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*Research Article*

# A Novel Optimization Algorithm for Modifying the Parameter Unit of Solar PV Cell

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Because of the rise in solar electricity, photovoltaic research has increased. A precise model of the PV-based cell/unit is ideal for conceptually examining the capabilities of alternative control approaches. Extraction of precise values for relevant unknown elements of solar photovoltaic models is crucial for modeling PV systems. Optimization strategies for this topic have been increasingly important and dynamic in recent history due to their efficiency in dealing with extremely nonlinear multidimensional optimization challenges. The strategy avoids stalling by deleting the best solution; this keeps the engine diverse and increases global search capacity. Pattern searching, on either side, is a multiobjective approach that has a high convergence speed as well as good stability, which can increase the whale optimization algorithm's traditional optimization ability. As a result, combining these two mechanisms can considerably improve the whale optimization algorithm capacity to find the optimal answer. The modified whale optimization algorithm may also be used to evaluate parameters in single-diode models, double-diode models, and photovoltaic panels, as well as to find independent variables in two distinct methods of PV modules under various light temperature and pressure circumstances. The analytical results show that the modified whale optimization algorithm is both valid and practical for predicting solar cell and photovoltaic unit characteristics. The study goes into great depth on a new optimization approach for changing the parameter unit of solar PV cells.

## 1. Introduction

Power generation has traditionally become the most approachable, kind of energy, but it must first be generated before it could be utilized. Even though a major part of electric power is still generated from fossil fuels, the global energy mix has changed intensely in recent decades. Several issues have been forced by this kind of shift, including rising costs of conventional energy, resource constraints, and a responsibility to protect the ecosystem [1]. Carbon emissions and the degradation of available substance, especially, have prompted the use of new energy resources. Coal and oil are among the largest and most powerful energy sources, capable of meeting all of humanity's demands. The low price, converting leads, and simplicity of delivery of fossil energy have piqued the interest of all countries, resulting in a growth in their use. The drawbacks of fossil fuels should be weighed against their many benefits. Severely polluted air,

ozone layer depletion, climate change, and other factors have prompted advanced economies to turn to sustainable energy sources such as wind, photovoltaic, hydrothermal, and gravity force.

Those things are happening as a result of the benefits that energy production has over other alternative energy sources. Year-round unlimited type of power, low maintenance requirements, and ease of application, even in household large urban areas, are only a few of the benefits. As a result, there has been an increase in the quantity of study into the solar energy economy. PV panels generate clean, renewable electricity. There are no detrimental greenhouse gas emissions during the generation of power with PV panels, making solar PV environmentally beneficial. Solar energy is energy that comes from the sun. As a result, it is both free and plentiful. The primary goal of the research is to boost the effectiveness of photovoltaic cells/modules, which are the fundamental building blocks for harvesting solar energy [2]. Aside from wind, tidal, and geothermal power, power generation, energy is a major form of renewable energy. In India, for example, the national target of 175 Gigawatts of renewable power was output by 2022, with 100 Gigawatts coming from solar energy. Furthermore, China aspires to be a global leader in the renewable power organization by 2050, with a size of 1300 Gigawatts.

Machine intelligence is known as artificial intelligence. It is described as "the design approach of intelligent agents," where an intelligent agent is a technology that observes its surroundings and acts in a way that increases its likelihood of succeeding. Artificial intelligence investigation is very technical and specialized, and this is separated into numerous subject areas that frequently fail to interact with one another. Statistical modeling methodologies, conventional symbolic, and intelligent systems are currently prevalent artificial intelligent approaches [3]. The researcher said that in the synthetic Intelligence system, the linear combination comparatively straightforward rules. There is no centralized control system in place that dictates how individual agents should act. The genuine behaviors of the agents are local and to some degree chance; nonetheless, relations among such individual's outcome in the conception of "intellectual" global behavior that is unknown to the different agents. Termites, bird flocking, mammal herding, bacterial development, and schools of fish are all examples of synthetic intelligence.

Because solar energy is readily available, substantial inquiry and research on solar energy are carried out to maximize the use of this type of renewable energy. Because the solar energy is a clean source, it helps to lower pollution levels around the world, as well as the constraints on conventional exhaustible power insulation for generating electric power, such as condensation generation and hydroelectric power. As a consequence of this, numerous research investigations have been conducted to solve the challenges that have arisen as a result of greater advancement in the development of solar energy. To achieve optimal performance of photovoltaic panels and solar energy under various process situations, robust manufacturing methodologies must be created in response to such limitations. The solar cell layout approach is primarily based on the comparable physical equation of the solar cell [4]. The solar cell model's importance is seen in its potential to induce all variables that control the enthusiastic behavior of the real SC. Furthermore, the current-voltage (I-V) curve can be easily created by studying the behavior using the computational formula, which aids inefficiently, studying the dynamics of solar cell and photovoltaic systems under various weather circumstances.

