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Enhancing photovoltaic parameters based on modified puma optimizer

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ABSTRACT

This article presents a photovoltaic (PV) optimization approach using the puma optimizer (PO) approach, which has been enhanced by utilizing Lévy flight optimization. The name of this approach is modified puma optimizer (MPO). PV generation systems are essential for sustainable solar energy utilization. It is an innovation and clean energy. There is an urgent demand for suitable and reliable simulation and optimization techniques for PV systems. This will result in increased efficiency. Algorithms with a high degree of reliability are needed to ensure optimal PV parameters. This study was conducted with MATLAB software. This article introduces the original PO method as a means to evaluate the performance of the MPO approach. The root mean square error (RMSE) function serves as a benchmark. Based on the simulation findings, the MPO approach shows superior RMSE compared to the PO method, specifically at a value of 0.0026%.

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1. INTRODUCTION

The most recent energy solution is the utilization of renewable energy sources such as wind, solar, and tidal waves. Solar energy is a plentiful and renewable source that can be easily transformed into power [1]–[4]. Solar energy must undergo a conversion procedure using specialized equipment in order to be transformed into electricity [5], [6]. Outdoor sites are where solar-based photovoltaic (PV) generators are deployed. A PV device is utilized to convert solar energy into electrical energy. The potential of PV systems is frequently constrained by the limitations of the device itself, as well as the prevailing meteorological conditions and the geographical location of the system. As a consequence, there is a restricted capacity to carry out modifications [7]-[9]. Research on enhancing the precision of 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.

Several endeavors have been undertaken to enhance the efficacy of power conversion from solar cells, including the utilization of novel materials. Furthermore, it is crucial to simulate and optimize the exact configuration of the PV cell model [10], [11]. The purpose of this is to enhance the efficiency and durability of the generation system under various weather and temperature conditions. The single diode model (SDM) is an often utilized and well-liked model. The precision of the PV cell model is crucial in achieving the characteristic analysis (I-V curve). The primary concern revolves around 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 hinders the PV model from achieving optimal performance. PV parameters serve as a benchmark for constructing solar cells, enhancing PV conversion efficiency, and optimizing the tracking of maximum power spots. Conventional methods for identifying PV parameters involve analyzing multiple points on the I-V and P-V curves using a basic function. This approach offers the benefits of being computationally efficient and straightforward to implement. However, a significant limitation of this technique is the reliance on certain assumptions that are made in order to decrease the number of unknown parameters. The Newton-Raphson and Gauss-Seidel methods are utilized to overcome the constraints of the analytical technique. The outcome achieved with this method is greatly influenced by the starting conditions of the unknown variables and effectively identifies 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 techniques have been presented by researchers such as northern goshawk pptimization algorithm [12], differential evolution [13]–[15], nutcracker optimization algorithm [16], grey wolf optimization algorithm [17]–[20], tree seed algorithm [21], harris hawks optimization algorithm [22]–[25], and reptile search algorithm [26], [27]. However, optimization to obtain better PV parameters is still a popular and interesting field. This article presents a PV parameter optimization approach using a modified puma optimizer (MPO) [28]. Puma optimizer (PO) imitates the behavior of puma in nature. The puma algorithm has different operators in both the exploitation and exploration phases. Each of these operators demonstrated excellent abilities in dealing with problems with different dimensions and levels of difficulty. The contributions of this article are:
- PV parameter optimization approach with the PO improvement method using a combination with Lévy flight optimization. This method is named MPO.
- The performance of the MPO method is compared with the PO optimization algorithm.

The structure of this paper is the section 2 regarding the PO method, PV model and Lévy flight optimization. Section 3 is the concept of the proposed method. Section 4 is the results and discussion. Section 5 is drawing conclusion.

2. METHOD

2.1. Puma optimizer

Puma is one of the most successful and well-adapted predators in the Western Hemisphere, which allows them to live in a variety of environments and maintain healthy populations in many regions. Pumas have very strong hind legs, allowing them to jump. For the first time, a novel and useful phase change method for the PO optimization algorithm is provided, which allows the phases of exploration and exploitation to be changed [28]. According to the PO method, the region occupied by the male puma represents the whole optimization space, and it is also thought of as the best answer. Additionally, X_i, another option, has been compared as a female puma.

