IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 5 April 2024, accepted 27 June 2024, date of publication 8 July 2024, date of current version 16 July 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3424416

RESEARCH ARTICLE

Mathematical Modeling for Solar Cell Optimization: Evaluating Sustainability With Different Diode Configurations

MANISH KUMAR SINGLA[1,2], JYOTI GUPTA[3], MURODBEK SAFARALIEV[4], HAMED ZEINODDINI-MEYMAND[5], (Member, IEEE), AND AHMAD JAVID GHANIZADEH[6]

[1]Department of Interdisciplinary Courses in Engineering, Chitkara University Institute of Engineering and Technology, Chitkara University, Chandigarh, Punjab 140401, India
[2]Applied Science Research Center, Applied Science Private University, Amman 11931, Jordan
[3]School of Engineering and Technology, K. R. Mangalam University, Gurugram, Haryana 122103, India
[4]Department of Automated Electrical Systems, Ural Federal University, 620002 Yekaterinburg, Russia
[5]Department of Electrical and Computer Engineering, Graduate University of Advanced Technology, Kerman 7631133131, Iran
[6]Danial Javid Electrical Engineering (DJEE) Company, Kabul 3001, Afghanistan

Corresponding authors: Hamed Zeinoddini-Meymand (h.zeinaddini@gmail.com) and Ahmad Javid Ghanizadeh (ghanizadeh@djee.af)

ABSTRACT It is widely acknowledged within the scientific community that solar cells serve as an environmentally friendly and sustainable source of renewable energy, making them highly versatile in their applications within both the industrial and residential sectors. Consequently, existing algorithms for solar cell design primarily focus on meeting the energy demands of domestic settings, necessitating the development of precise mechanisms that can cater to the needs of both domestic and industrial environments. In light of this, the author of this study proposes an enhanced version of the crow optimization algorithm by incorporating opposition-based learning, thereby ensuring improved exploration of the search space. The primary objective of this algorithm is to estimate the parameters of solar cells, which can be achieved by employing three distinct diode models: the single diode model, the double diode model, and the three-diode model. It is of utmost importance to accurately estimate the internal parameters in these models in order to optimize the performance of solar cells, particularly in industrial applications. An algorithm that incorporates the three-diode model is better suited for industrial use due to its superior ability to accurately represent the behavior of solar cells. In order to validate the efficiency of the proposed approach, RMSE and computational time is been recorded of each algorithm using similar approaches and datasets from solar cells and photovoltaic modules. Furthermore, the algorithm's exploration capability across complex optimization problems was assessed by subjecting it to various benchmark optimization functions. Based on the outcomes of these experiments and comparisons, it can be confidently affirmed that the proposed algorithm is not only effective but also efficient in effectively addressing the challenges associated with this specific problem domain.

INDEX TERMS One diode, two diodes, three diodes, benchmark test function, sustainability, solar cell, optimization, mathematical modeling.

I. INTRODUCTION

Solar Energy (SE) has gained significant attention and experienced rapid growth in recent times due to the ubiquitous presence of solar radiation worldwide [1]. Sustainable

The associate editor coordinating the review of this manuscript and approving it for publication was Bijoy Chand Chatterjee.

energy sources play a crucial role not only in the generation of electricity but also in the mitigation of environmental pollution. Distinguished from conventional energy sources that rely on fuel combustion, sustainable energy sources such as solar, wind, and hydropower have the ability to produce electricity without emitting harmful pollutants or hazardous emissions [1]. This remarkable characteristic of sustainable energy sources contributes significantly to the reduction of air pollution, consequently minimizing the associated health risks. Consequently, research in the field of SE has witnessed a notable increase between 1996 and 2016 [2]. Numerous research articles and projects have been released in recent years, showcasing the significance of proposing fresh and innovative methods to tackle the inherent challenges in this particular field. Furthermore, Photovoltaic Modules (PV) containing Solar Cells (SC) have experienced a surge in their utilization and application. According to a study cited in reference [3], the costs of solar energy systems witnessed a substantial decrease in the year 2016, subsequently leading to a surge in the demand for PV modules in several developing nations. Despite these positive developments, it is important to note that PV modules possess several limitations, the most prominent being their inefficiency, which can be adversely influenced by external factors such as inclement weather conditions. Additionally, the expenses associated with the maintenance of these modules can be quite substantial, as highlighted in reference [4]. Hence, it becomes imperative to explore and adopt innovative approaches to effectively address these challenges in the design and implementation of PV modules and SCs.

Scientists, engineers, and researchers use a complex mathematical model to help in the process of constructing solar cells. By modeling the several factors that control the behavior of the solar cells, this model helps to estimate the different parameters of the cells. In particular, the simulation is centered on the current-voltage relationship, or I-V. Two common models—the Single Diode (SD) model and the Double Diode (DD) model—are used to achieve this. By using electrical circuits, these models are intended to faithfully represent the nonlinear properties of solar cells. There are a number of essential elements in the SD and DD models that are critical to understanding how the solar cells behave and function. These constituents comprise the diode ideality factor, series resistance, photo-generated current, and diode saturation current. It is noteworthy that the exact arrangement of these components has a substantial impact on the overall efficacy and efficiency of photovoltaic panels and solar cell modules. The solar cell can be adequately characterized by five different factors in the Single Diode model, while seven parameters need to be taken into account in the Double Diode model. To attain the appropriate balance between current and voltage, which ultimately dictates the best possible functioning of the solar cells, it is critical to precisely estimate these values. These diode models have been used in many correlational research, and the outcomes that have been demonstrated are considered good. It is important to acknowledge that the SD and DD circuits have been painstakingly designed to specifically address the requirements of residential solar cells. As a result, the performance assessment of these circuits has only been carried out concerning their use in household settings. To address this specific issue, TD models have been presented as a novel approach, which also has the benefit of being equally applicable to solar modules [5]. As a result, the application of the TD model in an industrial context is now rendered feasible, thus broadening its potential scope.

A number of factors must be set up while designing diode circuits in order to get the desired output. One possible solution to this problem is to use an optimization strategy. Numerous implementations have been shown in the literature to be able to determine the optimal parameter configuration using numerical techniques. A nonlinear least-squares approach was used in research by [6] to extract the SC parameters from the Newton model. Moreover, in an additional study reported in [7], a representation for predicting the parameters in the DD model was developed using an approach based on the Lambert W-function. It is important to note that these methods have been shown to be effective in resolving the difficulties related to setting the parameters in diode circuits. Through the application of these techniques, practitioners may guarantee the attainment of the ideal parameter values, thus accomplishing the intended results for their diode circuits. Furthermore, these methodologies' use of numerical methods contributes to improving the precision and effectiveness of the parameter estimate procedure. Thus, it is clear that the layout of diode circuits may be efficiently aided by the use of both numerical approaches and optimization techniques. For the analytical computation of the I-V characteristics, there are additional methods that may be used [8]. Using a co-content function is one method that allows for a more accurate identification of these traits. Researchers in the field have investigated and assessed this approach, and several studies have shown its efficacy. A related comparison is given in another work by [9], which uses the SD model to evaluate three distinct analytical techniques for parameter extraction. The results of this investigation show that one of the approaches examined, the curve fitting method, produces erratic outcomes. Additionally, studies have looked at the application of a table-based technique for PV system analysis [10]. This approach requires a large amount of computer resources, albeit showing promising results. As a result, while selecting the best approach, experts have stressed the need of carefully weighing the trade-off between accuracy and computing requirements. In the paper by [11], a thorough comparison is made between the Levenberg-Marquardt algorithm and the Newton-Raphson method. Additionally, another study presented in [12] evaluates a total of six distinct methods, all of which are based on mathematical functions. However, it is important to note that deterministic methods, such as the ones discussed earlier, do have their limitations. One of the main drawbacks is the requirement of appropriately applying convexity and differentiability. This can often lead to the emergence of local optima, as the original solutions have a significant influence on the resulting outputs. As mentioned in reference [13], the DD model is subjected to the Newton-Raphson approach. As mentioned in reference [14], this causes notable differences between the estimated and measured current and voltage values. These disparities are distinguished not just by their exorbitant expenses but also by their restricted suitability for either SD or DD models.