In this arena, conventional swarm-based algorithms like PSO and ABC have already worked successfully. Nevertheless, because the challenge of determining the parameters of photovoltaic systems is a heterogeneous problem, there is no method to find the global best solution due to the immaturity of some different algorithms. WOA has been effectively implemented in numerous disciplines such as dynamic planning, artificial neural, image classification and extraction of features, and wind velocity forecasting due to its simple design, few variables, powerful search capability, and simplicity of implementation [5]. Traditional swarm-based techniques like PSO and ABC have already proved effective in this field. Nonetheless, due to the infancy of some distinct techniques, there is no approach to identify the global optimum answer because the difficulty of selecting the characteristics of photovoltaic systems is a diverse problem. Due to its simple architecture, few specifications, advanced search capabilities, and ease of effectuation, WOA has been effectively used in a variety of domains, including dynamic scheduling, machine learning, picture categorization, and features are extracted, and wind speed prediction.

Because photovoltaic systems are environmentally friendly, efficient, and safe power sources, they have played a significant part in sustainable power (RE) technology. PV-based renewable energy solutions have attracted a lot of interest for both standalone and energy systems. The generator should be capable of providing high energy to the load in the SA mode. To attach the demand to the PV, which generates DC electricity, an adapter is necessary. Under the SA operation mode, the inverter's output frequencies, voltage, and flow should be managed compared with the reference values. As a result, a power converter and an appropriate voltage management strategy are necessary [6]. The flexibility of a better power converter to supply amplitude and phase sinusoidal voltage and frequency irrespective of the nature of the load it is attached to is its most important attribute. The voltage transformer must also be able to recover fast from transient conditions caused by the disruptions without compromising power quality. However, the widespread usage of PV systems poses several issues, including harmonic emission, low conversion efficiency, power output variability, and power semiconductor conversion dependability.

PV modeling approaches can be categorized into quantitative, quantitative, and hybrid approaches, based on the literature subject. The alternative is the most straightforward to execute, as well as requiring less calculation time. For the mathematical description of the PV characteristic estimates issued, it uses the power-voltage (P-V) and current-

voltage (I-V) data curves, as well as selected data from the PV cell/unit spreadsheet [7]. The analytical approaches, on the other hand, are based on simplifying assumptions of appropriate quantitative formulas, which will have a substantial impact on reliability. Furthermore, the initial prediction from the I-V curve will very certainly alter this precision. To represent photovoltaic cells, a variety of methodologies have been devised, one of the most prevalent of which is the use of comparable circuit simulations. The double-diode and single-diode types are the most commonly utilized circuit models [8]. The reliability of the components associated with the structural model is critical for modeling, sizing, performance assessment, management, efficient calculations, and maximum power point of photovoltaic systems following choosing an appropriate structural model. The paper provides detail on the approach of parameter identification and its optimization process using the whale optimization algorithm. Section 1 provides the detail on the introduction on the optimization and the approach to the algorithm process in a photovoltaic system. The literature based on the different approaches to optimization and algorithm is defined in Section 2, and the material and method are provided in Section 3. Finally, the optimization technique is provided in Section 4.

## 2. Related Work

The identification of the parameters of solar cells using artificial bee colonies is proposed by the author, thereby optimizing solar energy. Various studies have focused on the precise prediction of current vs. voltage (I–V) properties of solar cells to enhance the effectiveness of photovoltaic systems. The absence of information about the specific model parameters that do characterize the solar panel is the fundamental obstacle in precise prediction. As these features cannot be derived from sheet requirements, a technique on optimization is necessary to adjust the experimental results to photovoltaic models. The new algorithm is effective and developed that was motivated by honey bees' clever foraging activity. ABC outperforms other optimization techniques when it comes to searching for multimodal optimization methods. The proposed methodology is contrasted to other well-known optimization techniques to show its efficacy. The method performs well in terms of resilience and precision, as evidenced by the experimental outcomes [9].

This research presents a photovoltaic cell input parameter identification approach based on adaptive lion swarm optimization. An improved lion swarm optimization proposed by researcher defines the process of identifying the parameter of photovoltaic cell modes. The lion swarm optimization element method is a numerical intelligence algorithm that has been developed in recent times, although it has issues like a locally optimal and delayed completion. To solve these disadvantages, we may use a combination of the tent chaos map, adaptable variable, and chaos search technique to enhance the individual's suitability and minimize trapping in local optimums. The efficiency of the improved lions swarm algorithm surpasses the other six methods in a simulation of a classic test function. The algorithm is then used to identify the parameters of photovoltaic cells using multiple models and various irradiances. The simulation results indicate that the modified lion swarm evaluation is better and successful in the implementation of photovoltaic cells estimating the parameters [10].

The proposed a method for parameter extraction based on swarm optimization. The photovoltaic specifications were extracted from illuminated current-voltage characteristics using particle swarm optimization (PSO). For single- and double-diode models, the PSO's results are compared to that of genetic algorithms. The suggested technique can get higher variable accuracy with greater computational performance than the GA method, according to synthetic and actual existing information. Relative to traditional diffusion methods, the PSO technique is used to produce photovoltaic characteristics as near to the real values as feasible even without a good initial prediction by specifying a wider spectrum for each characteristic [11].

Relative to conventional diffusion methods, the PSO technique is used to obtain photovoltaic characteristics as near to the real values as feasible even without a good initial prediction by specifying a wider spectrum for each characteristic. The author proposed a method for the variable identification of solar cells, and the researchers used the hybrid firefly and pattern search technique to derive the parameter identification. The firefly method has been a recently developed swarm intelligence-based efficient algorithm that has shown to be very effective in addressing optimization issues. If used alone, this technique is effective for exploring solutions, but it requires a local optimization strategy to increase exploitation. To improve this technique, researchers integrate design search as a local optimization technique with the firefly algorithm in this research. To demonstrate the algorithm's effectiveness, the outcomes are presented to those of other optimization techniques for PV parameters. The findings show that the proposed technique is a competing technique that should be part of the solar panel system modeling [9].

