Assessing Solar Cell Parameters with Novel Hybrid Whale-Simulated Swarm Optimization

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Concentration on solar power as a feasible alternative has increased due to the rapid degradation of traditional energy resources and the urgent requirement for energy options. The optimization of critical parameters, including the maximum power point (MPP), load component, and voltage in the open circuit, is a difficult task, even with the major advances in solar cell technologies. The effective design and performance improvement of solar cells are hampered by the constraints of current optimization approaches, which show limits with regard to converging speed and accuracy. To evaluate important solar cell characteristics, this work presents an innovative hybrid whale-simulated swarm optimization (HWSSO) technique. Comprehensive studies and simulations show that the suggested approach performs better in identifying important solar cell properties. The outcomes demonstrate the suggested strategy works to achieve optimized solar cell design, which advances renewable energy technology. The results point to bright futures for using the suggested method in the field of solar energy growth.

Keywords: Solar energy, PV cells, critical parameters, hybrid whale-simulated swarm optimization (HWSSO).

1. Introduction

Solar energy is growing in popularity as an essential part of the upcoming energy supply. Solar energy is experiencing significant growth in industrialized nations with favorable sunlight conditions and substantial public backing [1]. Sunlight is the most reliable, safe, and pure energy source that can be utilized for the purpose of achieving sustainable economic growth. One of the effective and realistic methods for collecting Photovoltaic energy is the process of using solar cells to convert sunlight into electrical power [2]. Developing features in the photovoltaic industry are perovskite solar cells called PSCs. The PSC area has developed a result of several factors, including long charge-carrier diffusion lengths, high absorption coefficients, inexpensive and plentiful precursors, and ease of processing [3]. A photovoltaic (PV) panel is a sustainable system capable of converting solar energy into electricity. This system is comprised of individual elements known as solar cells (SC), which facilitate this energy conversion process [4]. The primary factors to consider in the discussion of promoting developing solar energy include its efficiency, determined by the production costs, stability over a long period or lifetime, and solar-to-electric energy conversion effectiveness PCE [5]. The assessment of solar cell characteristics is subject to several constraints, such as weather dependence, spectral sensitivity, and device accuracy. To overcome this obstacle, we proposed the HWSSO methodology for the assessment of solar cell characteristics.

The remaining studies can be categorized using the following criteria: Similar works are discussed in Section 2. In section 3, the circuit equivalency of a PV cell with a single-diode design is described. In section 4, we outline the methods we propose. In section 5, we shall examine the outcomes of our methodology. A summary of the paper's contents is provided in Section 6.

2. Related works

According to the author of, [6] proposed a novel mathematical framework with adaptive weights that finds the best path for attaching material while displaying a high degree of tendency for both exploration and exploitation. This model replicates negative as well as positive feedback of the propagated wave. Study [7] presented a method for estimating the parameters of solar cell devices with one and two diodes. The presented the Flexible Particle Swarm Optimisation (FPSO) [8] technique for the purpose of calculating parameter values in the PV cell model. To developed a novel dynamic variation method for predicting solar panel parameters utilizing the basic data that can be found in the manufacturer's instructions [9]. Research [10] presented an improved iteration of the improved particle swarm optimization approach to find the optimal settings for several photovoltaic models, including single, double, and photovoltaic modules.

Study [11] proposed the adaptable multiple-learn backtrack search technique to improve the solar models' parameter identification. The suggested a productive method for deriving the characteristics of the powered circuit of double-diode models based on PV cells, which is based on the Salp Swarm Algorithm (SSA) [12]. Research [13] created a novel hybrid algorithm called grey wolf optimization and cuckoo search (GWOCS) to extract parameters from experimental data for several PV cell models operating under various situations. The recommended [14] presented the Performance-Guided JAYA (PGJAYA) technique for parameter extraction from several PV models. Author [15] Presented an improved model of the covariance value Matrix Adaptive Evolution Strategy (CSA) called ImCSA. This technique overcomes the issue of parameter estimation in PV models by utilizing real-world I-V data from solar energy cells and modules. Study [16] presented a strategy for predicting solar energy levels using deep learning and machine learning techniques. According to the author of, [17] proposed an in-depth assessment of the variables that need to be considered when making decisions related to the production of perovskite solar power cells. Research [18] developed an innovative technique to find and map the PV panels using spectral and textural properties. Study [19] developed an optimization strategy to enhance the efficiency of perovskite solar cells. Study the adopted time-series deep learning techniques to forecast a PV/T system's performance when it is subjected to cooling by nano fluid [20].