Over the past few years, evolutionary computation algorithms (ECAs) have proven to be a popular method for calculating the parameters of solar panels and solar cells. In order to discover the most appropriate solution, an ECA may search multimodal search spaces and may use different operators. In order to approach parameter estimation of SC as an optimization problem, the Root Mean Square Error (RMSE) is typically used as an objective function. A diode model's RMSE is a measure of the difference between the estimated outcome and experimental data or manufacturer-supplied information.

PV modules can benefit from ECA by reducing the need for prior knowledge of the search space, one of which is the requirement for previous experience with PV modules. The result has been the development of several methods in the literature. In order to improve the predicted parameter accuracy of the DD model, [15] utilizes Genetic Algorithms (GA). As part of their investigation, Particle Swarm Optimization (PSO) was used to determine the parameters of solar cells. This methodology was applied to both synthetic and experimental data [16]. Simulated annealing (SA) may also be used to calculate the SD and DD values [17]. When compared to other approaches used for comparison, SA provides better results, according to the authors' findings. In 2016, it was suggested that utilizing SD and DD models, Cat Swarm Optimization (CSO) may be utilized to find the most optimum SC settings. To evaluate the caliber of CSO's solutions, they were also contrasted with those of other techniques used in the same investigation.

Based on a recently published equation, the Bacterial Foraging Algorithm (BFA) is presented in [19] as an alternative approach to describing the properties of SC with greater precision. Additionally, [20] provides different iterations of the Harmony Search (HS) technique to determine parameters that remain unknown in the single and double diode models of solar cells. For the purpose of identifying solar cell models, a variant of the Teaching-Learning-Based Optimization (TBLO) known as the Simplified Teaching-Learning Based Optimization (STBLO) is presented in [21]. In spite of the fact that these techniques offer good results, conventional ECA has been modified in order to improve accuracy even further. The iterative process of ECAs frequently substitutes chaotic maps for random values in solar cells. According to the Chaotic PSO [16], the SD and DD models perform better than the standard PSO. A similar approach, CWOA (Chaotic Whale Optimization Algorithm) [22], utilizes chaotic maps to generate more accurate solutions for SD and DD models based on actual SC and PV module data. In [23], data from earlier iterations is incorporated into a chaotic improved artificial bee colony (CIABC) in order to maintain data from earlier iterations. In spite of the presence of noise in the dataset, the results obtained with CIABC are more accurate. Additionally, an enhanced version of the Chaotic Gravitational Search Algorithm (CGSA) [24] is applied in this paper in order to overcome the difficulty of estimating PV cell parameters with precision by utilizing chaos to calculate an internal parameter during the optimization process. Despite their promise, these techniques still have difficulty reaching high levels of accuracy. In order to lower the cost of energy systems, accurate outputs are necessary in real-world applications such as solar PV or solar thermal [7]. A further disadvantage of the TD model is that it has only been applied to PSO [5], whereas the other methods have only been applicable to SD or DD models.

According to the literature study, researchers mostly use the fundamental PV solar cell models, single diode and double diode models, to estimate electrical parameters. Three diode model has received very little investigation because to its increased complexity as the number of unknown factors grows. However, the usage of three diode model PV cells is justified in terms of efficiency and precision in multicrystalline solar cells when compared to single diode and double diode model PV cells. The typical optimization approach, as described in the literature, was applied to three diode model, which takes longer to process. As a result, a more efficient technique with higher accuracy and shorter execution time must be designed and implemented for parameter extraction utilizing single diode, double diode and three diode models of PV cells.

The rest of the manuscript is arranged as follows. The solar diode mathematical modeling of each diode i.e. single double and triple is specified in section II. The problem formulation and objective function is described in details in section III. The detail structure of the proposed crow search algorithm is discussed in section IV. The CSA implementation for optimization is discussed in section V. The details results and discussions are provided in the section VI. In the last, the conclusions are summarized in section VII.

II. SOLAR DIODE MATHEMATICAL MODELING

To facilitate the design of solar cells and PV modules, the estimation of internal parameters of SC relies on a mathematical model. Electronic circuits based on diodes are commonly employed to model the behavior of SC. There has been a remarkable and substantial utilization of both the Single Diode (SD) and Double Diode (DD) models in the vast expanse of literature, as documented by various sources [25]. An even more recent and pioneering advancement in this field was the advent of the Three Diode (TD) circuit, which was introduced for the very same rationale [5]. This particular section meticulously delves into the intricacies of how these three models can be adeptly employed in the context of an optimization problem, thereby meticulously scrutinizing and evaluating their respective fundamental concepts and principles.

A. SINGLE DIODE MODEL

By utilizing a solitary diode, the photo-generated current source (I_{ph}) is effectively eradicated in this particular concept. It is important to highlight that the diode functions as a rectifier within this circuit, while also accommodating an additional parameter to incorporate its non-physical ideality [17]. Due to its inherent simplicity, this particular model can be successfully implemented in a diverse array of scenarios. However, accurately forecasting the five parameters associated with the Single Diode (SD) model presents a notable challenge, as the ideal configuration significantly impacts its overall performance. It is worth mentioning that the circuit diagram for the SD model is visually depicted in Figure 1.

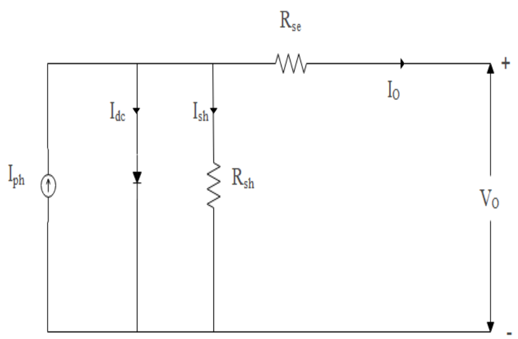


FIGURE 1. Single diode equivalent circuit model.

Figure 1 showcases the computation of the SC current (It) according to the following equation:

$$I_L = I_{ph} - I_{dc} - I_{sh} \tag{1}$$

In the equation, I_L, I_{ph}, I_{dc}, and I_{sh} denote the terminal current, photo generated current, diode current, and shunt resistor current, respectively. The utilization of the comparable Shockley diode equation, which is akin in nature to the given equation, offers the possibility to modify the internal characteristics of the diode to achieve a more precise and exact output. In light of this, it is plausible to reframe Equation (1) in an alternative manner, thereby yielding a revised expression that encapsulates the desired adjustments and refinements to enhance the overall accuracy and effectiveness of the diode's performance. This approach facilitates a more comprehensive understanding of the underlying principles and mechanisms governing the operation and behavior of the diode, enabling researchers and practitioners to fine-tune and optimize its internal parameters and functionalities to a greater degree.

$$\mathrm{I_L} = \mathrm{I_{ph}} - \mathrm{I}_{rsd}\left[\exp\left(\frac{\mathrm{q(V_O + I_O R_{se})}}{\mathrm{nKT}}\right) - 1\right] - \frac{\mathrm{V_O + I_O R_{se}}}{\mathrm{R_{sh}}} \tag{2}$$

In the equation, V_O represents the terminal voltage, I_{sd}corresponds to the diode saturation currents, and R_{se} and R_{sh} denote the series and shunt resistances, respectively. Additionally, the non-physical ideality factor is denoted by the variable n. Equation (2) incorporates the Shockley diode equation, which also includes certain physical constants. These constants include the charge on an electron (q = 1.602×10^{-19} C), the Boltzmann constant (k = 1.380×10^{-23} J/K), and the cell temperature (T in Kelvin). As mentioned earlier, the proper configuration of this model is evident in the output provided by V_O and I_O.

