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Parameter Estimation Of Photovoltaic based on Chaotic Elite Mountain Gazelle Optimizer

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ABSTRACT

This research presents a technique for optimizing photovoltaic (PV) characteristics using a modified version of the Mountain Gazelle Optimizer (MGO). The method under consideration is referred to as CEMGO. The Mountain Gazelle Optimizer (MGO) is a meta-heuristic algorithm that draws inspiration from the social structure and hierarchy observed in wild mountain deer. This paper utilizes CEMGO to ascertain the parameters of photovoltaic solar panels using a single diode model, relying on experimental datasets. To verify the effectiveness of the CEMGO approach. This article employs the original MGO algorithm for the sake of comparison. The comparison function utilized is the root mean square error. Based on the simulation findings, the CEMGO value outperforms the MGO approach, with a superiority of 23.07%.

1. INTRODUCTION

Solar power is a plentiful form of renewable energy that can be easily transformed into electricity[1]–[6]. The conversion of solar energy into electricity necessitates a systematic procedure facilitated by specialized equipment[7]–[11]. Outdoor sites are where solar-based photovoltaic (PV) generators are deployed[12]–[14]. A photovoltaic (PV) device is utilized as a mechanism for converting solar energy into electrical energy[15]–[17]. The utilization of outdoor photovoltaic (PV) systems is contingent upon effective maintenance management[18]–[20]. The performance of photovoltaic (PV) systems is frequently constrained by the limitations of the device itself, as well as by weather conditions and the geographical area where it is installed[21]–[25]. This leads to a restricted capacity to carry out alterations. Research that aims to enhance the precision of photovoltaic (PV) system characteristics is gaining popularity and generating attention. The challenge of determining the fundamental parameters is frequently attributed to the process of aging and the imperfect nature of the instrument.

Multiple endeavors have been undertaken to enhance the efficacy of power conversion from solar cells, one of which involves the utilization of novel materials. Furthermore, it is crucial to simulate and optimize the exact configuration of the photovoltaic (PV) cell model. The purpose of this is to enhance the efficiency and durability of the generation system, ensuring its resilience in various weather and temperature situations. The single diode model (SDM) is a frequently utilized and widely accepted model[26]–[30]. The precision of the PV cell model is crucial in achieving the characteristic analysis (I-V curve). The primary concern is the determination of the PV parameter. Obtaining the value of model parameters that closely match the experimental data has proven to be challenging. This aspect hampers the optimization of the PV model's performance. PV parameters serve as a benchmark for constructing solar cells, enhancing PV conversion efficiency, and optimizing the tracking of maximum power spots. Conventional approaches for identifying PV parameters involve analyzing many curve spots, specifically the I-V (current-voltage) and P-V (power-voltage) curves. This approach offers the benefits of being computationally inexpensive and straightforward to implement. However, the primary disadvantage of this strategy is the utilization of certain assumptions that are

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made in order to decrease the quantity of unknown factors[31]–[33]. The Newton-Raphson and Gauss-Seidel methods are employed to overcome the constraints of the analytical technique. The outcome derived from this method is greatly influenced by the starting conditions of the unknown variables and effectively captures the best answer within a specific region.

The method is unsuitable for extracting PV model parameters in any environmental circumstances. Computational methodologies were employed to enhance the precision and dependability of optimization. Several academics have proposed several strategies, including the utilization of Particle Swarm Optimization (PSO) as a strategy[34]–[37].

Nevertheless, efforts to improve PV characteristics through optimization remain an interesting and widely explored field of study. This paper introduces a method to optimize PV parameters using a modified Mountain Gazelle Optimizer (MGO). Mountain Gazelle Optimizer (MGO), a meta-heuristic algorithm inspired by the social life and hierarchy of wild mountain gazelles[38]. The contributions of this paper include:

- This study proposes a way to optimize PV parameters using the modified MGO method using elite[39] and chaotic equations[40]. The proposed method is named Chaotic Elite Mountain Gazelle Optimizer (CEMGO)
- CEMGO is evaluated against whale optimization algorithm, Aquilla Optimizer, and hunger games search in terms of performance.

