{4}
10^{2}
10^{0}
5 10 15 20 25 30
Iteration
AO
WOA
HGS
GJO

(e)


Objective space
Best score obtained so far
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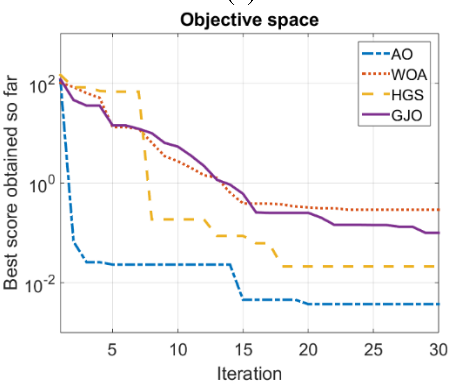
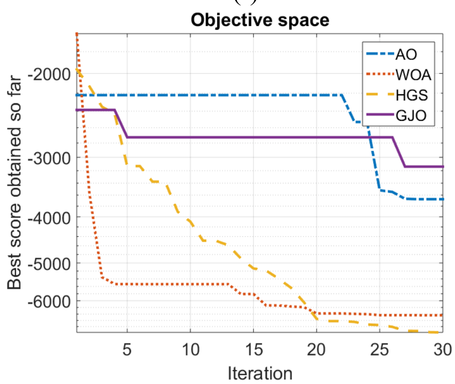
10^{2}
10^{0}
10^{-2}
5 10 15 20 25 30
Iteration
AO
WOA
HGS
GJO

(f)


Objective space
Best score obtained so far
10^{2}
10^{0}
10^{-2}
5 10 15 20 25 30
Iteration
AO
WOA
HGS
GJO

(g)


Objective space
Best score obtained so far
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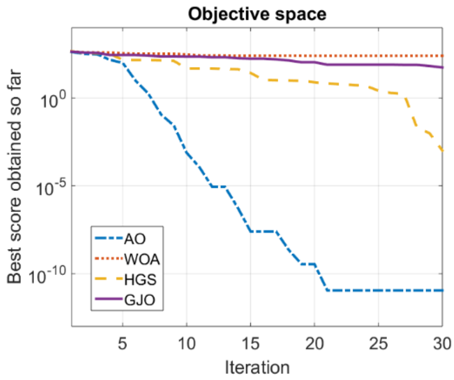
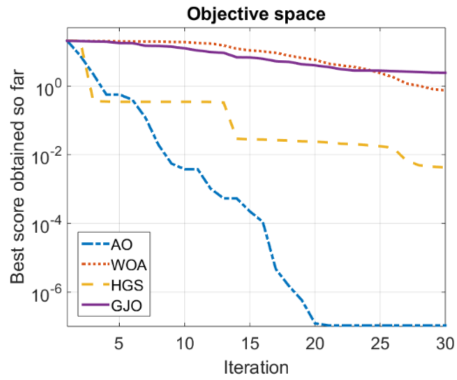
-3000
-4000
-5000
-6000
5 10 15 20 25 30
Iteration
AO
WOA
HGS
GJO

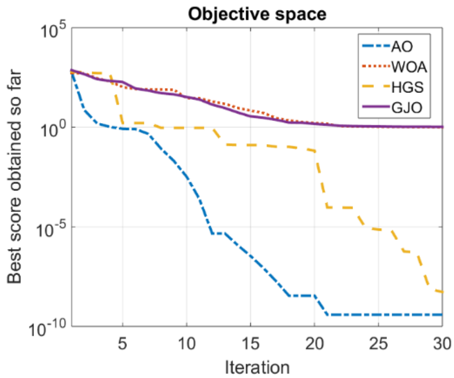
(h)


Objective space
Best score obtained so far
Iteration
AO
WOA
HGS
GJO

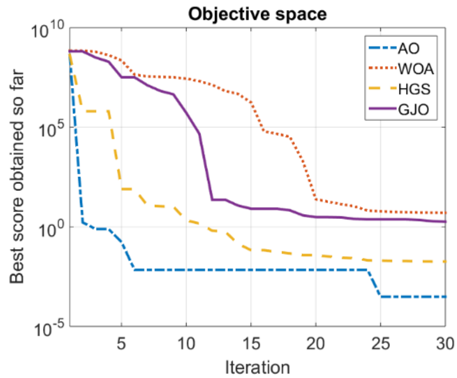
(i)