2.1.1. Inexperienced stage

The mathematical formulas and statements that clarify the optimization processes carried out by PO are then provided. Pumas are brilliant animals and have a perfect memory. For hunting, they often go to places where hunting is more likely, which is based on their previous experiences. These targeted hunting trips can be to areas where it has previously hunted and hidden its prey. It can be modeled in (1) to (10).

$$f1_{Explore} = \mathrm{PF}_1\left(\frac{Seq^1_{CostExplore}}{Seq_{Time}}\right) \tag{1}$$

$$f1_{Exploit} = \mathrm{PF}_1\left(\frac{Seq^1_{CostExploit}}{Seq_{Time}}\right) \tag{2}$$

$$f1_{Explor} = \mathrm{PF}_1\left(\frac{Seq^1_{CostExplore}+Seq^2_{CostExplore}+Seq^3_{CostExplore}}{Seq^1{}_{Time}+Seq^2{}_{Time}+Seq^3{}_{Time}}\right) \tag{3}$$

$$f2_{Exploit} = \mathrm{PF}_2(\frac{Seq^1_{CostExploit}+Seq^2_{CostExploit}+Seq^3_{CostExploit}}{Seq^1{}_{Time}+Seq^2{}_{Time}+Seq^3{}_{Time}}) \quad (4)$$

$$Seq^1_{CostExplore} = \left|Cost^{initial}_{Best} - Cost^1_{Explore}\right| \quad (5)$$

$$Seq^2_{CostExplore} = \left|Cost^2_{Explore} - Cost^1_{Explore}\right| \quad (6)$$

$$Seq^3_{CostExplore} = \left|Cost^3_{Explore} - Cost^2_{Explore}\right| \quad (7)$$

$$Seq^1_{CostExploit} = \left|Cost^{initial}_{Best} - Cost^1_{Exploit}\right| \quad (8)$$

$$Seq^2_{CostExploit} = \left|Cost^2_{Exploit} - Cost^1_{Exploit}\right| \quad (9)$$

$$Seq^3_{CostExploit} = \left|Cost^3_{Exploit} - Cost^2_{Exploit}\right| \quad (10)$$

In the initialization phase, the cost of the first-rate solution developed is denoted as $Cost^{initial}_{Best}$. Additionally, there are six variables: $Cost^1_{Explore}$, $Cost^2_{Explore}$, $Cost^3_{Explore}$, $Cost^1_{Exploit}$, $Cost^2_{Exploit}$, and $Cost^3_{Exploit}$. Utilize the cost of the optimal solution achieved from each phase. Exploitation and exploration occur in iterations 1, 2, and 3. After evaluating the functions f_1 and f_2 at the conclusion of the 3rd iteration, only one of the exploration and exploitation phases will be chosen going forward. Other pumas had a positive experience; thus, they can select one of the two phases by calculating the exploitation and exploration points using (11) and (12).

$$Score_{Explore} = \left(PF_1 \cdot f1_{Explore}\right) + \left(PF_2 \cdot f2_{Explore}\right) \quad (11)$$

$$Score_{Exploit} = \left(PF_1 \cdot f1_{Exploit}\right) + \left(PF_2 \cdot f2_{Exploit}\right) \quad (12)$$

2.1.2. Advanced stage

Pumas has gained sufficient expertise to make the decision to modify the phase. As the iterations continue, they chose to select only one phase for the optimization process. During this phase, three distinct functions f_1, f_2, and f_3, are employed for the purpose of scoring. The primary function places greater focus on the phase of exploration. The initial function is computed using (1).

$$f1^{Exploit}_t = \mathrm{PF}_1 \left|\frac{Cost^{Exploit}_{old} - Cost^{Exploit}_{new}}{T^{Exploit}_t}\right| \quad (13)$$

$$f1^{Explore}_t = \mathrm{PF}_1 \left|\frac{Cost^{Explore}_{old} - Cost^{Explore}_{new}}{T^{Explore}_t}\right| \quad (14)$$

$$f2^{Explore}_t = \mathrm{PF}_2 \left|\frac{\left(Cost^{Explore}_{old,1} - Cost^{Explore}_{new,1}\right)+\left(Cost^{Explore}_{old,2} - Cost^{Explore}_{new,2}\right)+\left(Cost^{Explore}_{old,3} - Cost^{Explore}_{new,3}\right)}{T^{Explore}_{t,1}+T^{Explore}_{t,2}+T^{Explore}_{t,3}}\right| \quad (15)$$

$$f2^{Exploit}_t = \mathrm{PF}_2 \left|\frac{\left(Cost^{Exploit}_{old,1} - Cost^{Exploit}_{new,1}\right)+\left(Cost^{Exploit}_{old,2} - Cost^{Exploit}_{new,2}\right)+\left(Cost^{Exploit}_{old,3} - Cost^{Exploit}_{new,3}\right)}{T^{Exploit}_{t,1}+T^{Exploit}_{t,2}+T^{Exploit}_{t,3}}\right| \quad (16)$$

$$f3^{Exploit}_t = \begin{cases} if\ selected, f3^{Exploit}_t = 0 \\ otherwise, f3^{Exploit}_t + \mathrm{PF}_3 \end{cases} \quad (17)$$

$$f3^{Explore}_t = \begin{cases} if\ selected, f3^{Explore}_t = 0 \\ otherwise, f3^{Explore}_t + \mathrm{PF}_3 \end{cases} \quad (18)$$