In order to obtain five unknown parameter ($I_{ph}, I_o, \alpha, R_S, R_{Sh}$) as mention earlier in introduction to obtain the I-V curve open circuit, short circuit, are used as described below:

At open circuit $I = 0$ and $V = V_{OC}$; then eq. (1) becomes equation (3);

$$0 = I_{ph} - I_{rsd}\left[exp\left(\frac{qV_{OC}}{nKT}\right) - 1\right] - \frac{V_{OC}}{R_{Sh}} \tag{3}$$

Therefore equation (4) is;

$$I_{ph} = I_{rsd}\left[exp\left(\frac{qV_{OC}}{nKT}\right) - 1\right] + \frac{V_{OC}}{R_{Sh}} \tag{4}$$

At short circuit $V = 0$ and $I = I_{SC}$; then eq. (1) becomes equation (5);

$$I_{SC} = I_{ph} - I_{rsd}\left[exp\left(\frac{qI_{SC}R_{Se}}{nKT}\right) - 1\right] - \frac{I_{SC}R_{Se}}{R_{Sh}} \tag{5}$$

Therefore equation (6) is;

$$I_{ph} = I_{SC} + I_{rsd}\left[exp\left(\frac{qI_{SC}R_S}{nKT}\right) - 1\right] + \frac{I_{SC}R_S}{R_{Sh}} \tag{6}$$

To achieve accurate results, the problem can be summarized as the estimation of the values of these parameters.

B. DOUBLE DIODE MODEL

The Single Diode (SD) model provides a reasonable approximation to real solar cells. According to the relevant literature [20], it is possible that the statement made may not be entirely accurate for various implementations. In order to address this issue, the Double Diode (DD) model has been proposed as a potential solution [20]. This model incorporates an additional diode to account for the recombination current and other non-ideal characteristics of the solar cell. The circuit diagram of the DD model can be observed in Figure 2, where both diodes are utilized to prevent the occurrence of a photo-generated current source.

Taking into account Figure 2, Equation (1) can be rephrased as follows:

$$I_L = I_{ph} - I_{dc1} - I_{dc2} - I_{sh} \tag{7}$$

In Equation (7), I_{dc1} and I_{dc2} represent the currents flowing through the first and second diodes, respectively. The remaining elements remain the same as in Equation (1). To adjust the internal configuration of the diodes, the Shockley equivalence

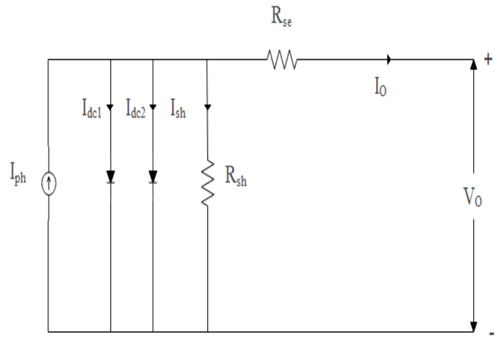


FIGURE 2. Model with double diode equivalent circuit.

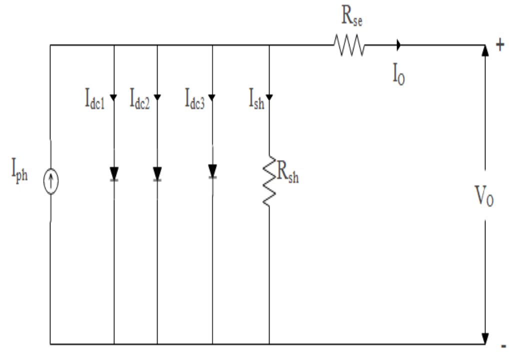


FIGURE 3. Three diode equivalent circuit model.

is employed, resulting in a modification of Equation (7) as shown in Equation (8).

$$I_L = I_{ph} - I_{rsd1}\left\lfloor \exp\left(\frac{q(V_O + I_O R_{se}}{n_1 KT}\right) - 1\right\rfloor - I_{rsd2}\left\lfloor \exp\left(\frac{q(V_O + I_O R_{se}}{n_2 KT}\right) - 1\right\rfloor - \frac{V_O + I_O R_{se}}{R_{sh}} \tag{8}$$

A double diode (DD) model is similar to the single diode (SD) model, since it consists of two diodes (d_1 and d_2), each with its own diffusion and saturation currents (I_{rsd1} and I_{rsd2}). The ideality factors n_1 and n_2 represent the diffusion diode and recombination diode, respectively. It is important to remember that the other components discussed in relation to Equation (2) are already known. It is therefore necessary to estimate precisely the following seven parameters of the DD circuit: $R_{se}, R_{sh}, I_{ph}, I_{rsd1}, I_{rsd2}, n_1, n_2$. To ensure the accuracy and dependability of the DD model, it is important to identify these previously mentioned elements carefully.

C. THREE DIODE MODEL

A high level of precision is essential when employing photovoltaic (PV) and solar cell models for the purpose of optimizing energy systems. In order to cater to the requirements of industrial environments, this particular model serves as a replacement for both the Single Diode (SD) and Double Diode (DD) versions. By incorporating the TD circuit, which takes into account recombination in the defect zones, a third diode is introduced in parallel with the two diodes that can be observed in the DD model, as demonstrated in Figure 3. It is crucial to note that the correct adjustment of the intrinsic settings of each diode is imperative, in accordance with the guidelines provided in reference [26]. Thus, it is of utmost importance to ensure that these adjustments are made accurately and in line with the recommendations outlined in the aforementioned reference.

With the inclusion of the third diode, Equation (1) is redefined as follows:

$$I_L = I_{ph} - I_{dc1} - I_{dc2} - I_{dc3} - I_{sh} \tag{9}$$

A three-diode (TD) model focuses on the analysis and inspection of recombination defects, expanding on the single diode and double diode models. This fault is critical to diode device efficiency and performance, and it is precisely addressed and accounted for in the TD model. A Shockley equivalency can be used to convey Equation (9) in a concise, accurate, and efficient manner. As a result of this approach, a deeper understanding of the mechanics and behavior of diodes can be gained. By providing engineers and researchers with a powerful tool to improve their understanding and analysis of diode devices, the TD model represents a significant development in the field of diode modeling.

$$I_O = I_{ph} - I_{rsd1}\left\lfloor \exp\left(\frac{q(V_O + I_O R_{se}}{n_1 KT}\right) - 1\right\rfloor - I_{rsd2}\left\lfloor \exp\left(\frac{q(V_O + I_O R_{se}}{n_2 KT}\right) - 1\right\rfloor - I_{rsd3}\left\lfloor \exp\left(\frac{q(V_O + I_O R_{se}}{n_3 KT}\right) - 1\right\rfloor - \frac{V_O + I_O R_{se}}{R_{sh}} \tag{10}$$

Based on Equation (10), the value of I_{rsd3} is influenced by the same set of parameters as I_{rsd1} and I_{rsd2} in the Double Diode (DD) model. In the Three Diode (TD) model, a total of nine parameters govern the current-voltage relationship in the solar cell. These parameters include R_{se}, R_{sh}, I_{ph}, I_{rsd1}, I_{rsd2}, I_{rsd3}, n_1, n_2, and n_3.

III. PROBLEM FORMULATION AND OBJECTIVE FUNCTION

By treating the mathematical models of Single Diode (SD), Double Diode (DD), and Three Diode (TD) as global optimization problems, an objective function can be established to evaluate the quality of parameter sets based on a given dataset. In essence, the objective function measures the degree of accuracy in approximating the current-voltage (I-V) characteristics of the physical solar cell using the values predicted by the mathematical model. For the SD model, the error function can be expressed as:

$$f_{SD}(V_t, I_t, x) = I_L - I_{ph} - I_{rsd}\left\lfloor \exp\left(\frac{q(V_O + I_O R_{se}}{nKT}\right) - 1\right\rfloor - \frac{V_O + I_O R_{se}}{R_{sh}} \tag{11}$$

For the DD model, the error function can be expressed as:

$$\begin{aligned}
&\mathrm{f_{DD}}(V_t, I_t, \mathrm{x}) \\
&\quad = \mathrm{I_L} - \mathrm{I_{ph}} - \mathrm{I_{rsd1}}\left[\exp\left(\frac{\mathrm{q(V_O + I_OR_{se}}}{\mathrm{n_1KT}}\right) - 1\right] \\
&\qquad - \mathrm{I_{rsd2}}\left[\exp\left(\frac{\mathrm{q(V_O + I_OR_{se}}}{\mathrm{n_2KT}}\right) - 1\right] - \frac{\mathrm{V_O + I_OR_{se}}}{\mathrm{R_{sh}}}
\end{aligned} \tag{12}$$