Objective space
Best score obtained so far
Iteration
AO
WOA
HGS
GJO

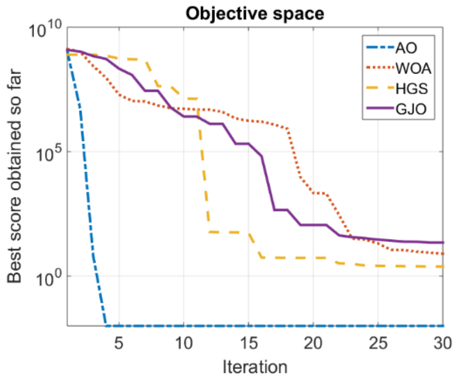
(j)


Objective space
Best score obtained so far
Iteration
AO
WOA
HGS
GJO

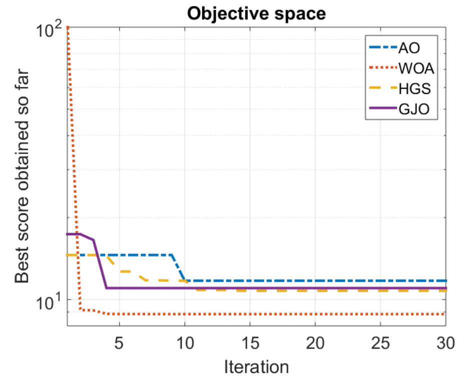
(k)


Objective space
Best score obtained so far
Iteration
AO
WOA
HGS
GJO

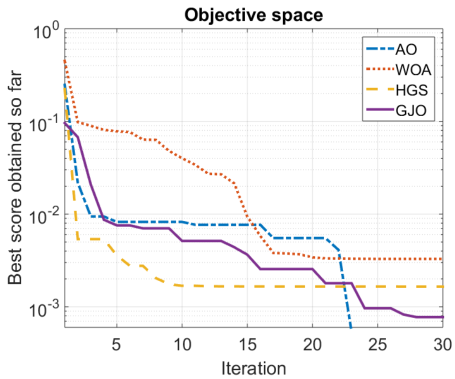
(l)


Objective space
Best score obtained so far
Iteration
AO
WOA
HGS
GJO

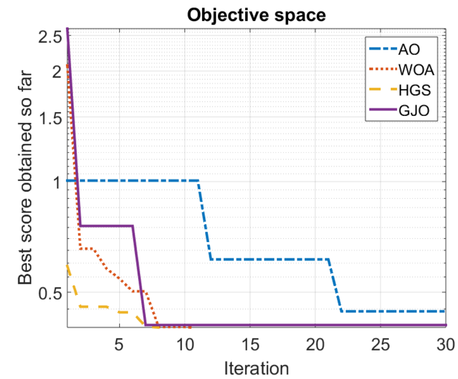
(m)


Objective space
Best score obtained so far
Iteration
AO
WOA
HGS
GJO

(n)


Objective space
Best score obtained so far
Iteration
AO
WOA
HGS
GJO

(o)


Objective space
Best score obtained so far
Iteration
AO
WOA
HGS
GJO

(p)