The structure of this paper consists of two parts, with the second part focusing on the MGO approach and the PV model. The third part of this document deals with the presentation and analysis of the findings. The final step entails drawing conclusions.

2. METHOD

2.1. Mountain Gazelle Optimizer (MGO)

MGO is a nature-inspired algorithm that draws inspiration from the behavior of mountain gazelles.These animals, native to the Arabian peninsula, possess characteristics that closely resemble those of the robinia tree. This species possesses a distinct territorial nature, resulting in significant distances between individuals. This species exhibits a social structure that consists of three distinct groups: parent-child territory, young male territory, and lone male zone. The MGO algorithm optimization incorporates four crucial components: non-grouping, Stag Male groups, maternity groups, male zones, and the migration process for food exploration.

a. Male Zones

This lesson explores the competition for resources and mates among mountain gazelles. Every person possesses an individual and distant territory. The nature of the young male is to assert dominance over either the territory or the female. Simultaneously, the additional responsibility is to maintain and attend to the specific location. This session can be mathematically derived as follows:

$$M_z = m_g - |(ri_1 \times YM - ri_2 \times X(t)) \times F| \times cv \tag{1}$$

$$YM = X_{ra} \times \lfloor r_1 \rfloor + M_{pr} \times \lceil r_2 \rceil, ra = \left\{\left|\frac{N}{3}\right| \dots N\right\} \tag{2}$$

$$F = N_1(D) \times exp\left(2 - it \times \left(\frac{2}{maxit}\right)\right) \tag{3}$$

$$cv = \begin{cases} (\alpha + 1) + r_3 \\ \alpha \times N_2(D) \\ r_4(D) \\ N_3(D) \times N_4(D)^2 \times \cos((r_2 \times 2) \times N_3(D)) \end{cases} \tag{4}$$

$$\alpha = -1 + it \times \left(\frac{-1}{maxit}\right) \tag{5}$$

Where the position of the optimum global breaking is m_g. The ri_1And ri_2 are the random value. cv is a coefficient vector which is random and updated in each iteration. X_{ra} is illustrated as a random value with a range ra. M_{pr} is illustrated as the average value of the search agent. The total of search agents is N. A random value from the basic distribution is $N_1(D)$. it and $maxit$ are the current interation and maximum iteration. r_3, and r_4 are random numbers [0,1]. N_2, N_3 and N_4 are random numbers in the natural space and the sizes of the issue.

b. Maternity Groups

In this section, the maternity group holds the key to the life cycle of the mountain gazelles. This session will get a tough stag. This session can be modeled mathematically as follows

$$MG = (YM + cv) + (ri_3 \times m_g - ri_4 \times x_{rand}) \times cv \tag{6}$$

Where x_{rand} is the vector position of a agent that is randomly chosen from the all population. The ri_3 And ri_4 are the integer and the random value

c. Stag Male Groups

In this session, adult males are encouraged to dominate the territory and females. This power struggle occurs between young males and adult males. behavior in this session can be formulated as follows:

$$STG = (X(t) - D) + (ri_5 \times m_g - ri_6 \times MG) \times cv \tag{7}$$

$$D = \left(|X(t)| + |m_g|\right) + (2 \times r_6 - 1) \tag{8}$$

Where The ri_5 And ri_6 are integers 1 or 2 that are selected randomly. $X(t)$ and r_6 are the positions of the agent vectors in the current iteration and random value.

d. Migration Process

In this session it is described that this animal has a good running and jumping character. They always move long distances in search of food. This session can be formulated as follows:

$$M = (UB - LB) \times r_7 + LB \tag{9}$$

2.2. Solar PV modelling

When analyzing, it is important to numerically simulate the photovoltaic cells. This study employs a photovoltaic modeling methodology utilizing a solar photovoltaic system with a single diode model. This device possesses the benefit of exhibiting high precision while maintaining a straightforward design. The source is supposed to be solar photovoltaic (PV). Figure 1 displays an illustration of an equivalency circuit diagram. This architecture is ideal for photovoltaic systems that necessitate cost-effectiveness and rapid responsiveness. The mathematical equation for the SDM system is as follows:

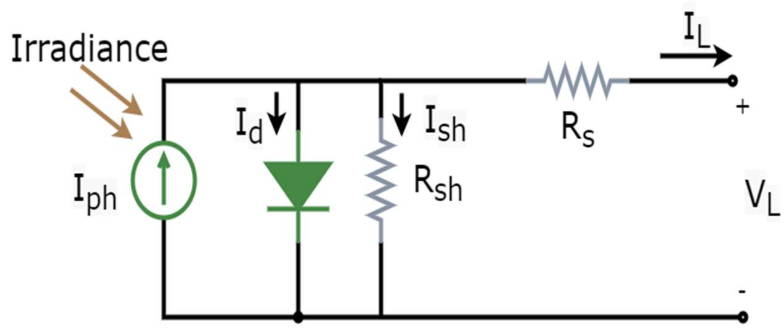

Figure. 1. Single diode circuit of PV

$$I_L = I_{ph} - I_d - I_{sh} \tag{10}$$

$$I_d = I_{sd}\left[\exp\left(\frac{(V_L + R_{sI_L})}{V_t}\right) - 1\right] \tag{11}$$

$$I_{sh} = \frac{V_L + R_{sI_L}}{R_{sh}} \tag{12}$$

$$V_t = \frac{\alpha KT}{q} \tag{13}$$

Where α represents the ideality factor of the diode, $q = 1.60217646 \times 10^{-1}$ C represents the electron charge, $q = 1.3806503 \times 10^{-2}$ J/K. From Eq. (15), it is seen that the parameters (I_{ph}, I_{sd}, R_s, R_{sh}, and α) 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:

$$I_{L_{(m+1)}} = I_{L_{(m)}} - \frac{f(I_{L_{(m)}}}{f'(I_{L_{(m)}}}, m \geq 0 \tag{14}$$

$$f(I_{L_{(m)}} = I_{L_{(m)}} - I_{ph} + I_{sd}\left[\exp\left(\frac{(V_L + R_{sI_L})}{V_t}\right) - 1\right] + \frac{V_L + R_{sI_L}}{R_{sh}} = 0 \tag{15}$$

.

$$f'(I_{L_{(m)}} = 1 + \frac{I_{sd} \cdot R_s}{V_t}\left[\exp\left(\frac{(V_L + R_{sI_L})}{V_t}\right) - 1\right] + \frac{R_s}{R_{sh}} = 0 \quad (16)$$

The NR approach offers the benefit of rapid and uncomplicated convergence. Nevertheless, the NR approach has limitations. The NR approach proved unsuitable for estimating a significant number of unknown variables. Obtaining an accurate initial value for commencing this procedure with a significant number of unknown variables is a considerable challenge. Inaccurate beginning values can result in inaccurate estimations.

2.3. The Proposed Of Chaotic Elite Mountain Gazelle Optimizer (CEMGO)

This article presents a modification of MGO by using the parameters elite individual and chaotic. Individual elites are individuals with minimum fitness.

$$X_{elite} = argmin(f(X_i)) \quad (17)$$

Eq.17 is integrated into equation 2 and equation 5. So that equation 2 becomes Eq.18 and Eq.19 becomes equation 12.

$$YM = X_{ra} \times \lfloor r_1 \rfloor + M_{pr} \times \lceil r_2 \rceil \times X_{elite}, ra = \left\{\left|\frac{N}{3}\right| \dots N\right\} \quad (18)$$

$$\alpha = -1 + it \times \left(\frac{-1}{maxit}\right) \times X_{elite} \quad (19)$$