The researcher proposed a method for optimization of solar power panels by identifying the parameter of the energy storage system. The smart grid strategy is designed to take benefit of the extensive current technology on altering the current electrical laws to support all participants in the areas of energy efficiency and conservation integration. Energy storage systems may be able to deal with some of the challenges that arise from the use of renewable energy, such as stabilizing irregular power generation, improving voltage stability, and reducing power peaking. The suggested method is based on an integrated optimization strategy that combines a deterministic and stochastic algorithm, has a limited calculation overhead, and can thus be performed under similar working conditions to account for variable fluctuations owing to battery lifetime and use. The research provides a method for determining the ranges of battery design variables that best suit experimental data and integrating them, together with simulations of forms of energy and electric loads, into a comprehensive structure that reflects a real-time smart grid monitoring system [12].

A method for the variable estimation of the photovoltaic cell model enhances the exploratory shape based on the approach on a chain-based algorithm. Photovoltaic systems (PV) are becoming a more viable solution for future energy systems. As a result, research into the working of PVSs has sparked a lot of interest. Due to the obvious nonlinearity of PV cell properties and their large dependence on climatic circumstances of contamination level and temperature, study into finding PV cell model parameters continues a fluid subject. The resistance-based learning modified salp swarm algorithm is suggested in this study for accurate determination of the two-diode design variables of the PV cell/electrical module's transmission line. The results of the experiment as well as in comparison, investigation show that OLMSSA is very competitive, even much better than the published results of the bulk of previously established parameter identification techniques [13].

*2.1. Problem Definition.* The difficulty in estimating the parameters for photovoltaic system and solar cells is in estimating the parameters of the model using the voltage and current values that have been observed. Furthermore, SD and DD designs are the most generally used equivalency models to mimic the asymmetric current-voltage relationship of solar cells and photovoltaic panels, with SDM is the most widely used.

## 3. Materials and Method

*3.1. Mathematical Formulation*

*3.1.1. Solar Cell Model.* Photovoltaic, single-diode (SD) model, and double-diode (DD) model designs are the three most common comparable circuit types of photovoltaic cells. In contrast to the double-diode model, the photovoltaic panel takes longer to execute since it needs to retrieve more variables [14]. The estimation methods in the two models change only slightly. The analogous circuit models of SD design, photovoltaic modules and DD models will be deliberated in the following subsections.

*3.1.2. Single-Diode Design.* In Figure 1, the equivalent circuit of SDM is presented in which the function of the output voltage could be computed from the output current $I_o$; hence ,the equation could be written as

$$I_o = I_p - I_s \times \left[\exp\left(\frac{V_o + I_o \times R_a}{n \times V_d}\right)\right] - \frac{(V_o + I_o \times R_a)}{R_s}. \quad (1)$$

*3.1.3. Double-Diode Design.* In contrast to the absorption and combination losses included in SDM, the precision of the PV model can be improved by accumulation an additional diode that reflects space charge loss. Figure 2 shows the equivalent circuit of the double-diode model. The calculation for the DDM is expressed below:

$$\begin{aligned} I_o = I_p - I_{s,1} \times \left[\exp\left(\frac{V_o + I_o \times R_a}{n_1 \times V_d} - 1\right)\right] - I_{s2} \\ \times \left[\exp\left(\frac{V_o + I_o \times R_a}{n_2 \times V_d} - 1\right)\right] - \left[\exp\left(\frac{V_o + I_o \times R_a}{R_s} - 1\right)\right]. \end{aligned} \quad (2)$$

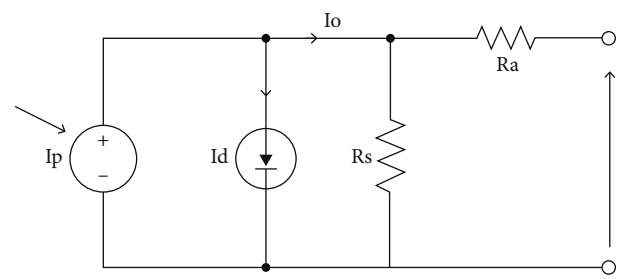


Figure 1: Equivalent circuit of the single-diode model.

In the above two equations, $I_o$ is the output current, $I_p$ denotes the photovoltaic current, $V_o$ denotes the output voltage, and $R_a$ denotes the series resistance and $R_s$ denotes the shunt resistance. In the challenge of estimating the parameters of PV cells and batteries, the information on terminal voltage current is obtained [15]. All that remains to be improved in the recognition process is to determine the best set of unidentified model parameters that minimize the difference between the present predicted value based on the finite element model and the experimentally recorded value.

*3.1.4. Whale Optimization Algorithm Background.* The basic whale optimization algorithm is a method of artistic intelligence based on a simulation of the humpback whale feeding behavior [16]. The activity of humpback whales is divided into three sections by the method: surrounding prey, bubble-net assaulting, and seeking for prey.