The variables $f1^{Exploit}_t$ and $f1^{Explore}_t$ reflect the quantity of the first function during the exploration phase or the exploitation phase, respectively. The variable t represents the current iteration number. $Cost^{Exploit}_{old}$ and $Cost^{Explore}_{old}$ represent the expenses associated with the optimal option prior to any enhancements in the current selection. However, $Cost_{new}^{Exploit}$ and $Cost_{new}^{Explore}$ represent the expenses of the optimal solution achieved through enhancing the current selection. $T_t^{Exploit}$ and $T_t^{Explore}$ represent the count of iterations that were not chosen in the prior selection but are included in the current selection. The PF_1 parameter is a user-adjustable variable that must be assigned a value between 0 and 1 prior to the optimization process. The variables $f2_t^{Exploit}$ and $f2_t^{Explore}$ denote the second function associated with the exploration stage or the exploitation step. $f3_t^{Exploit}$ and $f3_t^{Explore}$ denote the third function associated with the exploration stage or the exploitation step, with t representing the current iteration number.

$$F_t^{Exploit} = \left(\propto_t^{exploit} \cdot (f1_t^{Exploit})\right) + \left(\propto_t^{exploit} \cdot (f2_t^{Exploit})\right) + \left(\delta_t^{exploit} \cdot (lc.f3_t^{Exploit})\right) \quad (19)$$

$$F_t^{Explore} = \left(\propto_t^{explore} \cdot (f1_t^{Explore})\right) + \left(\propto_t^{explore} \cdot (f2_t^{Explore})\right) + \left(\delta_t^{explore} \cdot (lc.f3_t^{Explore})\right) \quad (20)$$

$$lc = \{\{(cost_{old} - cost_{new})\}^{exploitation}, \{(cost_{old} - cost_{new})\}^{exploration}\}, 0 \notin lc \quad (21)$$

$$x_t^{Explore,Exploit} = \begin{cases} if\ F^{exploit} > F^{explore}, \alpha^{exploit} = 0.09, \alpha^{explore} = \lceil \alpha^{explore} - 0.01, 0.01 \rceil \\ otherwise, \alpha^{explore} = 0.09, \alpha^{exploit} = \lceil \alpha^{exploit} - 0.01, 0.01 \rceil \end{cases} \quad (22)$$

$$\delta_t^{explore} = 1 - \propto_t^{explore} \quad (23)$$

$$\delta_t^{exploit} = 1 - \propto_t^{exploit} \quad (24)$$

2.1.3. Exploration

At this stage, pumas engage in a stochastic exploration throughout their region to locate food or approach other pumas in a random manner to exploit their prey. Hence, the puma sporadically leaps into the search area or forages for sustenance within the vicinity of the puma. Initially, the complete population is arranged in ascending order. Then, puma enhances its solutions during the exploration phase by employing (24).

$$\begin{aligned} &if\ Rand > 0.5, Z_{i,g} = R_{Dim} \times (Ub - Lb) + Lb\text{n} \\ &otherwise, Z_{i,g} = X_{a,G} + G \cdot \left(X_{a,G} - X_{b,G}\right) + G \cdot \left(\left(\left(X_{a,G} - X_{b,G}\right) - \left(X_{c,G} - X_{d,G}\right)\right) + \right. \\ &\left.\left(\left(X_{c,G} - X_{d,G}\right) - \left(X_{e,G} - X_{f,G}\right)\right)\right) \end{aligned} \quad (25)$$

$$\text{G} = 2 \cdot Rand - 1 \quad (26)$$

In (25), Ub and Lb represent the minimum and maximum values of the problem. R_{Dim} refers to randomly generated integers that fall between 0 and 1 and are in the same dimensions as the problem. $Rand$ is a randomly generated number that falls within the range of 0 and 1. $X_{a,G}$, $X_{b,G}$, $X_{c,G}$, $X_{d,G}$, $X_{e,G}$, and $X_{f,G}$ are randomly picked solutions from the entire population. The value of G is determined by applying (26).

$$x_{new} = \begin{cases} z_{i,G}\ if j = j_{rand}\ or\ rand \le U \\ x_{a,G,} Otherwise \end{cases} \quad (27)$$

$$NC = 1 - U \quad (28)$$

$$p = \frac{NC}{Npop} \quad (29)$$

$$p = \frac{NC}{Npop} \quad (29)$$

where $z_{i,G}$ is a solution that is obtained using (25). j_{rand} is an integer that is created randomly within the range of dimensions of the problem. The parameter U is defined before to the optimization phase and takes on a value between 0 and 1. With each iteration, the quantity of dimensions that are substituted by new solutions grows.

$$if\ costx_{new} < costx_i, U = U + p \quad (30)$$

$$x_{a,G} = x_{new}, if\ x_{i,new} < x_{a,G} \quad (31)$$

2.1.4. Exploitation

During the exploitation stage, the PO algorithm employs two distinct operators to enhance the solutions. These operators are derived from the two behaviors exhibited by pumas, namely hunting through ambush and dashing.