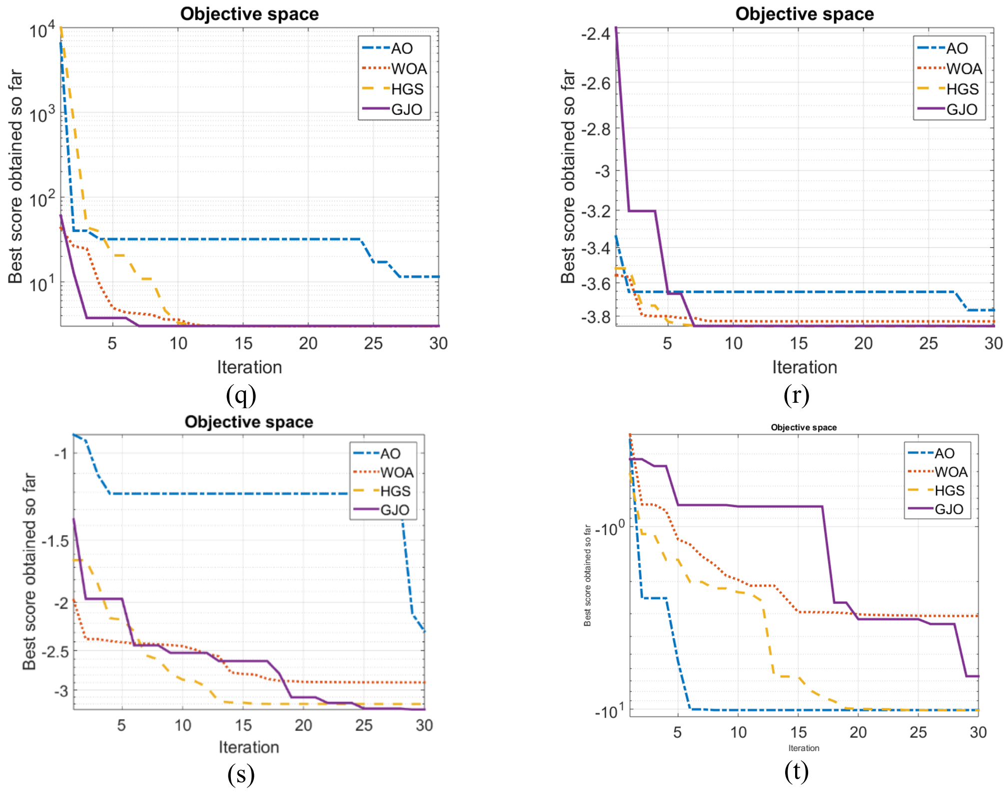


Fig. 2. The convergence curve of benchmark function (a) F1, (b) F2, (c) F3, (d) F4, (e) F5, (f) F6,(g) F7, (h) F8, (i) F9, (j) F10, (k) F11, (l) F12, (m), F13, (n) F14, (o) F15, (p) F16, (q) F17, (r) F18, (s) F19, (t) F20.

The actual experimental parameter values are solar cells from R.T.C France. It is a solar cell with a diameter of 57 mm, and the data are simulated at a temperature of 33 C. Table 1 shows the detail values for SDM. The solar PV characteristic curves covering P–V and I–V to be shown in Fig. 3. Fig. 3(a) shows experimental current and estimated current data with voltage measurements. Fig. 3(b) presents the experimental power trend and the estimated power with increasing voltage. The solar PV characteristic curves covering P–V and I–V to be shown in Fig. 3.

Table 1. Parameter Range For SDM.

Parameter	LB	UB
I_{ph}	0	1
I_{sd}	0	1
α	1	2
R_{sh}	0	100
R_s	0	0.5

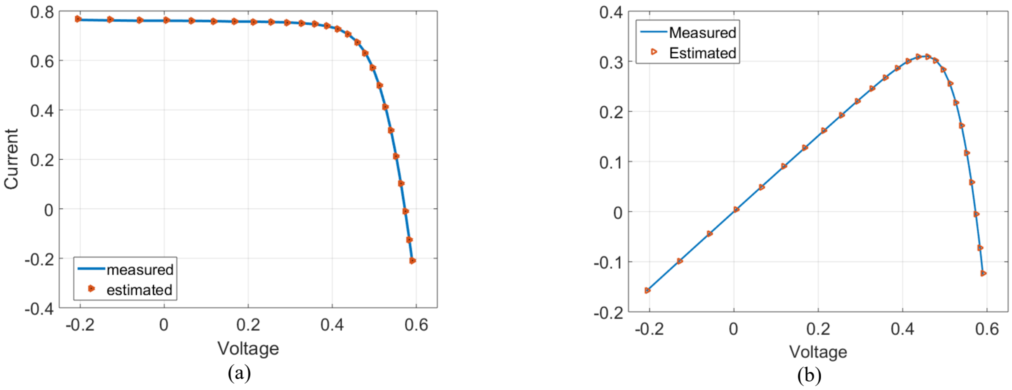


Fig. 3. (a) Simulation current curve of GJO, (b) Simulation power graph of GJO.

Table 2. Performance comparison between GJO and its competitors with SDM.