For the TD model, the error function can be expressed as:

$$\begin{aligned}
&\mathrm{f_{TD}}(V_t, I_t, \mathrm{x}) \\
&\quad = \mathrm{I_L} - \mathrm{I_{ph}} - \mathrm{I_{rsd1}}\left[\exp\left(\frac{\mathrm{q(V_O + I_OR_{se}}}{\mathrm{n_1KT}}\right) - 1\right] \\
&\qquad - \mathrm{I_{rsd2}}\left[\exp\left(\frac{\mathrm{q(V_O + I_OR_{se}}}{\mathrm{n_2KT}}\right) - 1\right] \\
&\qquad - \mathrm{I_{rsd3}}\left[\exp\left(\frac{\mathrm{q(V_O + I_OR_{se}}}{\mathrm{n_3KT}}\right) - 1\right] - \frac{\mathrm{V_O + I_OR_{se}}}{\mathrm{R_{sh}}}
\end{aligned} \tag{13}$$

In equations (11)-(13), V_t and I_t represent the measured values of voltage and current from the real solar cell, respectively. In equation (11), the solution vector $x = [R_{se}, R_{sh}, I_{ph}, I_{rsd1}$ and $n_1]$ corresponds to the SD model, while for the DD model, $x = [R_{se}, R_{sh}, I_{ph}, I_{rsd1}, I_{rsd2}, n_1,$ and $n_2]$, and for the TD model, $x = [R_{se}, R_{sh}, I_{ph}, I_{rsd1}, I_{rsd2}, I_{rsd3}, n_1, n_2,$ and $n_3]$. The functions f_{SD}, f_{DD}, and f_{TD} assess the similarity between the output of each circuit and the desired current value. In this way, it is clearly stated that the optimization problem is a laborious process of finding a parameter arrangement that minimizes the error resulting from the difference between the estimated current derived from complex diode models and the desired current derived from the desired current. The unbreakable Root Mean Squared Error (RMSE), defined specifically as the unbreakable Root Mean Squared Error (RMSE), must be carefully selected to complete this rather difficult task. One must construct the objective function carefully, which is defined as the unbreakable Root Mean Squared Error (RMSE). The RMSE, as an outstanding mathematical metric, is crucial for determining the overall effectiveness, or lack thereof, of an optimization approach, thus making it an indispensable tool for researchers.

$$\mathrm{RMSE} = \sqrt{\frac{1}{\mathrm{N}}\sum\nolimits_{\mathrm{i}=1}^{\mathrm{N}}\left(\mathrm{f_i}\left(\mathrm{V_t}, \mathrm{I_t}, \mathrm{x}\right)\right)} \tag{14}$$

In equation (14), the parameter i is used to select the specific diode model being evaluated. For the assessment to be successful, it is necessary to have a dataset, which can be gathered from product documentation or generated through experimental procedures. Despite direct input from manufacturers, numerical values in datasets may contain errors, even if they were obtained directly from manufacturers. Photovoltaic (PV) panels and solar cells can be adversely affected by these errors; however, they can also give rise to search spaces that exhibit multiple modes when attempting to optimize parameters. These factors significantly impact the effectiveness of the search strategies [27].

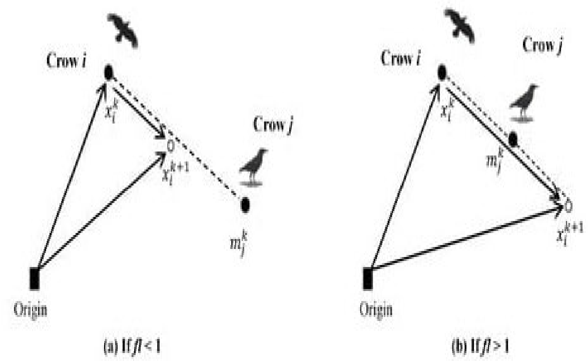


FIGURE 4. Schematic of CS in state 1.

Random initialize the position of a flock of crow

Evaluate the position &fitness function of the crow

Initialize the memory of each crow

While ($t < iter_{max}$)

For i = 1 to N

Random choose one of the crows to follow

Define an awareness probability

If ($r_i \geq AP_i^t$)

$P_i^{t+1} = P_i^t + r_i * f1_i^t * (M_j^t - P_i^t)$

Else

P_i^{t+1} = random position of the search space

End if

End For

Check the feasibility of new positions

Evaluate the new position of the crows

Update the memory of crows

End while

FIGURE 5. Pseudocode of CS.

IV. PROPOSED CROW SEARCH ALGORITHM

Among all species of avian creatures, the corvids, commonly known as crows, are widely acknowledged to possess an extraordinary level of intelligence. They boast the largest brain size when compared to their physical dimensions.

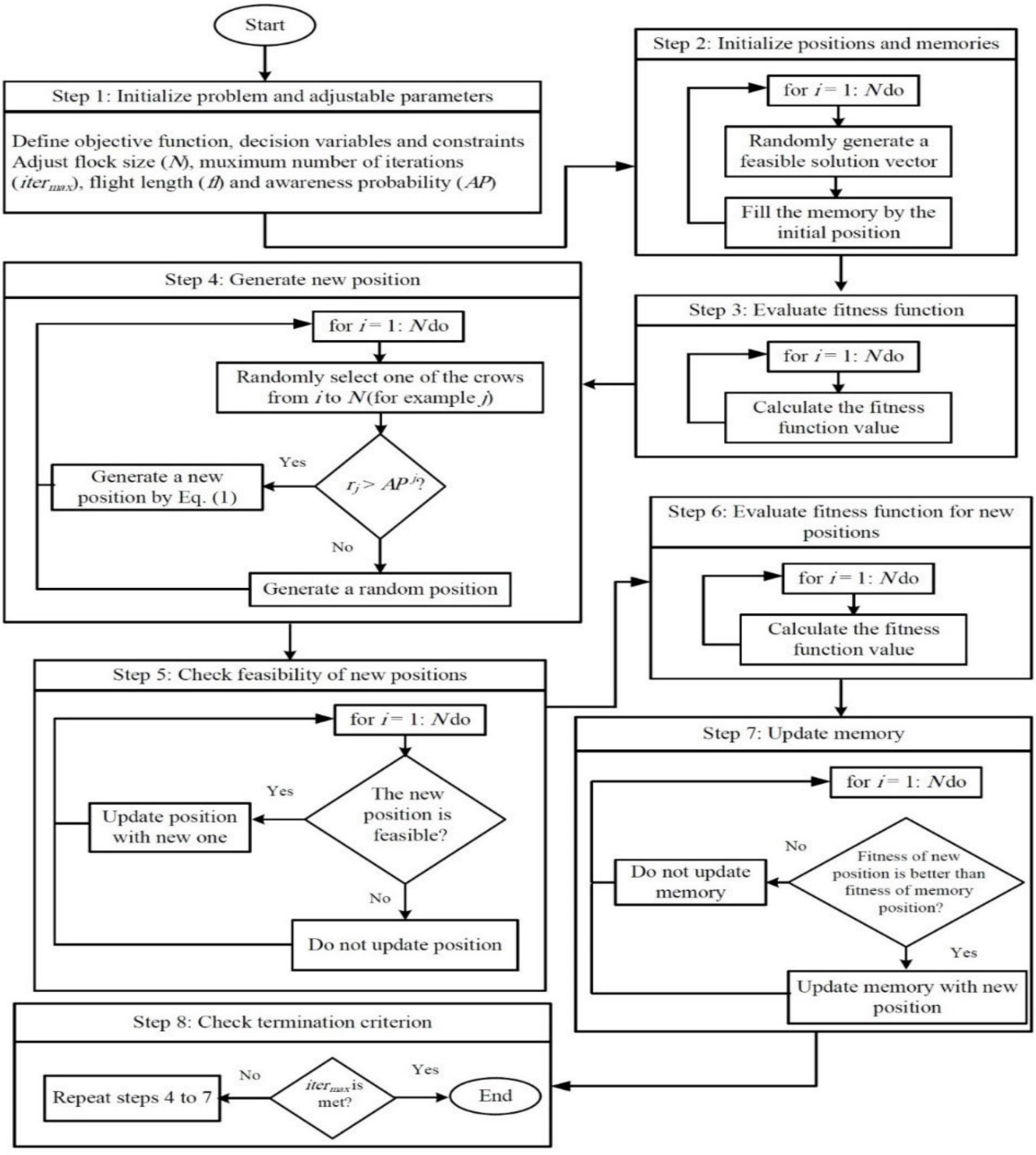


FIGURE 6. Flow chart of CS.