3. PV cell equivalent circuit for a single diode model

A circuit that is electrically equal to a solar cell can be modeled by adding a diode, series resistance, shunt resistance, and current source anti-parallel, as seen in Figure 1.

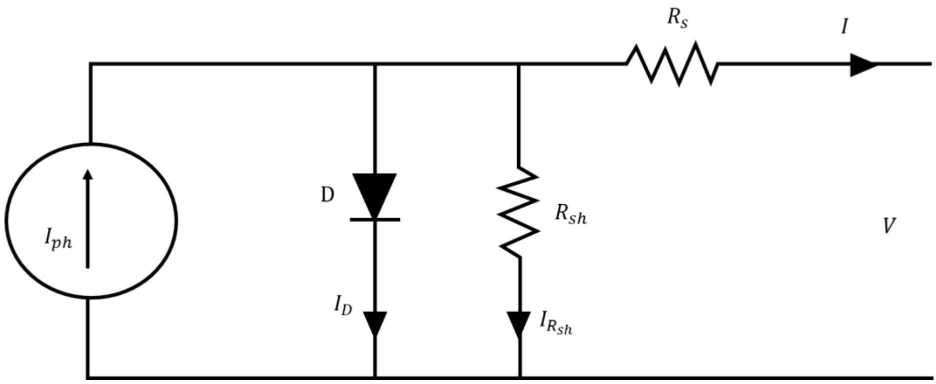

Figure 1: Equivalent Circuit for Solar Cells (Source: https://link.springer.com/article/10.1007/s11633-014-0828-z)

A direct current that changes with solar irradiance is produced when a cell gets exposed to direct sunshine. The irregular I-V properties of the solar cell are caused by the current $I_D$passing through the anti-parallel diode. Kirchhoff's current law provides the fundamental equation that describes a solar cell's I-V relationship as shown in Equations (1-2)

$$I = I_{ph} - I_C - I_{R_{sh}} \quad (1)$$

Using the appropriate expressions to replace the diode current $I_D$and I_{sh}.

$$I = I_{ph} - I_D\left(\exp\left(\frac{(V+IR_s)}{\frac{AkT}{q}} - 1\right) - \frac{(V+IR_s)}{R_{sh}}\right) \quad (2)$$

Where I and V stand for the currents and voltages of the solar panel, photo-generated Current under standard test conditions (STC) is denoted by I_{ph}, the saturation current by I_D, the electron charge is represented by P, the diode quality factor by B, the Boltzmann constant by k, the solar panel's. The resistivity in serial and shunt is illustrated by $R_s$and R_{sh}, exact degree represented by T. The resistance provided by the solar cell's semiconductor material and connections is denoted byR_s . The presence of toxins along the cell's edges that offer a route for short circuiting at the intersection of p-n and the defective nature of the junction factors that contributes to the resistivity R_{sh}. Ideally, R_s would be 0 and R_{sh}would be unconstrained.

4. Methods

4.1 WOA Architecture

The "whale optimization algorithm" is a population-based optimization technique that mimics the social behavior of humpback whales. The physical proportions of the humpback whale are longer and exhibit a notable aptitude for locating sustenance. Specifically, they employ a bubble-net hunting technique to pursue their prey, which primarily consists of krill and small fish. The three stages of WOA are derived from this hunting activity. It looks for prey first, and then circles around it before attacking it. When circling their food, humpback whales either swim in a spiral pattern or along a path that gets smaller. One of the two movements will be chosen by a probability factor p, which is considered to be 50%.