$$x_{new} = \begin{cases} if\ rand\ \geq 0.5, x_{new} = \frac{\left(\frac{mean(Sol_{total})}{Np}\right) \cdot x_1^r - (-1)^\beta\ x\ x_i}{1+(\alpha \cdot rand)} \\ otherwise, if\ rand \geq L, x_{new} = Puma_{male} + (2 \cdot rand) \cdot exp(rand) \cdot x_2^r - x_i \\ otherwise, x_{new} = (2 \cdot rand) \cdot \frac{(F_1 \cdot R \cdot X(i) + F_2 \cdot (1-R) \cdot Puma_{male})}{(2 \cdot rand - 1 + randn)} - Puma_{male} \end{cases} \quad (32)$$

$$x_2^r = round(1 + (Np - 1) \cdot rand_{10} \quad (33)$$

$$R = 2 \cdot rand - 1 \quad (34)$$

$$F_1 = randn \cdot exp\left(2 - Iter \cdot \left(\frac{2}{MaxIter}\right)\right) \quad (35)$$

$$F_2 = w \times (v)^2 \cdot \cos\left((2 \times rand) \cdot w\right) \quad (36)$$

$$w = randn \quad (37)$$

$$v = randn \quad (38)$$

The variable Np represents the total number of populations that will be used in the optimization procedure. Sol_{total} is the aggregate of all solutions. $Puma_{male}$ is the optimal solution for the entire population.

2.2. Lévy flight optimization

A random walk is a probabilistic process in which particles or waves traverse unpredictable trajectories. The initial utilization of random walks was to elucidate the motion of particles in fluids, specifically known as Brownian motion. Lévy flight refers to a specific type of random walk where the duration of each step is determined by a probability distribution that has a large tail [29]. They have the ability to characterize all stochastic processes that exhibit scale invariance.

$$L(X_j) \approx |X_j|^{1-\alpha} \quad (39)$$

$$f_L(x;\alpha,\gamma) = \frac{1}{\pi}\int_0^\infty exp(-\gamma q^\alpha) \cos\ (qx)\ dq \quad (40)$$

$$f_L(x;\alpha,\gamma) = \frac{\gamma\Gamma(1+\alpha)\sin(\frac{\alpha\pi}{2})}{\pi X^{(1+\alpha)}}\ , x\ \rightarrow \infty \quad (41)$$

$$Levy(\alpha) = 0.05 \times \frac{x}{|y|^{1/\alpha}} \quad (42)$$

$$x = Normal\ (0, \sigma_x^2) \quad (43)$$

$$y = Normal\ (0, \sigma_x^2) \quad (44)$$

$$\sigma_x = \left[\frac{\Gamma(1+\alpha)\sin(\frac{\alpha\pi}{2})}{\Gamma\left(\frac{(1+\alpha)}{2}\right)\alpha\ 2^{\frac{(\alpha-1)}{2}}}\right]^{1/\alpha} and\ \sigma_x\ = 1\ \text{dan}\ \alpha = 1.5 \quad (45)$$

where X_j is the flight length, and $1 < \alpha \leq 2$ is the exponential power. The probability density of the Lévy stable process in integral form is defined as (40). α is the distribution index and controls the scale properties of the process while γ selects the scale units. Integrals in (39) have an analytical solution only in some cases. When α equals 2, it represents a Gaussian distribution and when α equals 1, it represents a Cauchy distribution. Γ is gamma function. Mantegna proposed an accurate and fast algorithm to generate stable Lévy processes for absolute values of the index distribution (α) ranging between 0.3 and 1.99. x and y are two normally distributed variables with standard deviations σ_x and σ_y.

2.3. Solar photovoltaic modelling

This is necessary to mathematically simulate the behavior of PV cells. This work employs a PV modeling approach utilizing a single diode solar PV model system. This device possesses the benefit of exhibiting high precision while maintaining a straightforward design. The source is supposed to be solar PV. Figure 1 displays an illustration of an equivalency circuit diagram [30]. This variant is ideal for PV systems that necessitate cheap production expenses and rapid response. The mathematical equations for the SDM system are as stated:

$$I_L = I_{ph} - I_d - I_{sh} \tag{46}$$

$$I_d = I_{sd}\left[\exp\left(\frac{(V_L+R_{s}I_L)}{V_t}\right) - 1\right] \tag{47}$$

$$I_{sh} = \frac{V_L+R_{s}I_L}{R_{sh}} \tag{48}$$

$$V_t = \frac{\alpha KT}{q} \tag{49}$$

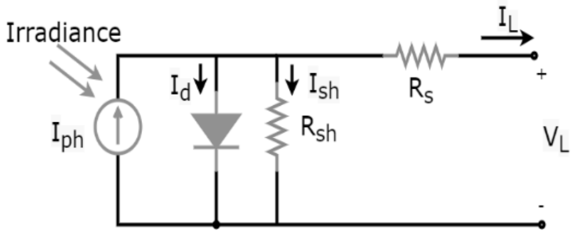

Figure 1. PV circuit consisting of a single diode

The symbol α denotes the ideality factor of the diode. The value of q is $1.60217646 \times 10^{-19}$C, which represents the charge of an electron. The value of q is also $1.3806503 \times 10^{-23}$J/K, which represents the Boltzmann constant. In (46) reveals that accurate estimation of the parameters (I_{ph}, I_{sd}, R_s, R_{sh}, and α) is essential in SDM.