Algorithm	I_{ph}	I_{sd}	α	R_{sh}	R_s	RMSE
WOA	0.76078796	0.5148089	1.53160630	52.88990875	0.03291342	0.0012
HGS	0.76060349	0.5281029	1.48194016	68.46716687	0.03417693	0.0011
AO	0.76100780	0.9415406	1.60009632	39.17053349	0.03416272	0.0061
GJO	0.76077137	0.3442620	1.48801901	39.17053349	0.03581353	0.001386

Table 2 provides a comparison of the related parameters estimated by several algorithms. In order to get an accurate estimate of the parameters of the PV model, the first thing is to determine an error function that can describe the difference between the measured and experimental current data. Obviously, the aim of this article is to obtain a set of PV parameters that has the smallest error. Root mean square error (RMSE) was applied to measure the overall error, mathematical modeling as follows:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N} f\left(V_L, I_L, X\right)}, \qquad (2.22)$$

where N is the number of experimental data. The values of the five PV parameters, namely $I_{ph}, I_{sd}, \alpha, R_{sh}$ and R_s obtained from the optimization of the WOA, HGS, AO and GJO methods in detail can be seen in Table 2. From the RMSE vtalue, the proposed method GJO has a value of 0.001386. This value is better than the AO method. However, the RMSE value of the comparison method is also very competitive. Table 3 is the detail of the individual absolute error (IAE). Where P_{sim} is the current value of the simulation results, P_{sim} is the power value of the simulation results, $IAE-I$ is the deviation of the current. And $IAE-P$ is the deviation of power. The maximum $IAE-I$ value occurs in item 2 of 0.00312. While the maximum $IAE-P$ occurred in item 17 of 0.00104.

Table 3. Individual absolute error (IAE) from GJO with SDM.

Simulation Current (A)		Simulation Power (W)		
$I_{sim}(A)$	$IAE-I$	$P(W)$	$P_{sim}(W)$	$IAE-P$
0.76709	0.00309	-0.1571	-0.1577	0.00060
0.76513	0.00312	-0.0983	-0.0987	0.00039
0.76334	0.00284	-0.0447	-0.0448	0.00010
0.76169	0.00119	0.00433	0.00434	0.00001
0.76019	0.00019	0.04909	0.04910	0.00001
0.7588	0.00019	0.08994	0.08991	0.00003
0.75751	0.00051	0.12702	0.12711	0.00009
0.75624	0.00075	0.16139	0.16123	0.00015
0.7549	0.00059	0.19227	0.19212	0.00014
0.75321	0.00078	0.22046	0.22023	0.00022
0.75068	0.00018	0.24533	0.24539	0.00006
0.74641	0.00009	0.26762	0.26758	0.00004
0.73896	0.00045	0.28602	0.28619	0.00017
0.72612	0.00187	0.30117	0.30039	0.00078
0.70562	0.00087	0.30895	0.30856	0.00039
0.67403	0.00146	0.31005	0.30937	0.00068
0.62982	0.00217	0.30234	0.30130	0.00104
0.57134	0.00165	0.28420	0.28338	0.00081
0.49913	0.00013	0.25543	0.25550	0.00007
0.41349	0.00049	0.21744	0.21770	0.00026
0.3175	0.001	0.17084	0.17138	0.00054
0.21254	0.00054	0.11704	0.11734	0.00029
0.10316	0.00033	0.05830	0.05811	0.00018
-0.0089	0.0011	-0.0057	-0.0051	0.0006
-0.1243	0.0013	-0.0717	-0.0725	0.00079
-0.2095	0.0005	-0.1239	-0.1236	0.00029
Sum IAE	Sum IAE			0.0075

4. Conclusion

Golden jackal optimization (GJO) is an optimization algorithm that duplicates the behavior of the golden jackal in foraging in mathematical models. In this article, GJO is applied to determine the parameters of photovoltaic solar panels with a single diode model based on an experimental dataset. to validate the performance of the GJO method. This article uses the whale optimization algorithm, hunger game search and aquilla optimization as a comparison. the function used as a benchmark is the root mean square error. From the simulation results, it is found that the GJO value is better than the AO method, which is 77.28%. while the best value of RMSE is owned by the HGS method. RMSE value also shows a very competitive value between the WOA, HGS and GJO methods.

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