*3.1.5. Surrounding Prey.* Because the optimal solution to many problems is not planned, it is believed that perhaps the present solution obtained is the intended prey or is near to the prey in WOA. Individual people in humpback whale communities will seek to upgrade their positions in the route of the prey once the prey position has been determined by the following equation:

$$\overrightarrow{A(t-1)} = \overrightarrow{A_{\text{prey}}(t)} - \vec{X}.\vec{Y}. \quad (3)$$

In Equation (3), the number of current iterations is denoted by $t$ and the vector current prey position is denoted by $\overrightarrow{A_{\text{prey}}(t)}$ and the coefficient vectors were denoted by $\vec{X}$ and $\vec{Y}$.

$$\vec{X} = 2\vec{r}.\vec{x} - \vec{x}, \quad (4)$$

$$\vec{Y} = \left|\vec{Z}.\overrightarrow{A_{\text{prey}}(t)} - \overrightarrow{A(t)}\right|. \quad (5)$$

In equation (4), the linearly decreasing parametric vector is denoted as $\vec{x}$ and it starts from 2 to 0 while the random vector is denoted by $\vec{r}$ within $[0, 1]$ and Equation (5); the absolute value of the coefficient is denoted by $\vec{Z}$, and it is illustrated as

$$\vec{Z} = 2\vec{r}. \quad (6)$$

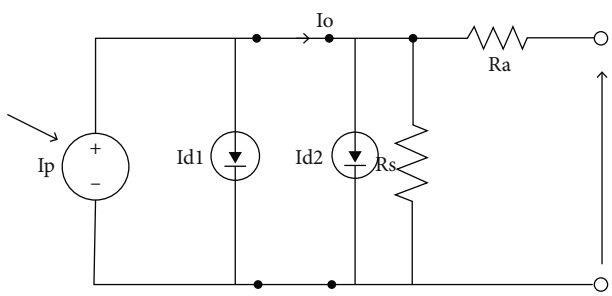


Figure 2: Equivalent circuit of the double-diode model.

*3.1.6. Bubble-Net Attacking.* A bubble-net attack occurs when humpback whales swim concurrently surrounding their victim in a spiral pattern in a confined circle. Both the expansion wide angle process and the iterative design are used in WOA to replicate their behavior. Elements of the population have the same cases in both methods during the optimization procedure. Aside from that, the precise mathematical design is given:

$$\overrightarrow{A(t+1)} = \left\{\overrightarrow{A_{\text{prey}}(t)} - \vec{X}.\vec{Y}, p < 0.5, e^{bl}\cos(2\pi l) + \overrightarrow{A_{\text{prey}}(t)}, p \geq 0.5.\right. \tag{7}$$

The element $b$ is specified to be constant in the preceding equation, and this is used to determine the spiral's logarithmic shape. The random variable is denoted as l inside the domain $[-1, 1]$, while $p$ is inside $[0, 1]$. A spiral equation is created among the location of the prey and the whale, which aids in the stimulation of a humpback whale's rotating motion.

$$\vec{Y} = \left|\vec{Z}.\overrightarrow{A_{\text{prey}}(t)} - \overrightarrow{A(t)}\right|. \tag{8}$$

*3.2. Prey Searching.* The whale optimization algorithm updates the population's position during the stage of seeking for prey using the following expression:

$$\overrightarrow{A(t+1)} = \overrightarrow{A_{\text{ran}}(t)} - \vec{X}.\vec{Y}. \tag{9}$$

In Equation (9), $\overrightarrow{A_{\text{ran}}(t)}$ represents the position vector of a random sector in the current population and based on the equation $\vec{Y}$ is computed:

$$\vec{Y} = \left|\vec{Z}.\overrightarrow{A_{\text{ran}}(t)} - \overrightarrow{A(t)}\right|. \tag{10}$$

During this phase, humpback whales are searched at random depending on their relative positions. The constriction wide angles method, in which the component of $\vec{X}$ is higher than 1, indicates that whales in the exploration are forcibly ejected from the prey position, is distinct from the algorithm, which investigates the having the greatest as per the modification of $\vec{X}$. To put it another way, the whale optimization algorithm at this point prioritizes worldwide search.

The mismatch between exploitation and exploration is typically a major issue affecting the success of classic swarm intelligence algorithms. Levy flight, on the other hand, is a non-Gaussian probability distribution method with an indefinite stage duration. This approach is also very unpredictable, with a course that resembles natural metabolic processes, which can aid swarm intelligence systems in balancing exploitation and exploration. As a result, the process is taken into account in this research [17]. In addition, some enhanced WOAs have been developed and implemented to the challenge of evaluating solar model parameters. Therefore, the principle of the no-free lunch dictates that more optimization techniques be developed to improve the problem's solution.