4.1.1 Shrinking Momentum

During the initial phase of exploration, humpback whales use the following mathematical framework to hunt around randomly selected prey in the search space as shown in Equations (3-4).

$$\vec{C} = \left|\vec{D} \times \vec{W}_{rand} - \vec{W}\right| \qquad (3)$$

$$\vec{W}(s+1) = \vec{W}_{rand} - \vec{B}\vec{C} \qquad (4)$$

The location of the present phase s, The subsequent iteration is $(s+1)$, the prey's random position is $\vec{W}_{rand}$, the coefficient vectors are $\vec{B}$and $\vec{D}$, and is defined as in Equations (5-6).

$$\vec{B} = 2\,\vec{b}\vec{q} - \vec{b} \qquad (5)$$

$$\vec{D} = 2 \times \vec{q} \qquad (6)$$

where $\vec{q}$is the random number in the interval [0, 1] and $\vec{b}$decreases from 2 to 0 during the duration of iterations. Whale positions are updated during the exploitation phase according to the location of the best search prey $\overrightarrow{W^*}$.Its mathematical definition in Equations (7-8):

$$\vec{C} = \left|\vec{D} \times \overrightarrow{W^*} - \vec{W}\right| \qquad (7)$$

$$\vec{W}(s+1) = \overrightarrow{W^*} - \vec{B} \times \vec{C} \qquad (8)$$

4.1.2 Spiral Motion

The humpback whale's spiral movement begins with measuring the distance between its location at (W, X) and its best search prey at $(\overrightarrow{W^*},\overrightarrow{X^*})$. The following mathematical equation defines the whale's helix-shaped movement around its prey once the distance has been determined in Equation (9).

$$\overrightarrow{W}(s+1) = \overrightarrow{C'}.f^{bl}.\cos(2\pi k) + \overrightarrow{W^{*}}(s) \quad (9)$$

The variable "l" represents randomly generated integer defined inside the interval [–2, 2], the progressive loop's form is preserved by the constant c, and $\overrightarrow{C'} = \overrightarrow{W^{*}}(s) - \overrightarrow{W}(s)$ is the length of distance among the whale and most searched prey. When p is less than 0.5 and A is greater than 1, the spots are modified by Equations (4) and (8). When p is less than 0.5 and A is less than 1, the spots are up-to-date by equations (8) and (9), and when p is less than 0.5, the spots are updated by equation (9). The coefficient variable "B" in WOA keeps the search and extraction in balance.

4.2 Mechanism for Simulated Annealing (SA)

SA is a meta-heuristic optimization technique that finds the best answer by applying the Metropolis probabilistic strategy. SA essentially mimics the annealing process of the metals. A number of variables, including the starting temperature, the disturbance mechanism, the equilibrium state, and the cooling process, are major determinants of SA performance.

4.2.1 Starting temperature

It is important to choose the starting temperature to prolong the optimum phase and avoid the local minimum trap.

4.2.2 Mechanism of interruption

The general procedure is governed by the interruption system. By exploring a search space and gradually stepping out from the local optimum, SA calculates the likelihood of accepting weak responses using the probability-based Metropolis criteria for acceptance. By definition, this rule is

$$o = f^{-\frac{\Delta F}{l_{ap}} S_j} \quad (10)$$

Where ΔF is the cost difference between the current and neighboring solutions, o is the rate of success, and $S_j$and $l_{ap}$are the Boltzmann coefficients and temperature at time j.

4.2.3 Equilibrium state

When a system is in equilibrium, its temperature remains steady, and its energy content remains unchanged. Acceptance rate is seen as a sign of balance. At this temperature, a large energy variance necessitates a disturbance continuation, as indicated by the acceptance rates near one. The system approaches balanced at a temperature when acceptance rates are close to zero, and the temperature can decline if the ideal broad solution is not found.