It is worth noting, however, that their brain-to-body ratio is smaller than that of humans, which implies that their brains are comparatively smaller. The astuteness exhibited by crows has been abundantly illustrated in numerous instances. For instance, during mirror tests conducted on them, they have demonstrated a remarkable sense of self-awareness, indicating a higher cognitive capacity. Additionally, they have exhibited the remarkable ability to fashion tools, further

TABLE 1. Benchmark test functions.

Function	Dim	Range
$F_1(k) = \sum_{j=1}^{m} k_j^2$	40	[-100, 100]
$F_2(k) = \sum_{j=1}^{m} \lvert k \rvert + \prod_{j=1}^{m} \lvert x \rvert$	40	[-10, 10]
$F_3(k) = \sum_{j=1}^{m} \left(\sum_{j=1}^{m} k_j^2\right)^2$	40	[-100, 100]
$F_4(k) = max_j \lvert k_j \rvert, 1 \le j \le m$	40	[-100, 100]
$F_5(k) = \sum_{j=1}^{m-1} [100(k_{j+1} - k_j^2)^2 + (k_j - 1)^2]$	40	[-30, 30]
$F_6(k) = \sum_{j=1}^{m} (\lvert k_j + 0.5 \rvert)^2$	40	[-100, 100]
$F_7(k) = \sum_{j=1}^{m} ik_j^4 + random[0,1]$	40	[-1.28, 1.28]
$F_8(k) = \sum_{j=1}^{m} -k_j \sin\left(\sqrt{\lvert k_j \rvert}\right)$	40	[-500, 500]
$F_9(k) = \sum_{j=1}^{m} [k_j^2 - 10\cos(2\pi k_j) + 10]$	40	[-5.12, 5.12]
$F_{10}(k) = -20\exp\left(-0.2\sqrt{(1/m)\sum_{j=1}^{m} k_j}\right) - \exp\left((1/m)\sum_{j=1}^{m} \cos(2\pi k_j) + 20 + e\right)$	40	[-32, 32]

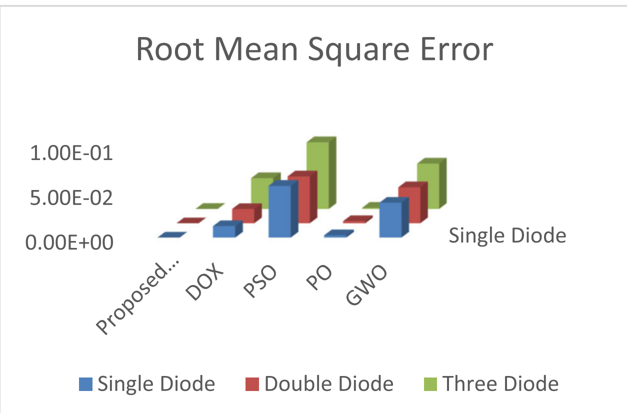


FIGURE 7. RMSE of all models.

attesting to their resourcefulness. It is fascinating to observe that when faced with an intrusion, crows go above and beyond in their communication skills, alerting their fellow crows by recognizing each other's facial features. Remarkably, these

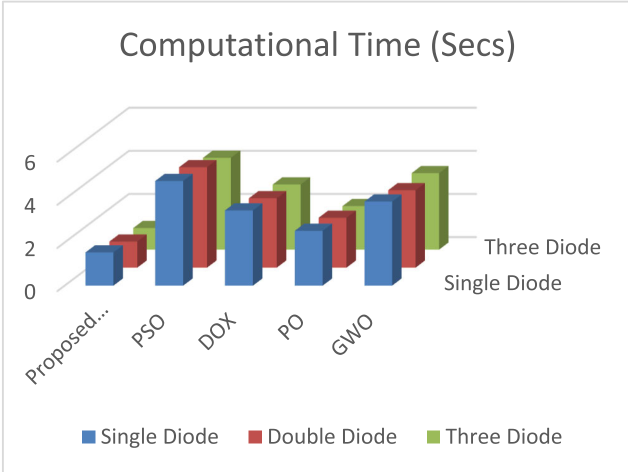


FIGURE 8. Computational time of all models.

avian creatures are not only adept communicators, but they also display a high level of proficiency in tool use. Moreover, their cognitive prowess extends to their ability to remember the precise locations where they have hidden their food for an astonishing duration of several months [28].

Crows are highly intelligent creatures that engage in a complex and strategic behavior known as thievery. In this behavior, crows meticulously examine the habits and behaviors of other birds, allowing them to identify the precise location where their potential victims store their valuable resources, such as food. Once the crows have gathered this crucial information, they patiently await the opportune moment when the rightful owner of the resources is absent, allowing them to swoop in and seize their ill-gotten gains. Interestingly, crows do not simply rely on their initial successful theft; rather, they take additional measures to ensure that their future thievery endeavors are equally as fruitful. They do so by relocating their hiding spots, thereby minimizing the chances of their hidden treasures being discovered and pilfered. This adaptive behavior showcases the crows' exceptional ability to learn from their personal experiences as thieves and effectively anticipate the actions of potential thieves to safeguard their precious caches from theft [29].

Based on the aforementioned intelligent behaviors that have been elucidated above, the present study embarks on the development of a cutting-edge metaheuristic algorithm termed CSA, which is anchored on a population-based approach. It is crucial to delineate the fundamental principles that underlie the CSA algorithm, as they serve as the guiding framework for its implementation and subsequent success. The following are some of the principles of CSA:

- The crow is a species that lives in flocks.
- Crows become familiar with the locations of their hiding places.
- Stealing occurs when crows follow each other.
- To protect their stockpiles from thieves, crows guard their nests.

TABLE 2. Results statistical data.

Algorithms	Function	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10
PSO	Mean	1.75E+03	1.26E+01	3.98E+04	7.24E+01	8.42E+06	3.28E+03	2.38	-1.43E+03	2.63E+02	1.40E+01
	SD	1.70E+03	2.31E+01	5.45E+03	1.47E+01	2.22E+07	8.69E+03	8.20	1.55E+02	2.06E+01	5.63
GWO	Mean	3.26E+01	5.01	1.10E+04	1.08E+01	3.62E+06	1.98E+03	1.66	-3.86E+03	7.96E+01	4.51
	SD	1.26E+02	2.81	1.78E+04	2.33E+01	3.58E+06	1.61E+03	1.04	2.61E+02	8.52E+01	6.69
DOX	Mean	6.19E-15	4.31E-10	5.86E+01	1.03E-03	2.68E+01	1.79	3.18E-03	-4.38E+03	1.46	9.14E-09
	SD	1.01E-14	4.63E-10	9.54E+01	1.10E-03	9.02E-01	2.35E-01	2.78E-03	2.37E+02	3.30	1.15E-08
PO	Mean	2.90E-15	4.47E-20	3.01E-09	1.32E-08	2.67E+01	1.31	1.26E-03	-6.72E+03	9.52E-01	3.29E-14
	SD	1.12E-14	4.63E-20	5.25E-09	1.78E-08	3.84E-01	3.25E-01	6.83E-04	6.38E+02	3.69	1.48E-14
PROPOSED ALGORITHM	Mean	0	2.76E-109	0	2.83E-92	1.95E-01	2.42E-06	6.87E-05	-1.26E+04	0	8.88E-17
	SD	0	6.00E-109	0	5.64E-92	2.81E-01	5.41E-06	2.88E-05	1.10E-01	0	0

TABLE 3. Estimating parameters for photovoltaic cell using the single diode model.