2.3.1. Newton–Raphson technique

The Newton-Raphson (NR) method is a commonly used technique for finding the roots of nonlinear equations. The NR method is defined as (50)-(52):

$$I_{L(m+1)} = I_{L(m)} - \frac{f(I_{L(m)}}{f'(I_{L(m)}}, m \geq 0 \tag{50}$$

$$f(I_{L(m)} = I_{L(m)} - I_{ph} + I_{sd}\left[\exp\left(\frac{\left(V_L+R_{s}I_L\right)}{V_t}\right) - 1\right] + \frac{V_L+R_{s}I_L}{R_{sh}} = 0 \tag{51}$$

$$f'(I_{L(m)} = 1 + \frac{I_{sd}\cdot R_s}{V_t}\left[\exp\left(\frac{\left(V_L+R_{s}I_L\right)}{V_t}\right) - 1\right] + \frac{R_s}{R_{sh}} = 0 \tag{52}$$

The NR approach offers the benefit of rapid and uncomplicated convergence. Nevertheless, the NR technique has disadvantages. The NR approach proved unsuitable for estimating a significant number of unknown variables. Determining the initial value to commence this procedure for a substantial number of unknown variables poses a significant challenge. Inaccurate beginning values can result in erroneous estimates.

3. METHOD

The suggested approach integrates the PO algorithm with Lévy flight optimization. The Lévy Flight method can attain a globally optimal solution in a vast and intricate search space. This is attributed to its capacity to integrate thorough exploration with the utilization of potential regions. Furthermore, employing the Lévy Flight algorithm in PO enhances the capacity to address situations that entail intricate parameters. Consequently, the Lévy flight trajectory is employed to revise the position following the position update. Figure 2 represents an object-oriented analysis flow diagram. The MPO method is a modified version of the PO method. It involves altering (11) and including (42) into (11). Therefore, it transforms into the subsequent:

$$Score_{Explore} = \left(PF_1 \cdot f1_{Explore}\right) + \left(PF_2 \cdot f2_{Explore}\right) \times Levy(\alpha) \tag{53}$$

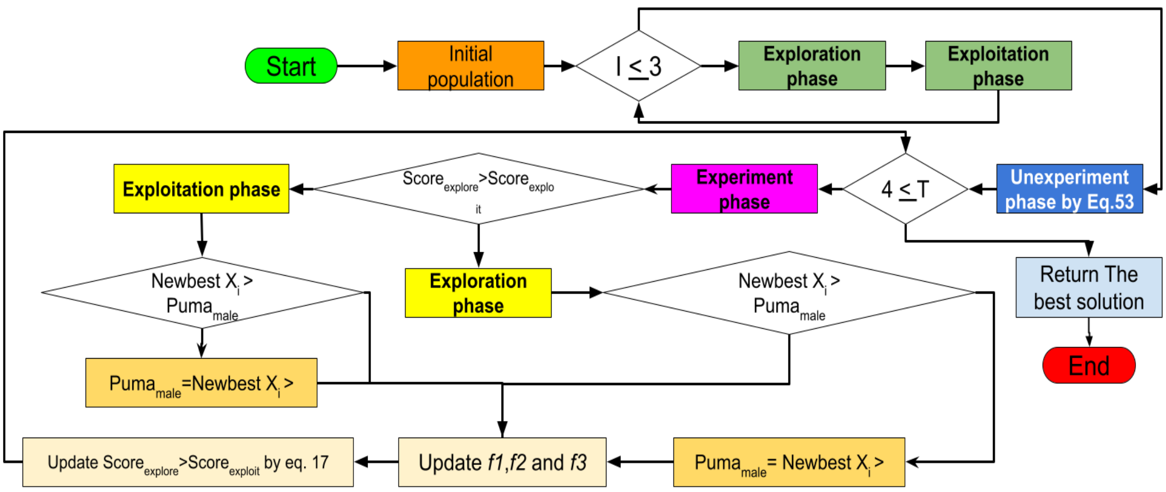

Figure 2. Proposed method MPO

4. RESULTS AND DISCUSSION

MPO performance is measured and validated with the global optima function and applied to obtain solar PV parameters with the SDM model. The results are compared with the original PO. The simulation was carried out using MATLAB/Simulink on a laptop with AMD A9-9425 (3.1 Ghz) specifications with 4 GB 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 optimum and no local optimum. This function can be seen in Figures 3(a) to (g) (in Appendix). F8-F13 are multimodal functions. This function plays a role in reducing the local optimal position of the algorithm. This function can be seen in Figures 3(h) to (m) (in Appendix). F14-F23 are composite functions. This function is a combination of multimodal test functions. This function can be seen in Figures 3(n) to (w) (in Appendix).