*3.3. Proposed Algorithm.* Multiple processes will be explained in great detail in this part, as well as the framework for the proposed technique [18]:

*3.3.1. Levy Fight.* Exploration and exploitation, as well as diversity and development, all benefit from unpredictability. Furthermore, the substance of randomized is chance of walking, which is a stochastic procedure that includes taking a sequence of randomized steps in a row. One of these haphazard procedures is levy flight. Levy flying has also been used as an improvement tool to increase the efficiency of some metaheuristic algorithms.

$$\text{Levy}(s) \sim |s|^{1-\gamma}, \gamma \epsilon (0, 2). \tag{11}$$

In Equation (11), $\gamma$ represents the exponential function based on the figure of levy distribution and $s$ denotes the accidental step and this could be defined by the following equation:

$$s = \frac{\tau}{|\vartheta|^{(1/\gamma)}}, \tag{12}$$

with $\vartheta$ and $\tau$ being the elements related to the normal distribution which is defined as $\tau \sim L(0, \sigma_\tau^2)$ and $\vartheta \sim L(0, \sigma_\vartheta^2)$. The derivation for $\sigma_\tau$ and $\sigma_\vartheta$ are given below:

$$\sigma_\tau = \left(\frac{\Gamma(1+\gamma).\sin(\pi\gamma/2)}{\Gamma(1+(\gamma/2)).\gamma.2^{(\gamma-1/2)}}\right)^{(1/\gamma)}, \quad \sigma_\vartheta = 1, \tag{13}$$

where $\Gamma$ represents the gamma function.

*3.3.2. Pattern Search.* Pattern search is widely recognized as a resident derivative-free enhancing approach that is useful to overcome many objective functions that are outside the reach of traditional optimization algorithms. The design search method starts with a set of dots, and the grid is created by adding the associated requirements to a set of integer multiples of a vertex named pattern. Furthermore, among the points on the grid, a point with superior fitness is chosen

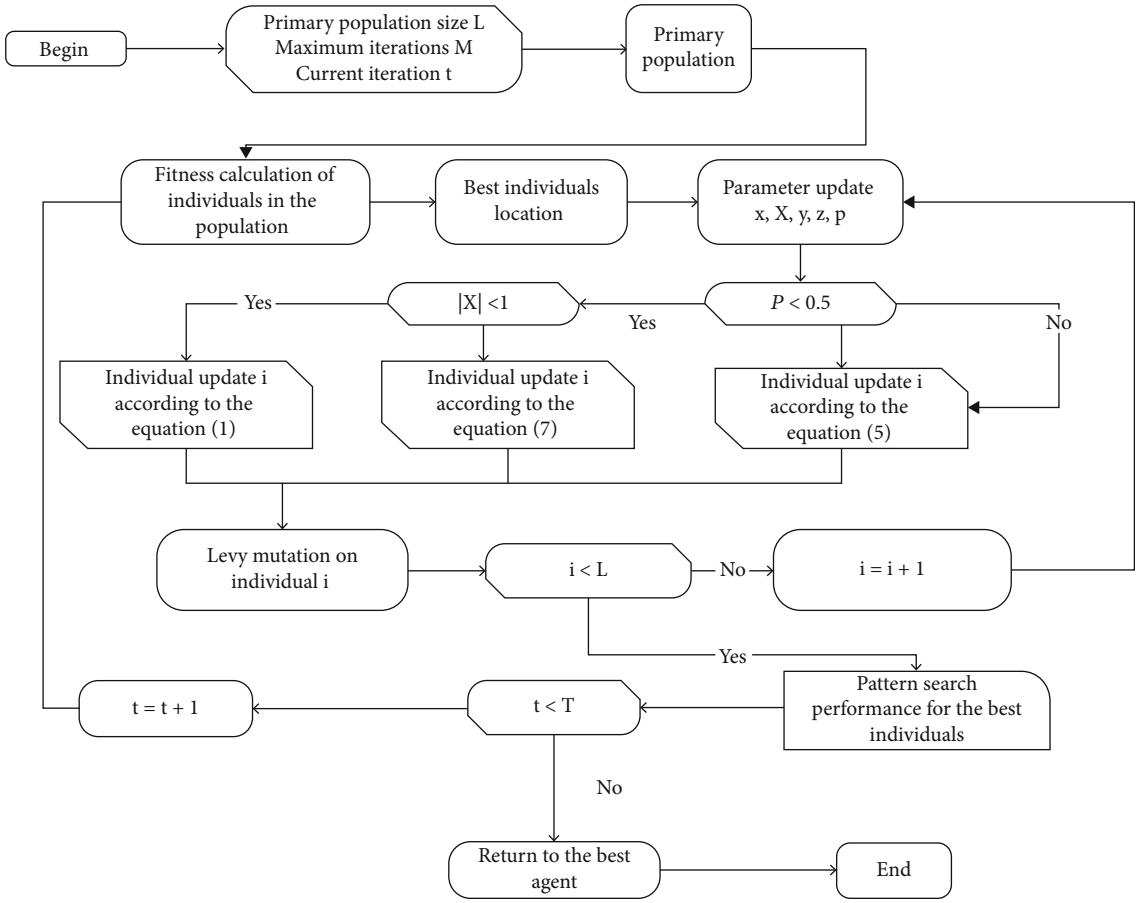


Figure 3: Framework of the modified whale optimization.

```
Initializing the Whale, A population;
Calculate each search agent's ability:
Lead_position = the best search agent
while (t > maximum no of repetition)
   for each search agent
   Upgrade x, X, Y, z, and p;
      if (p < 0.5)
      if (|X | <1)
         Upgrade the current search agent position by Equation (3)
      else if (|X | ≥1)
         Upgrade the current search agent position by Equation (9)
end if
else if (p ≥ 0.5)
   Upgrade the current search agent position by Equation (7)
      end if
   Carry on the levy flight using Equation (17) for each agent
      end for
With a pattern search to the best agent Lead_ position:
Check that a research officer energy out there the research space and revise it;
Compute the fitness of each search agent;
Upgrade Lead_ position if there is a better solution;
t = t + 1
end while
get back Lead_ position:
```