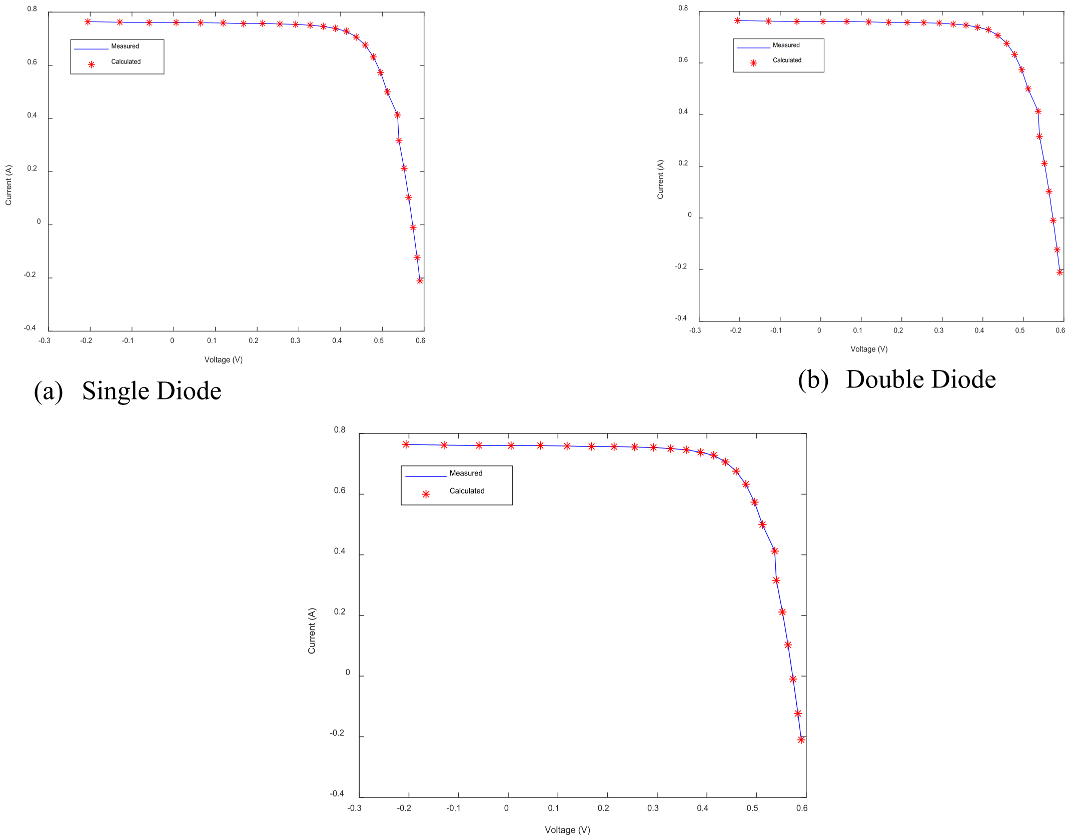
Parameters/ Algorithm	Ipv	n1	Rse	Rsh	Irsd1	RMSE	Computational Time
Proposed Algorithm	0.8771	1.4924	0.0833	29.394	0.7560	1.01E-07	1.073
DOX	6.4479	1.5459	0.1082	368.109	3.7E-07	1.28E-02	1.489
PSO	8.5018	1.7066	0.3153	322.346	6.3E-07	5.77E-02	1.865
PO	8.1952	1.3177	0.0625	288.582	4E-07	2.50E-03	1.427
GWO	9.5989	1.5756	0.0612	133.121	3.6E-07	3.89E-02	1.591

TABLE 4. Estimating parameters for photovoltaic cell using the double diode model.

Parameters/ Algorithm	I_{pv}	n_1	n_2	R_{se}	R_{sh}	I_{rsd1}	I_{rsd2}	RMSE	Computational Time
Proposed Algorithm	0.6944	1.0300	1.0368	0.0132	25.462	0.4218	0.1825	2.1E-07	1.127
DOX	8.3456	1.4718	1.4873	0.2662	438.823	4.1E-07	1.04E-07	1.59E-02	1.521
PSO	8.2138	1.6907	1.5822	0.1230	278.119	5.7E-07	4.57E-07	5.22E-02	1.947
PO	8.2133	1.4612	1.7156	0.1256	309.348	5.3E-07	4.39E-07	2.38E-03	1.468
GWO	8.2134	1.7232	1.6100	0.1341	326.564	5.5E-07	5.19E-07	4.01E-02	1.611

TABLE 5. Estimating parameters for photovoltaic cell using the three diode model.

Parameters/ Algorithm	I_{pv}	n_1	n_2	n_3	R_{se}	R_{sh}	I_{rsd1}	I_{rsd2}	I_{rsd3}	RMSE	Computational Time
Proposed Algorithm	0.7753	1.3097	1.4853	1.7983	0.0620	1.2036	2.2E-07	0	4.1E-06	1.89E-07	1.143
DOX	8.2129	1.6082	1.5063	1.6141	0.1295	367.112	5.9E-07	3.4E-07	3.3E-07	3.43E-02	1.867
PSO	8.2126	1.8693	1.5066	1.5162	0.1077	339.696	5.7E-07	6.03E-07	6.04E-07	7.40E-02	2.713
PO	8.2135	1.4788	1.5686	1.9717	0.0819	188.514	6.6E-07	4.5E-07	8.37E-07	1.24E-03	1.794
GWO	8.2131	1.6506	1.4213	1.6219	0.1487	390.744	3.04E-07	4.06E-07	1.75E-07	5.04E-02	1.948



(a) Single Diode

(b) Double Diode

(c) Three Diode

FIGURE 9. I-V curve of all models.

TABLE 6. Computational time (Secs) of all three diode models.

Algorithm	Single Diode	Double Diode	Three Diode
Proposed Algorithm	1.541	1.210	1.002
PSO	4.854	4.657	4.258
DOX	3.487	3.215	3.021
PO	2.541	2.312	2.018
GWO	3.897	3.587	3.547

A d-dimensional environment is believed to contain a large number of crows. $Iter_{max}$ is the maximum number of iterations and crow j position in the search space at time ($iter$) $iter$ is described by a vector. It is estimated that there are N crows in the flock. It is believed that every crow has a memory in which it stores information regarding where it hides. During iteration $iter$ by, the location of Crow j hiding spot is shown. Until now, this has been the best position j have been able to obtain. Certainly all crows retain a memory of the location of their most memorable experiences. In order to find a more appropriate place to hide and eat, crows wander around their surroundings.

Assume that at iteration $iter$, crow j wants to visit its hiding place, $m^{j,iter}$. At this iteration, crow i decides to follow crow j to approach to the hiding place of crow j. In this case, two states may happen:

Stage 1: Crow j does not know that crow i is following it. As a result, crow i will approach to the hiding place of crow j. As a result, the new position of crow i is shown in Equation (15):

$$x^{i,iter+1} = x^{i,iter} + r_i \times fl^{i,iter} \times \left(m^{j,iter} - x^{i,iter}\right) \tag{15}$$

where r_i is a random number with uniform distribution between 0 and 1 and $fl^{i.iter}$ denotes the flight length of crow i at iteration $iter$.

Figure 4 shows the schematic of this state and the effect of fl on the search capability. Small values of fl leads to local search (at the vicinity of $x^{i,iter}$) and large values results in global search (far from $x^{i,iter}$). As Figure 4 (a) shows, if the value of fl is selected less than 1, the next position of crow i is on the dash line between $x^{i,iter}$ and $m^{j,iter}$. As Figure 4 (b) indicates, if the value of fl is selected more than 1, the next position of crow i is on the dash line which may exceed $m^{j,iter}$.

Stage 2: Crow j knows that crow i is following it. As a result, in order to protect its cache from being pilfered, crow

TABLE 7. I-V curve and IAE of all three diode models.