The current experimental parameter values consist of solar cells manufactured by R.T.C France. The solar cell has a diameter of 57 mm and the data is simulated at a temperature of 33 °C. Table 1 provides the specific numerical information about SDM. Figure 4 will display the characteristic curves of solar PV, specifically the P-V and I-V curves. Figure 4(a) displays the empirical current and predicted current data with voltage observations. Figure 4(b) displays the observed power trend and the calculated power as the voltage increases. Figures 4(a) and (b) 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 the related parameter sets calculated by several algorithms. To obtain accurate parameter estimates in a PV model, the initial step involves identifying an error function that is able to capture the differences between the measured and experimental current data. The parameter values of the proposed and benchmark methods have little difference. Table 3 is the result of SDM using MPO. The proposed method has a small power error value. The primary objective of this essay is to get a collection of PV parameters with the least amount of inaccuracy. The root mean square error (RMSE) was utilized to quantify the entire error, employing the following mathematical model:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N} f(V_L, I_L, X)} \tag{54}$$

where N is the number of experimental data.

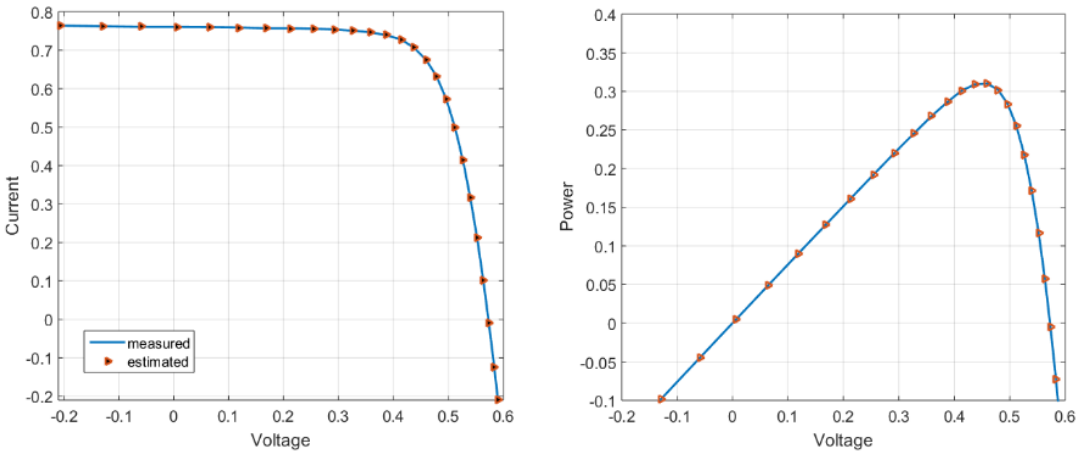

Figure 4. Comparison of curves with; (a) simulation model I-V of MPO and (b) simulation model P-V of MPO

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

Algorithm	I_{ph}	I_{sd}	α	R_{sh}	R_s	RMSE
PO	0.76079	0.3108	1.47732	52.8871	0.0365	7.7298e-04
MPO	0.76079	0.3107	1.4773	52.8899	0.0365	7.7296e-04

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

Simulation current (A)		Simulation power (W)		
I_{sim}(A)	IAE − I	P(W)	P_{sim}(W)	IAE − P
0.76415	0.00015	-0.15715	-0.15719	0.00003
0.76270	0.00070	-0.09837	-0.09846	0.00009
0.76137	0.00087	-0.04472	-0.04477	0.00005
0.76015	0.00035	0.004335	0.00433	0.00000
0.75904	0.00096	0.049096	0.04903	0.00006
0.75801	0.00099	0.089942	0.08982	0.00012
0.75705	0.00005	0.127025	0.12703	0.00001
0.75608	0.00092	0.161392	0.16120	0.00020
0.75502	0.00048	0.192275	0.19215	0.00012
0.75360	0.00040	0.22047	0.22035	0.00012
0.75133	0.00083	0.245338	0.24561	0.00027
0.74731	0.00081	0.26762	0.26791	0.00029
0.74008	0.00158	0.286021	0.28663	0.00061
0.72743	0.00057	0.301174	0.30094	0.00024
0.70703	0.00053	0.308952	0.30918	0.00023
0.67540	0.00010	0.310055	0.31001	0.00005
0.63100	0.00100	0.302349	0.30187	0.00048
0.57217	0.00083	0.284208	0.28380	0.00041
0.49954	0.00054	0.255438	0.25571	0.00028
0.41348	0.00048	0.217445	0.21770	0.00026
0.31716	0.00066	0.170847	0.17120	0.00036
0.21202	0.00002	0.117045	0.11705	0.00001
0.10264	0.00086	0.058302	0.05782	0.00049
-0.00930	0.00070	-0.00574	-0.00533	0.00040
-0.12436	0.00136	-0.07175	-0.07254	0.00079
-0.20910	0.00090	-0.1239	-0.12337	0.00053
Sum IAE	0.00068		Sum IAE	0.00025