Apart from that, the random values are N_3 and N_4 multiplied by the choatic parameters in Eq.20

$$ylog_{(i+1)} = a \times ylog_{(i)}\left(1 - ylog_{(i)}\right) \quad (20)$$

3. RESULTS AND DISCUSSION

The efficacy of MMGO is assessed and verified using the global optima function and utilized to acquire solar PV parameters using the SDM model. The findings are compared with the RTH, AO, and MPA techniques. The simulation was conducted utilizing Matlab/Simulink on a laptop equipped with an AMD A9-9425 processor (3.1Ghz) and 4 GB of RAM. By considering and comparing optimal functions, Figure 2 is convergence curve of CEMGO.

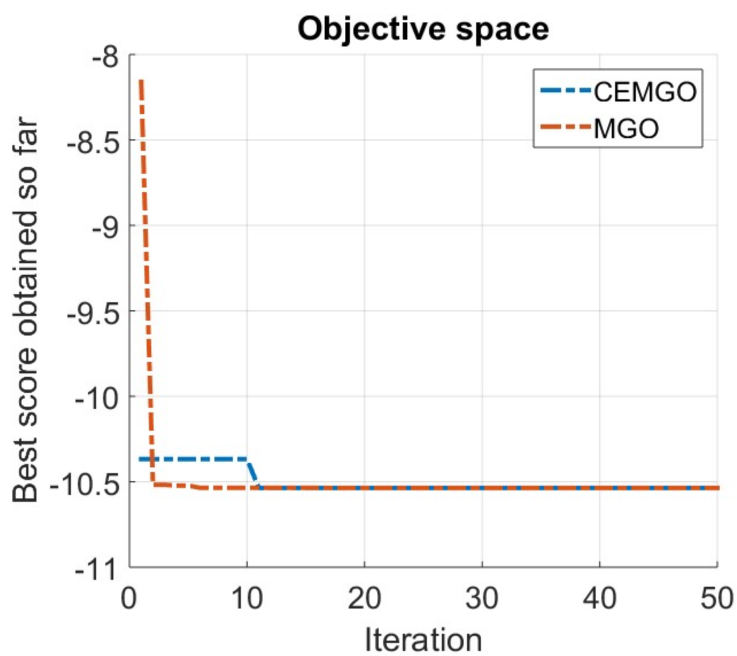

Figure 2. Comparison convergence curve between CEMGO and MGO

The current experimental parameter values consist of solar cells manufactured by R.T.C France. The diameter of this solar cell is 57 mm, and the data was simulated at a temperature of 33 C. Table 1 provides a comprehensive breakdown of the specific measurements for SDM. Figure 3 displays the characteristic curves of solar photovoltaic (PV) systems, specifically the power-voltage (P-V) and current-voltage (I-V) curves. Figure 3(a) displays the empirical current data alongside the current estimation based on voltage measurement. Figure 3(b) displays the relationship between experimental power and power estimation as voltage increases. Figure 3 displays the characteristic curves of solar PV, specifically the P-V and I-V curves.

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

Table 2 presents a juxtaposition of the corresponding parameters calculated by multiple algorithms. In order to acquire precise estimates of the PV model parameters, the initial step is to identify the error function that can effectively capture the disparity between the measured current data and the experimental data. The objective of this essay is to get a collection of PV parameters with minimal inaccuracy. The root mean square error (RMSE) is utilized to quantify the overall error. The mathematical formulation is as follows:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N} f(V_L, I_L, X)} \tag{20}$$

Where N is the number of experimental data.