V_L (Measured) (V)	I_L (Measured) (A)	Single Diode		Double Diode		Three Diode	
		I_L (Calculated) (A)	IAE	I_L (Calculated) (A)	IAE	I_L (Calculated) (A)	IAE
-0.2057	**0.7640**	0.7638	0.0002	0.7643	0.0003	0.7647	0.0007
-0.1291	**0.7620**	0.7622	0.0002	0.7618	0.0002	0.7626	0.0006
-0.0588	**0.7605**	0.7603	0.0002	0.7608	0.0003	0.7600	0.0005
0.0057	**0.7605**	0.7610	0.0005	0.7601	0.0004	0.7605	0
0.0646	**0.7600**	0.7596	0.0004	0.7607	0.0007	0.7595	0.0005
0.1185	**0.7590**	0.7593	0.0003	0.7587	0.0003	0.7597	0.0007
0.1678	**0.7570**	0.7564	0.0006	0.7574	0.0004	0.7572	0.0002
0.2132	**0.7570**	0.7575	0.0005	0.7566	0.0004	0.7566	0.0004
0.2545	**0.7555**	0.7553	0.0002	0.7558	0.0003	0.7554	0.0001
0.2924	**0.7540**	0.7538	0.0002	0.7544	0.0004	0.7538	0.0002
0.3269	**0.7505**	0.7508	0.0003	0.7502	0.0003	0.7515	0.0010
0.3585	**0.7465**	0.7461	0.0004	0.7464	0.0001	0.7475	0.0010
0.3873	**0.7385**	0.7390	0.0005	0.7380	0.0005	0.7392	0.0007
0.4137	**0.7280**	0.7284	0.0004	0.7285	0.0005	0.7275	0.0005
0.4373	**0.7065**	0.7060	0.0005	0.7063	0.0002	0.7071	0.0006
0.4590	**0.6755**	0.6760	0.0005	0.6759	0.0004	0.6751	0.0004
0.4784	**0.6320**	0.6315	0.0005	0.6329	0.0009	0.6314	0.0006
0.4960	**0.5730**	0.5726	0.0004	0.5737	0.0007	0.5730	0
0.5119	**0.4990**	0.5001	0.0011	0.4997	0.0007	0.5013	0.0023
0.5365	**0.4130**	0.4132	0.0002	0.4124	0.0006	0.4150	0.0020
0.5398	**0.3165**	0.3169	0.0004	0.3159	0.0006	0.3170	0.0005
0.5521	**0.2120**	0.2122	0.0002	0.2113	0.0007	0.2139	0.0019
0.5633	**0.1035**	0.1030	0.0005	0.1030	0.0005	0.1036	0.0001
0.5736	**-0.0100**	-0.0100	0	-0.0098	0.0002	-0.0097	0.0003
0.5833	**-0.1230**	-0.1233	0.0003	-0.1232	0.0002	-0.1231	0.0001
0.5900	**-0.2100**	-0.2109	0.0009	-0.2101	0.0001	-0.2114	0.0014
SUM			**0.0104**		**0.0109**		**0.0173**

j will fool crow i by going to another position of the search space.

Totally, states 1 and 2 can be expressed as in Equation (16):

$$x^{i,iter+1} = \begin{cases} x^{i,iter} + r_i \times fl^{i,iter} \times \left(m^{j,iter} - x^{i,iter}\right) & r_j \geq AP^{j,iter} \\ a\ random\ position & otherwise \end{cases} \tag{16}$$

where r_j is a random number with uniform distribution between 0 and 1 and $AP^{j,iter}$ denotes the awareness probability of crow j at iteration *iter*.

A metaheuristic algorithm should be used in order to achieve a good balance between diversification and intensification [30]. There are several factors that affect CSA's initiation, intensification, and diversification and the awareness probability (AP) is one of these variables. A decrease in the awareness probability value results in CSA focusing its search efforts more likely to be centered on a small area in which a workable solution can be found at the moment. In other words, employing low AP values results in more intense intensification than employing high AP values.

CSA preferred to search globally (randomization) instead of searching in the neighborhood of already viable solutions when the awareness probability value decreased, and as a result, CSA prefers to search in the neighborhood of already viable solutions when the awareness probability value increased. Therefore, it is important to use AP values that are high in order to promote variety.

V. CSA IMPLEMENTATION FOR OPTIMIZATION

A pseudocode and flowchart for the CSA, which is a computational algorithm used for solving a specific problem, has been visually displayed in Figure 5 and Figure 6.

TABLE 8. P-V curve and IAE of all three diode models.

V_L (Measured) (V)	P_L (Measured) (W)	Single Diode P_L (Calculated) (W)	Single Diode IAE	Double Diode P_L (Calculated) (W)	Double Diode IAE	Three Diode P_L (Calculated) (W)	Three Diode IAE
-0.2057	**-0.1571**	-0.1571	0.00004	-0.1572	0.00006	-0.1572	0.00014
-0.1291	**-0.0983**	-0.0984	0.00003	-0.0983	0.00003	-0.0984	0.00008
-0.0588	**-0.0447**	-0.0447	0.00001	-0.0447	0.00002	-0.0446	0.00003
0.0057	**0.0043**	0.0043	0	0.0043	0	0.0043	0
0.0646	**0.0490**	0.0490	0.00003	0.0491	0.00005	0.0490	0.00003
0.1185	**0.0899**	0.0899	0.00004	0.0899	0.00004	0.0900	0.00008
0.1678	**0.1270**	0.1269	0.00010	0.1270	0.00007	0.1270	0.00003
0.2132	**0.1613**	0.1614	0.00011	0.1613	0.00009	0.1613	0.00009
0.2545	**0.1922**	0.1922	0.00005	0.1923	0.00008	0.1922	0.00003
0.2924	**0.2204**	0.2204	0.00006	0.2205	0.00012	0.2204	0.00006
0.3269	**0.2453**	0.2454	0.00010	0.2452	0.00010	0.2456	0.00033
0.3585	**0.2676**	0.2674	0.00014	0.2675	0.00004	0.2679	0.00036
0.3873	**0.2860**	0.2862	0.00019	0.2858	0.00019	0.2862	0.00027
0.4137	**0.3011**	0.3013	0.00017	0.3013	0.00021	0.3009	0.00021
0.4373	**0.3089**	0.3087	0.00022	0.3088	0.00009	0.3092	0.00026
0.4590	**0.3100**	0.3102	0.00023	0.3102	0.00018	0.3098	0.00018
0.4784	**0.3023**	0.3021	0.00024	0.3027	0.00043	0.3020	0.00029
0.4960	**0.2842**	0.2840	0.00020	0.2845	0.00035	0.2842	0
0.5119	**0.2554**	0.2560	0.00056	0.2557	0.00036	0.2566	0.00118
0.5365	**0.2215**	0.2216	0.00011	0.2212	0.00032	0.2226	0.00107
0.5398	**0.1708**	0.1710	0.00022	0.1705	0.00032	0.1711	0.00027
0.5521	**0.1170**	0.1171	0.00011	0.1166	0.00039	0.1180	0.00105
0.5633	**0.0583**	0.0580	0.00028	0.0580	0.00028	0.0583	0.00006
0.5736	**-0.0057**	-0.0057	0	-0.0056	0.00011	-0.0055	0.00017
0.5833	**-0.0717**	-0.0719	0.00017	-0.0718	0.00012	-0.0718	0.00006
0.5900	**-0.1239**	-0.1244	0.00053	-0.1239	0.00006	-0.1247	0.00083
SUM			**0.00393**		**0.00408**		**0.00715**

The purpose of this pseudocode is to provide a clear and concise representation of the various steps involved in implementing the CSA. It serves as a guide for programmers and researchers who wish to utilize the CSA in their work, allowing them to understand the sequential nature of the implementation process. In this particular section, the steps required to successfully implement the CSA are presented in a systematic and methodical manner. Each step is outlined in detail, allowing for a comprehensive understanding of the implementation process. By following these steps, individuals can effectively execute the CSA algorithm and obtain the desired results.

Stage 1: Initialize the settings and identify the problem.

An optimization problem is defined along with constraints, choice variables, and choice variables. After that, the four movable CSA parameters are assigned values: awareness probability (AP), flight duration (fl), maximum number of repetitions ($iter_{max}$), and flock size (N).