4.2.4 Cooling process

Annealing requires cooling at a pace that corresponds to the temperature decline. The temperature is decreased in simulated annealing by a variable or fixed factor. The degree of acceptance primarily determines when a temperature shifts from high to low. The temperature is typically lowered by Equation (11),

$$S_{j+1} = \alpha S_j \tag{11}$$

Where α is a measure of temperature drop, $\alpha < 1$.

The following are the labeled main phases of the SA algorithm utilized in this study.

- The first step is to configure the system's parameters, loading level, maximum number of iterations, and starting temperature. $\alpha = 0.5$ is used as the temperature decrease factor.
- The goal function is calculated after setting the iteration number to $i = 1$, which is the beginning value.
- Construct another plan based on the area around the existing one. Calculate ΔF, the amount of energy variations between the neighborhood solution and the current one.
- The evaluation of ΔF will determine whether to accept or reject the current point. The Metropolis accepting criteria Equation (10) will be used if ΔF is positive.
- In step five, change the amount of loops at $j = j + 1$. Proceed to step three if j is smaller than M.
- Determine that to preserve the disturbance at this point or lower in step six by assessing the acceptability rule by employing Equation (11).
- The program is reprocessed from step 3 if the stop criteria are not met.

HWSSO is a novel method used to assess solar cell characteristics. By fusing ideas from the Whale Optimization Algorithm and Swarm Intelligence, two powerful optimization methodologies, HWSSO provides a reliable and effective way to improve the efficiency of solar cells. With this hybrid technique, solar cell metrics like output and efficiency are optimized by taking advantage of the intelligent behavior of whale motions and swarm dynamics. Through the simulation of these organisms' collective behavior, HWSO offers a special and practical way to evaluate and fine-tune the critical characteristics of solar cells, advancing the development of renewable energy technologies.

5. Result

WOA model parameters and real data, as well as SA model parameters and actual data, are used to evaluate the deviation in I-V characteristics. Lastly, calculate the difference between the I-V characteristics derived from the HWSSO model parameter and the actual data.

5.1 Experimental setup

The proposed HWSSO technique is implemented using the software MATLAB 2018 platform, which has a portable Intel R cores TMi7-HQ CPU timed at 2.5 GHz and 16 GB of RAM. The solar cell model parameters are estimated using a HWSSO. Table 1 display the solar cell parameter values WOA, SA, and our proposed HWSSO approach. Figures 2 and 3 show the variation among the I-V characteristics obtained from the WOA method parameter and the actual data. Figures 4 and 5 show the variation between the SA method parameter-derived I-V characteristics and the actual data and the HWSSO system parameter values and the I-V characteristic derived from real data are perfectly matched, as seen in Figure 6 and Figure 7.

Table 1: Solar cell parameter values of WOA, SA, and our proposed HWSSO approach

S. No.	Parameter	GA	GA-NM	HWSSO
1	Photo-generated Current (Iph)	3.5	3.7	3.902
2	Diode Saturation Current (ID)	$3 * 10^{-7}$	$3.02 * 10^{-7}$	$3.558 * 10^{-7}$
3	Diode Quality Factor (B)	1.3	1.5	1.697
4	Series Resistance (Rs)	0.003	0.004	0.006
5	Shunt Resistance (Rsh)	8	9	10.3073

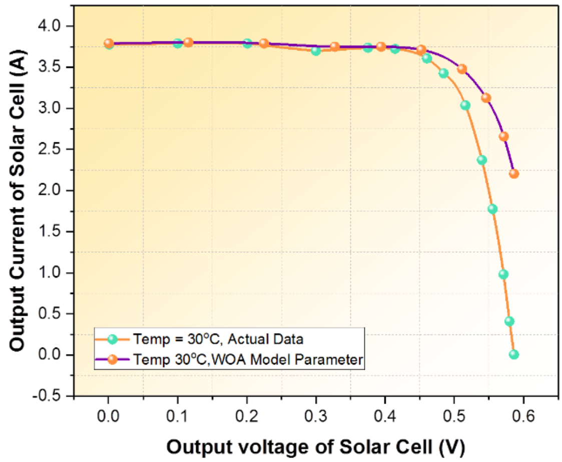

Figure 2: I-V Properties Using Real Data and Calculated WOA Results (30°*c*) [Source: Author]