Algorithm 1: Modified whale optimization

Table 1: Parameter for three different models.

| Elements | Double or single diode | | Photovoltaic module | |
|---|---|---|---|---|
| | Inferior border | Superior border | Inferior border | Superior border |
| $I_p$ | — | 1 | — | 2 |
| $I_s$ | — | 1 | — | 50 |
| $R_s$ | — | 0.6 | — | 2 |
| $R_{sa}$ | — | 101 | — | 2000 |
| $L$ | 1 | 2 | 1 | 51 |
| $I_{s1}$ | — | 1 | — | 51 |
| $I_{s2}$ | — | 1 | — | 51 |
| $l_1$ | 1 | 2 | 1 | 51 |
| $l_2$ | 1 | 2 | 1 | 51 |

as the starting point for the following iteration. The pattern search is broken down into the following steps:

(i) Stage 1: the primary point $a_o$ was determined and the fitness $f(a_0)$ is computed.

(ii) Stage 2: the other point $a_i$ around the primary point $a_o$ is computed based on the Equation (14) by computing the objective fitness $f(a_i)$. When there is a point better than the $a_o$, then, stage 3 is performed or else stage 4 is performed.

$$a_o = a_i + u(j).N, \tag{14}$$

where $u(j)$ denotes the vector pattern in which $j \epsilon (1, 2...2d)$ in which $d$ is the dimension of the issue or challenge to be solved and $N$ represents the search stage

(i) Stage 3: based on Equation (15), $N$ has to be updated where $\beta > 1$ and the search space could be extended based on the equation. Stage 5 is executed.

$$N = \beta N \tag{15}$$

(i) Stage 4: according to Equation (16), $N$ has to be updated, where $\zeta < 1$ and this helps to narrow the search space. Stage 5 is executed.

$$N = \zeta N \tag{16}$$

(i) Stage 5: continue with stage 1 if the provided the required is not fulfilled; else, terminate the repetition and display the optimal point

*3.4. Modified Whale Optimization Algorithm Design.* In this study, the researcher suggested the modified whale optimization algorithm (MWOA). The prototype for MWOA is presented in Algorithm 1, and its flowchart is displayed in Figure 3. In the modified whale optimization algorithm, levy flight is used to increase the computational efficiency and prevent it from slipping into a locally optimal solution too soon [19]. So, to summarize, MWOA initially updates the populations using the core strategy of the classic optimization algorithm.

Then, there is the levy flight, which goes like this. The individuals $U_i$ that has experienced levy variation is produced using Equation (17), and its fitness $f(U_i)$ is determined at the same time.

$$U_i = A_i + \alpha.\text{Levy}(\gamma) \bigoplus (A_i - \text{Lead\_position}). \tag{17}$$

The optimization algorithm in the present inhabitants is chosen as the start position of pattern search after executing levy flight of the overall inhabitants. The optimization algorithm in the present inhabitants is chosen as the start position of pattern search after executing levy flights on the overall population. The pattern search's repetition completion criterion is met to 0.1 times the extreme number of MWOA repetitions, with the outer limits established to standard values [20].

*3.5. Time Complexity Analysis.* Before examining the suggested technique's temporal intricacy, it must first be classified in the following stages:

(i) Stage 1: Parameter initialization: the generation counter it is initialized, $T$ represent the number of maximum repetitions, $L$ represent the size of inhabitants $d$ represent the dimensionality of the spaced, the searching area edge is defined as $[ib, sb]$

(ii) Stage 2: random whale population initialization

(iii) Stage 3: the fitness of the whale is calculated and the best agent is chosen

(iv) Stage 4: whale update: based on Equations (3)–(15), the whale in the population is updated

(v) Stage 5: if the fitness of $U$ is better than the previous, do a levy flight based on Equation (17) to obtain the variation $U$, and then upgrade the inhabitants if the fitness of $U$ is better than the original. If one is just outside of the bounds, introduce new whales.

(vi) Stage 6: pattern search: then, upgrade Lead_position if the fitness of the applicant acquired before is greater than that of Lead_position by using the present maximum Lead_position to achieve a pattern search function to create the applicant location and come back if it is over the border

(vii) Stage 7: continue or stop the repetition process: stage 3 to stage 8 is repeated until the exit disorder is met and then get back to Lead_position.