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

Algorithm	I_{ph}	I_{sd}	α	R_{sh}	R_s	RMSE
CEMGO	0.7508	0.216	1.4417	47.303	0.0381	0.0013
MGO	0.7581	0.7433	1.5708	100	0.0278	0.0010

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

Simulation Current (A)		Simulation Power (W)		
I_{sim}(A)	IAE − I	P(W)	P_{sim}(W)	IAE − P
0.7630	-0.0010	-0.1570	-0.1572	-0.0002
0.7620	0.0000	-0.0984	-0.0984	0.0000
0.7611	0.0006	-0.0447	-0.0447	0.0000
0.7602	-0.0003	0.0043	0.0043	0.0000
0.7594	-0.0006	0.0491	0.0491	0.0000
0.7586	-0.0004	0.0899	0.0899	0.0000
0.7579	0.0009	0.1272	0.1270	-0.0002
0.7571	0.0001	0.1614	0.1614	0.0000
0.7562	0.0007	0.1925	0.1923	-0.0002
0.7548	0.0008	0.2207	0.2205	-0.0002
0.7524	0.0019	0.2460	0.2453	-0.0006
0.7481	0.0016	0.2682	0.2676	-0.0006
0.7403	0.0018	0.2867	0.2860	-0.0007
0.7269	-0.0011	0.3007	0.3012	0.0004
0.7058	-0.0007	0.3086	0.3090	0.0003
0.6736	-0.0019	0.3092	0.3101	0.0009
0.6291	-0.0029	0.3009	0.3023	0.0014
0.5706	-0.0024	0.2830	0.2842	0.0012
0.4987	-0.0003	0.2553	0.2554	0.0001
0.4137	0.0007	0.2178	0.2174	-0.0003
0.3182	0.0017	0.1718	0.1708	-0.0009
0.2136	0.0016	0.1179	0.1170	-0.0009
0.1041	0.0006	0.0587	0.0583	-0.0004
-0.0084	0.0016	-0.0048	-0.0057	-0.0009
-0.1247	-0.0017	-0.0728	-0.0717	0.0010
-0.2108	-0.0008	-0.1243	-0.1239	0.0004
Sum IAE	0.006	Sum IAE		-0.0002

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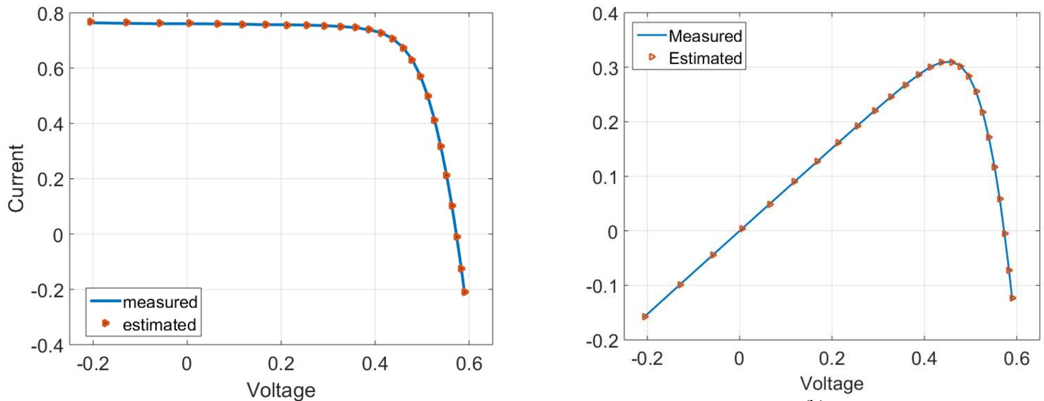

(a) (b)

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

4. CONCLUSION

This paper introduces a method to optimize PV parameters using a modified Mountain Gazelle Optimizer (MGO). The proposed method is named CEMGO. Mountain Gazelle Optimizer (MGO) is a meta-heuristic algorithm inspired by the social life and hierarchy of wild mountain deer. In this article, CEMGO is applied to determine the parameters of photovoltaic solar panels with a single diode model based on experimental datasets. to validate the performance of the CEMGO method. This article uses the original MGO algorithm as a comparison. The function used as a comparison is the root mean square error. From the simulation results, the CEMGO value is better than the MGO method, which is 23.07%.

This research is a development of the Mountain Gazelle Optimizer (MGO) method and applied to solar PV. The proposed method can be tested on complex controls or systems.

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