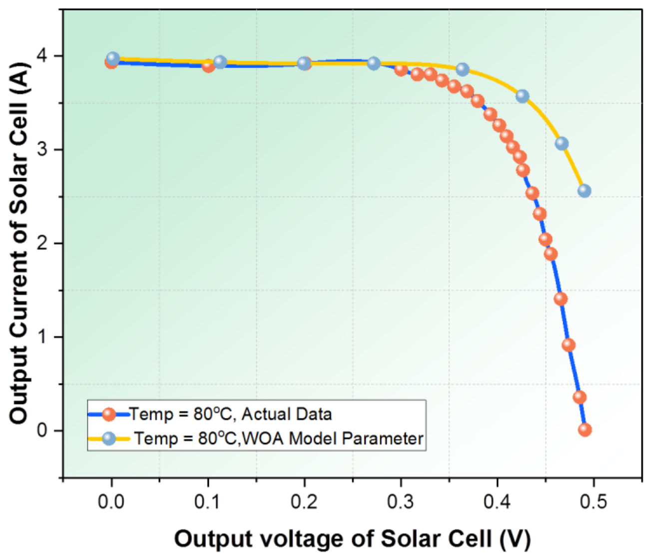

Figure 3: I-V Properties Using Real Data and Calculated WOA Results (80°*c*)

[Source: Author]

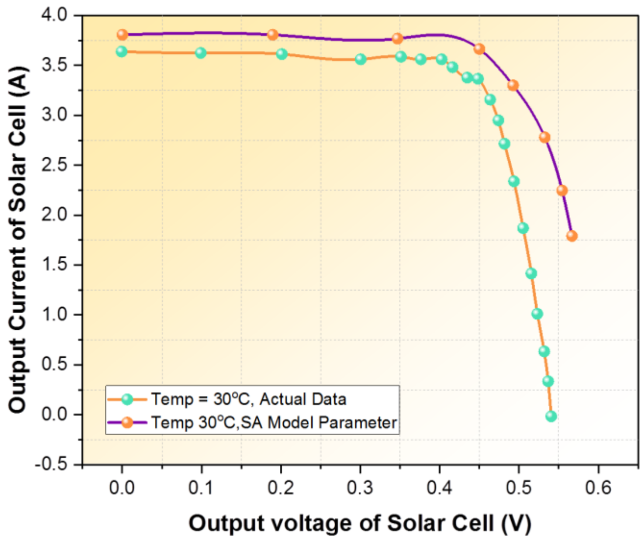

Figure 4: I-V Properties Using Real Data and Calculated SA Results $(30°c)$ [Source: Author]

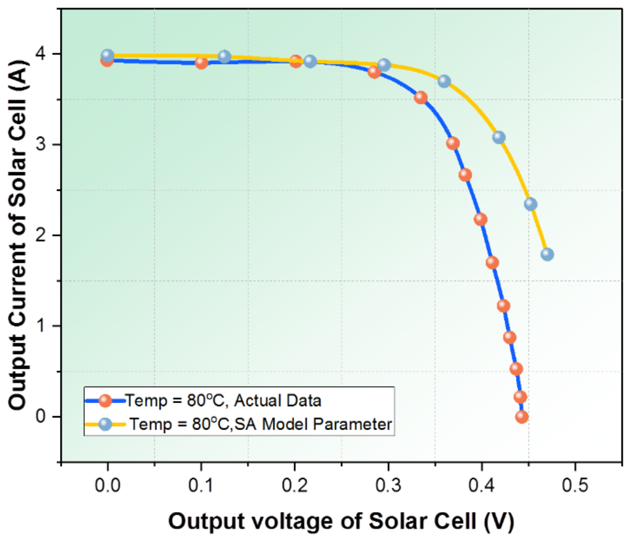

Figure 5: I-V Properties Using Real Data and Calculated SA Results $(80°c)$ [Source: Author]