Table 2: SDM result based on different algorithms.

| Parameter | Clonal particle swarm optimization | Enhanced Harris Hawks optimization | Local maximal search algorithm | Generalized oppositional teaching learning based optimization | Artificial bee swarm optimization | Chaotic whale optimization algorithm | Levy flight whale optimization algorithm | Modified whale optimization algorithm |
|---|---|---|---|---|---|---|---|---|
| $I_p$ | 0.7605 | 0.7612 | 0.76079 | 0.760782 | 0.7609 | 0.7606 | 0.7603 | 0.760773 |
| $I_s$ | 0.5 | 0.3615 | 0.31850 | 0.331553 | 0.30625 | 0.5045 | 0.4608 | 3.24 |
| $R_s$ | 0.0355 | 0.03584 | 0.03645 | 0.036265 | 0.033660 | 0.0342 | 0.0350 | 0.03676 |
| $R_{sa}$ | 59.013 | 53.755 | 53.32645 | 54.11545 | 52.2905 | 51.4779 | 75.4619 | 53.76690 |
| l | 1.5034 | 1.4815 | 1.47975 | 1.483825 | 1.47878 | 1.52783 | 1.5177 | 1.48128 |
| Root mean square error | $1.3901E-03$ | $1.0485E-03$ | $9.86401E-03$ | $9.8744E-04$ | $9.9125E-04$ | $1.5793E-03$ | $1.2353E-03$ | $9.8603E-04$ |

Table 3: Implemented information and related IAE based on MWOA.

| Element | Leisurely data | | Current information implemented | | Power information implemented | |
|---|---|---|---|---|---|---|
| | Voltage | Current | $I_{\text{simulated}}$ | $\text{IAE}_I(A)$ | $P_{\text{simulated}}$ | $\text{IAE}_P(A)$ |
| 1 | -0.2058 | 0.7642 | 0.764082568 | $8.25668E-06$ | -0.15717179 | $1.69840E-05$ |
| 2 | -0.1292 | 0.7625 | 0.762659235 | 0.006592630 | -0.09845932 | $8.51067E-05$ |
| 3 | -0.0589 | 0.7610 | 0.761352628 | 0.000852927 | -0.04476754 | $5.01346E-06$ |
| 4 | 0.0058 | 0.7610 | 0.760152393 | 0.000347610 | 0.004332870 | $1.98138E-06$ |
| 5 | 0.0645 | 0.7605 | 0.759054595 | 0.009455408 | 0.049034930 | $6.10734E-05$ |
| 6 | 0.1186 | 0.7592 | 0.758042628 | 0.000957376 | 0.089828055 | 0.000113450 |
| 7 | 0.1680 | 0.7573 | 0.757092745 | $9.27410E-06$ | 0.127040163 | $1.55611E-05$ |
| 8 | 0.2135 | 0.7573 | 0.755089265 | 0.000856834 | 0.161209725 | 0.000182678 |
| 9 | 0.2925 | 0.7556 | 0.753666678 | 0.000410741 | 0.192170218 | 0.000104534 |
| 10 | 0.3270 | 0.7470 | 0.751393928 | 0.000333323 | 0.220372138 | $9.74635E-05$ |

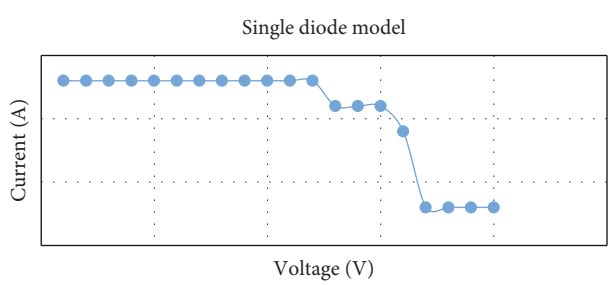


Figure 4: Current-voltage characteristic curve.

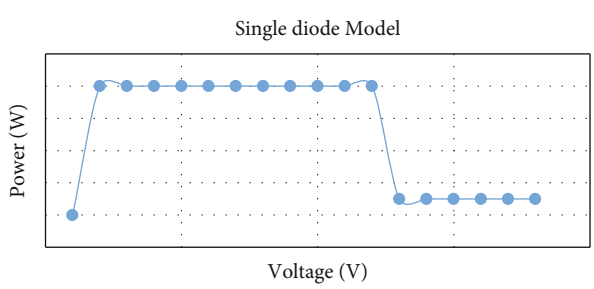


Figure 5: Power-voltage characteristic curve.

## 4. Result and Analysis

The characterization of solar cell and photovoltaic panel parameters is performed using the various datasets provided in the documentation to validate the functionality of the MWOA. These two sources of information, linked to the RTC solar cell and the PV Photo watt-PWP 201 unit, were extensively used to assess the effectiveness of the new methodologies. The RTC solar cell dataset covers 26 pairs of voltage and current values obtained under standard test settings (34°C, 1000 W/m$^2$powerstrength), whereas the Photo watt-PWP 201 dataset has 26 pairs of measurements obtained under standard operating situations (45°C light concentration).

In this section, MWOA was developed, and each investigation was ended when the number of repetitions (10,000) was reached. Table 1 shows the number of variations to be determined for the SDM, DDM, and PV modules. To verify the significance and durability of MWOA, it was used to determine the parameters for two distinct methods of photovoltaic units: thin-film photovoltaic unit ST40 and monocrystalline silicon photovoltaic unit SM55. Experimental information was acquired from their metadata volume,

Table 4: Comparison of modified whale optimization with three different models.