5. CONCLUSION

This paper discusses the enhancement of PO through the utilization of Lévy flight optimization. PO is introduced as a new optimization algorithm inspired by the intelligence and behavior of puma in nature. Lévy flight refers to a particular type of random walk where the distance traveled during each step is determined by a probability distribution that has a strong tail. This method is referred to as MPO. This article uses MPO to optimize the parameters of PV solar panels using a SDM, relying on an experimental data set. To verify the effectiveness of the MPO technique. This article uses the original puma as a reference point for comparison. The benchmark function used is the root mean square error. Simulation results show that the MPO approach outperforms the original PO method, with an accuracy of 0.0026%. The MPO technique has the most optimal RMSE value. This research needs to be further developed by conducting experimental tests and using more complex models to obtain validation of the MPO method.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

ETHICAL APPROVAL

The research related to human use has been complied with all the relevant national regulations and institutional policies in accordance with the tenets of the Helsinki Declaration and has been approved by the authors' institutional review board or equivalent committee.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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APPENDIX

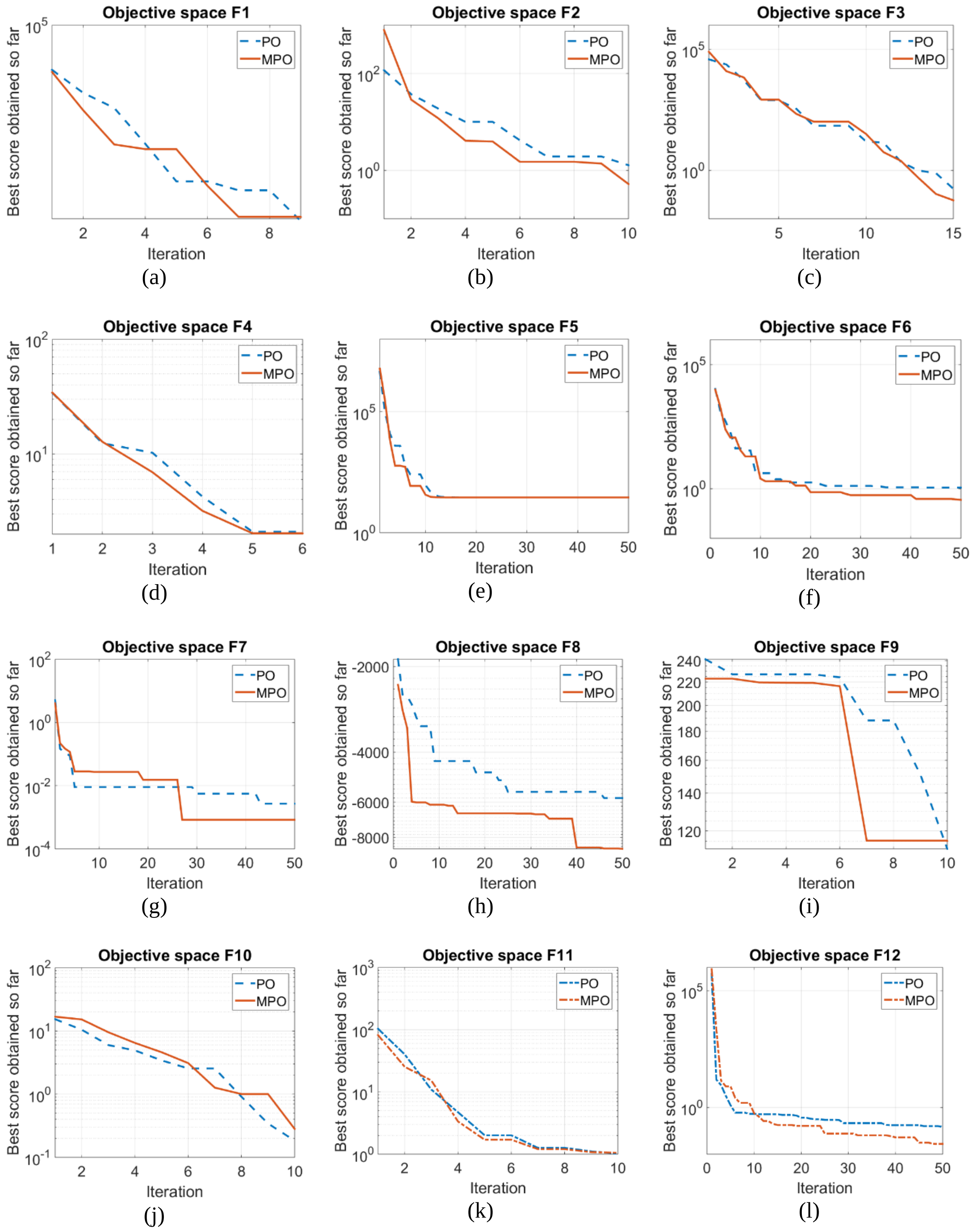

Figure 3. Convergence curve of benchmark function (a) F1, (b) F2, (c) F3, (d) F4, (e) F5, (f) F6(g) F7, (h) F8, (i) F9, (j) F10, (k) F11, and (l) F12

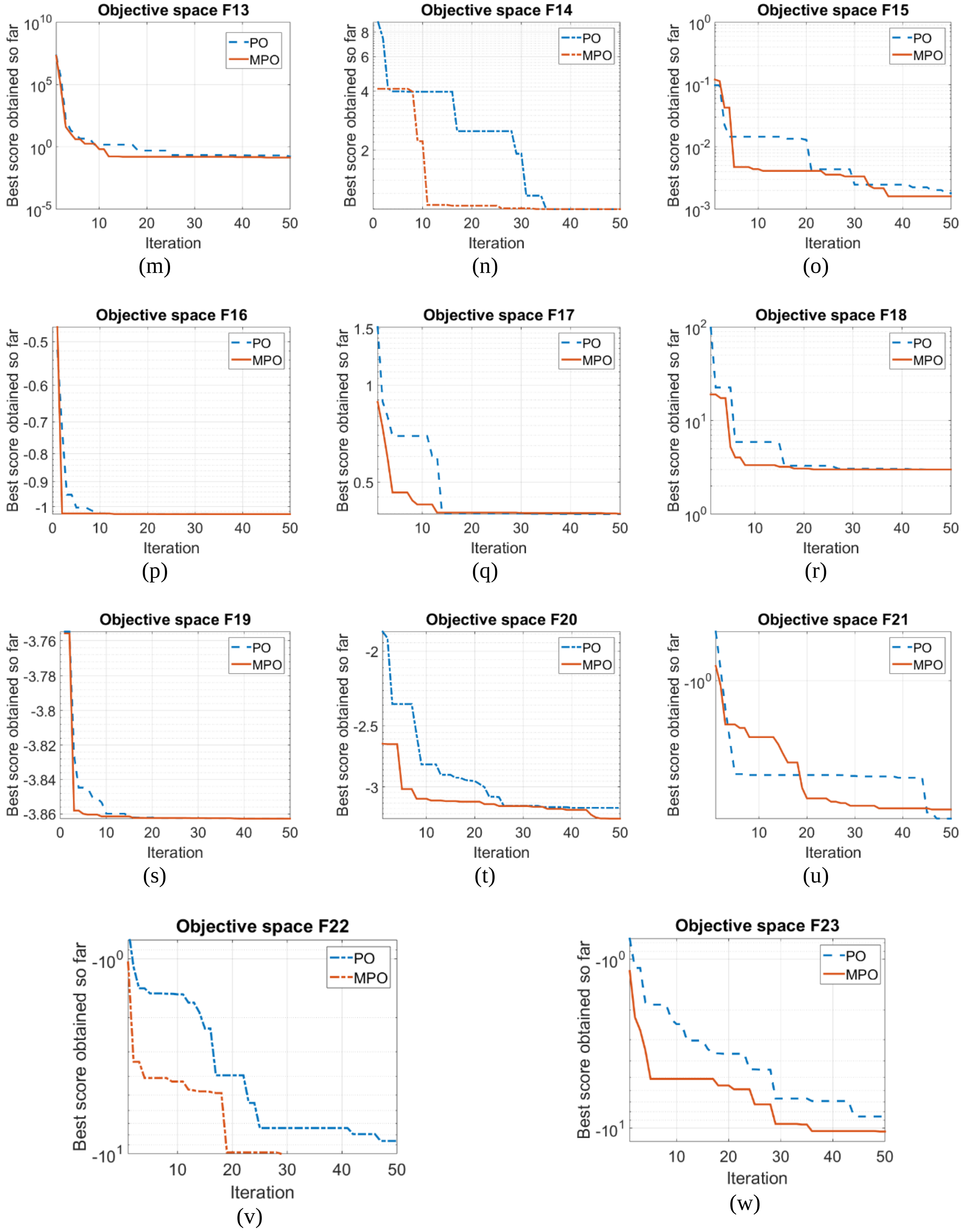

Figure 3. Convergence curve of benchmark function; (m) F13, (n) F14, (o) F15, (p) F16, (q) F17, (r) F18, (s) F19, (t) F20, (u) F21, (v) F22, and (w) F23 *(continued)*

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