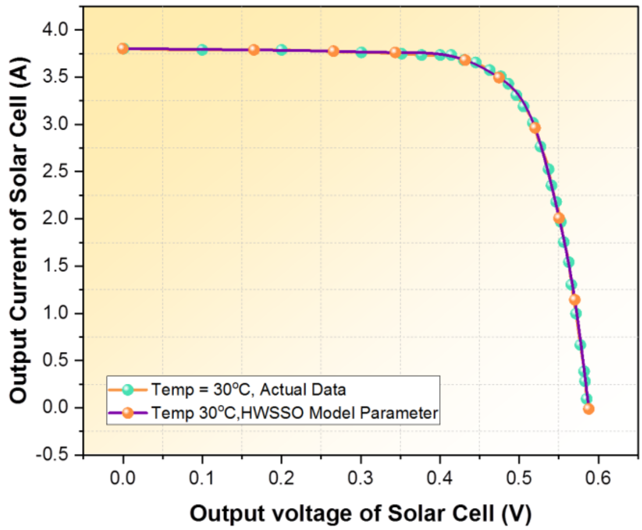

Figure 6: I-V Properties Using Calculated HWSSO Results and Real Data (30°c) [Source: Author]

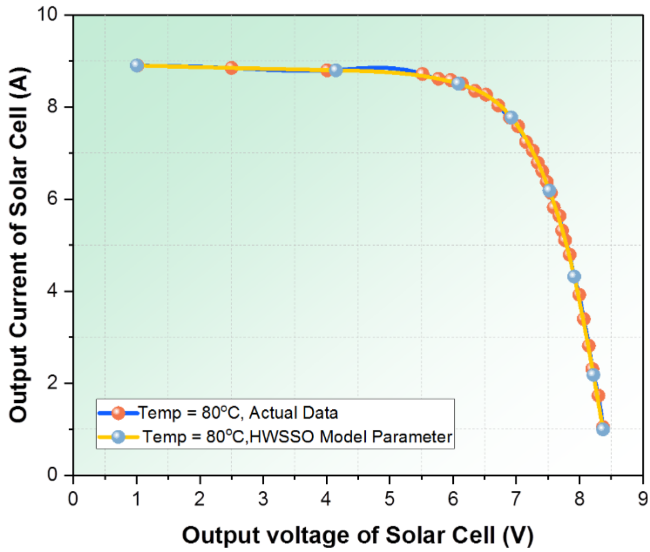

Figure 7: I-V Properties Using Calculated HWSSO Results and Real Data (80°c) [Source: Author]

6. Conclusion

The proposed HWSSO technique is applied to calculate the perfect solar cell design parameter values. By integrating the computing functions of the simulated annealing and whale optimization approaches, this novel approach improves the effectiveness and accuracy of parameter evaluation. It provides great opportunities to advance solar cell technology, enabling more efficient and long-lasting energy sources. MATLAB R2023a was utilized in the implementation of the methodology used in this investigation. The hybrid HWSSO algorithm combines the enhanced capabilities of the whale optimization and simulated annealing techniques for global search. It develops technology for renewable energy sources. The results indicate that the recommended approach has a promising future in the field of advancing solar energy. The evaluation of solar cell properties is limited by a number of factors, such as system accuracy, weather dependence, and spectrum sensitivity. Future developments in AI for real-time evaluation and novel materials for enhanced spectrum absorption will enable the solution of these limits and ensure a dependable and efficient solar energy infrastructure.

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