| Design | Technique | Maximum | Minimum | Mean | Standard deviation | Time cost (ms) |
|---|---|---|---|---|---|---|
| | MWOA | 0.00561032 | 0.00098610 | 0.00180882 | 0.00091695 | 1309 |
| Single diode model | LWOA | 0.4599370 | 0.00112372 | 0.01637348 | 0.01822289 | 192 |
| | PSWOA | 0.00375843 | 0.00098645 | 0.00176644 | 0.00057629 | 1285 |
| | MWOA | 0.0026340 | 0.00098605 | 0.00137715 | 0.00050242 | 4319 |
| Double diode model | LWOA | 0.04601360 | 0.00197693 | 0.00953997 | 0.01368630 | 206 |
| | PSWOA | 0.00369538 | 0.00098965 | 0.00177876 | 0.00075722 | 3299 |
| | MWOA | 0.0094305 | 0.00242788 | 0.00343323 | 0.00167525 | 1818 |
| Photovoltaic | LWOA | 0.27431198 | 0.00251423 | 0.11064790 | 0.12821915 | 193 |
| | PSWOA | 0.0171528 | 0.0024509 | 0.00350585 | 0.00203755 | 1694 |

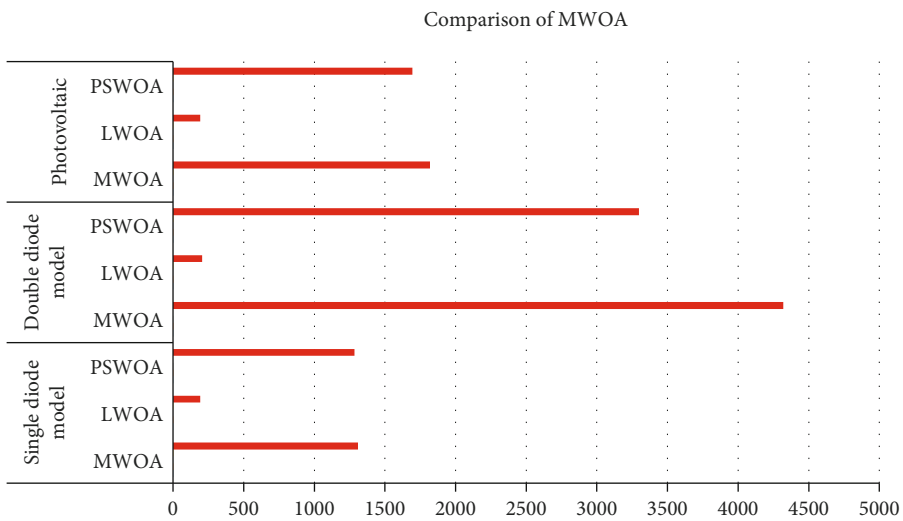


Figure 6: Comparison of the modified whale optimization algorithm.

which included information under various light intensities and temperature and pressure. The maximum repetitions and inhabitants' size were set to 5000 and 30 correspondingly, in this phase of the investigation.

*4.1. RTC Solar Cell.* The investigational outcomes of MWOA on double- and single-diode solar cells, as well as PV modules, will be detailed in this section. Because some competitive methods perform well on one model, but not for others, they may perform badly on others. As a result, the competitive method chosen for the three variables may vary. Yet, all computation parameters remain constant in the same system to ensure equality.

*4.2. Result of SDM.* The section presents the results, which include the standards of different variables in RMSE and SDM based on MWOA, as well as the results of the other different algorithms for comparison: ABSO, GOTLBO, LWOA, CPSO, LMSA, EHHO, and CWOA as in Table 2. Table 3 includes the relative errors (REs) and residual error (IAEs) between the experimental and simulated data, the IAE and RE between such information with their definition provided in Equations (18) (1)nd (19), correspondingly, further to reveal the validity of the results. Furthermore, IAE and RE can more naturally assist readers in observing the fault between the actual observed information and the information acquired by the imitation study at each quantity opinion, thereby displaying the suggested individual's efficiency. Figure 4 shows current and voltage characteristics, and Figure 5 shows power-voltage characteristic the best SDM achieved by MWOA.

$$\mathrm{IAE} = |I_{\mathrm{measured}} - I_{\mathrm{simulated}}|, \tag{18}$$

$$\mathrm{RE} = \frac{|I_{\mathrm{measured}} - I_{\mathrm{simulated}}|}{I_{\mathrm{measured}}}. \tag{19}$$

From the foregoing, it is clear that modified whale optimization employs two techniques: levy flight and pattern search. The mean value (mean), standard error (std), minimum (min), and maximum (max) of root mean square error are provided to further demonstrate the significance of these two processes to the suggested approach. Table 4 shows the comparison of modified whale optimization with three different models compares the outcomes of MWOA with variations that solely use one of these processes.

The graphic illustration of comparison is presented in Figure 6. The LWOA is assigned to the approach that only

incorporates levy flight, whereas PSWOA is assigned to the technique that only incorporates pattern search.

## 5. Conclusion

The unidentified constraints in the best models that characterize solar batteries and photovoltaic units are discovered using a modified whale optimization technique presented in this paper. Combining the levy flying approach with a pattern search tool yields the innovative MWOA method. The current best solution is utilized as the starting point for pattern search by MWOA, which then uses the population update approach of the basic WOA to explore for possible effective alternatives in the domain of this solution. Furthermore, levy flight is utilized to preserve the variety of replies, allowing you to search the entire field. Although MWOA is a population-based probabilistic estimates, it could still experience a community standstill for more complicated datasets. Improving the computational efficiency using other optimization methods is also a worthwhile direction for future research.

## Data Availability

The data used to support the findings of this study are included within the article. Further data or information is available from the corresponding author upon request.

## Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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