Stage 2: Initialize position and memory of crows

As a result of this experiment, N crows are randomly placed in a d-dimensional search area, where the crows will eventually find food. Each crow represents a possible solution to the problem in terms of the number of choice variables d, and each crow represents one possible solution to the problem d is shown in Equation (17):

$$Crows = \begin{bmatrix} y_1^1 & y_2^1 & \ldots\ldots & y_n^1 \\ y_1^2 & y_2^2 & \ldots\ldots & y_n^2 \\ y_1^M & y_2^M & \ldots\ldots & y_n^M \end{bmatrix} \tag{17}$$

All crows have had their memory initialized before they are released. Due to the fact that the crows are inexperienced at this time, it is believed that they buried their food in their original locations at this time is shown in Equation (18):

$$Memory = \begin{bmatrix} z_1^1 & z_2^1 & \ldots\ldots & z_n^1 \\ z_1^2 & z_2^2 & \ldots\ldots & z_n^2 \\ z_1^M & z_2^M & \ldots\ldots & z_n^M \end{bmatrix} \tag{18}$$

Stage 3: Evaluate fitness (objective) function

Depending on the values of the choice variable, the quality of each crow's location is calculated by inserting them into the goal function.

Stage 4: Generate new position

It is possible for a crow to create a new position in the search space in a number of ways. To illustrate this, let us say that *j* want to create a new role. A crow is tasked with finding the location of the food that he or she has hidden by choosing a flock member at random (crow *j*, for instance) and following it in order to find the food the crow has hidden (n^i).

TABLE 9. Values of unknown parameters at different temperatures of single, double and triple diode.

Parameters	Celsius (Degree cent.)	0	10	15	20	25	30	Model
	Kelvin (Degree Kelv.)	273.15	283.15	288.15	293.15	298.15	303.15	
I_{pv}		1.2140	1.1340	1.0586	1.1480	1.1656	1.1707	Single diode
n1		16.329	29.147	32.168	18.940	26.585	36.763	
Rse		0.8592	1.1567	0.7149	0.5591	0.0721	0.00035	
Rsh		316.90	1047.54	1205.51	812.018	773.562	750.171	
Irsd1		0.0809	0.3659	0.3537	0.0172	0.5901	0.8252	
RMSE		4.7E-08	4.4E-07	7.6E-09	2.8E-07	1.1E-07	1.9E-07	
I_{pv}		1.1584	1.1580	1.1639	1.1409	1.1259	1.1782	Double diode
n1		25.810	24.133	19.549	34.217	24.841	30.578	
n2		20.168	33.790	37.630	16.382	28.326	31.722	
Rs		0.2117	0.9548	0.5944	0.4	0.8692	0.6651	
Rsh		839.51	1329.21	1174.15	854.71	417.14	633.01	
Irsd1		0.3366	0.3712	0.4019	0.7466	0.0902	0.2044	
Irsd2		0.4601	0.3474	0.7484	0.3496	0.3459	0.4292	
RMSE		1.8E-08	3.1E-07	4.4E-08	2.E-08	4.9E-08	7.2E-08	
I_{pv}		1.0857	1.1542	1.1263	1.1111	1.0845	1.1080	Triple diode
$Alpha_1$		17.0315	32.678	27.1077	11.4484	14.194	22.297	
$Alpha_2$		8.1162	18.679	24.162	17.984	8.6304	9.6719	
$Alpha_3$		9.2956	30.593	19.275	24.393	27.049	10.171	
R_s		0.2887	0.0007	0.2305	0.3219	0.2435	0.0003	
R_{sh}		722.93	1028.41	1131.46	1177.07	1258.84	1039.97	
I_{o1}		2.9E-05	0.2950	0.1351	0.0098	0.0004	0.2187	
I_{o2}		0.0001	0.0474	0.1132	0.1572	0.0004	0.0069	
I_{o3}		0.0071	0.3492	0.0009	0.0278	0.0256	0.0001	
RMSE Error		3.2E-08	4.4E-08	4.9E-08	7.01E-08	7.5E-08	9.3E-08	

The second crow j is now located at the new location provided by Equation 2. This procedure should be repeated for each of the crows.

Stage 5: Check the feasibility of new positions

The new location of every crow is verified by a team of experts to make sure it is feasible. When its new location is viable, a crow changes its position. Crows don't move to the new spot if they don't have to; instead, they stay where they are.

Stage 6: Evaluate fitness function of new positions

Using the fitness function value of the crow's new position, the fitness function value will be calculated.

Stage 7: Update memory

The crows perform the following actions to maintain their memory prevailing as shown in Equation (19):

$$n^{j,iter+1} = \begin{cases} y^{j,iter+1} & f\left(y^{j,iter+1}\right) \text{ is better than } f\left(n^{j,iter}\right) \\ n^{j,iter} & o.w. \end{cases} \tag{19}$$

As the fitness function value of the new location is higher than that of the previously learned location, a crow was observed to refresh its memory with the new position as soon as the new fitness function value is higher than the previous fitness function value.

Stage 8: Check termination criterion

This process is repeated until the $iter_{max}$ has been reached, at which point stages 4 through 7 will be repeated. After the termination requirement is satisfied, the optimization problem's solution is the optimal memory location that occupies the highest percentage of the objective function value in relation to the optimal memory location.

VI. RESULTS AND DISCUSSIONS

A. BENCHMARK TEST FUNCTIONS

This segment presents an evaluation of the efficiency of the proposed algorithm by utilizing ten benchmark test functions. The functions used for this study include unimodal functions F_1 (k) to F_7 (k) as well as multimodal functions F_8 (k) to

TABLE 10. Calculated current for different temperature variation of three diode model of solar.

Celsius (Degree cent.)			0	10	15	20	25	30
Kelvin (Degree Kelv.)			273.15	283.15	288.15	293.15	298.15	303.15
S.NO	V_L (V)	I_L Measured (A)	I_L Calculated (A)	I_L Calculated (A)	I_L Calculated (A)	I_L Calculated (A)	I_L Calculated (A)	I_L Calculated (A)
1	0.1248	1.0315	1.0219	1.0289	1.0281	1.0314	1.0305	1.0319
2	1.8093	1.0300	1.0267	1.0254	1.0273	1.0295	1.0299	1.0367
3	3.3511	1.0260	1.0155	1.0155	1.0201	1.0268	1.0253	1.0255
4	4.7622	1.0220	1.0123	1.0168	1.0173	1.0229	1.0235	1.0223
5	6.0538	1.0180	1.0228	1.0286	1.0217	1.0197	1.0175	1.0228
6	7.2364	1.0155	1.0275	1.0255	1.0199	1.0155	1.0207	1.0155
7	8.3189	1.0140	1.0259	1.0237	1.0202	1.0130	1.0176	1.0140
8	9.3097	1.0100	1.0214	1.0231	1.0185	1.0128	1.0119	1.0100
9	10.2163	1.0035	1.0045	1.0048	1.0040	1.0034	1.0019	1.0035
10	11.0449	0.9880	1.0280	1.0321	1.0011	0.9875	0.9855	0.9898
11	11.8018	0.9630	0.9993	0.9800	0.9754	0.9629	0.9599	0.9633
12	12.4929	0.9255	0.9875	0.9699	0.9571	0.9254	0.9226	0.9254
13	13.1231	0.8725	0.9527	0.9521	0.9102	0.8686	0.8718	0.8715
14	13.6983	0.8075	0.8643	0.8520	0.8267	0.8074	0.8061	0.8060
15	14.2221	0.7265	0.7985	0.7862	0.7553	0.7246	0.7272	0.7265
16	14.6995	0.6345	0.6822	0.6963	0.6629	0.6347	0.6362	0.6344
17	15.1346	0.5345	0.6028	0.6034	0.5954	0.5354	0.5358	0.5345
18	15.5311	0.4275	0.4953	0.4841	0.4603	0.4304	0.4296	0.4275
19	15.8929	0.3185	0.3754	0.3647	0.3437	0.3211	0.3194	0.3185
20	16.2229	0.2085	0.2842	0.2730	0.2653	0.2106	0.2083	0.2085
21	16.5241	0.1010	0.1681	0.1555	0.1506	0.1017	0.1022	0.1010
22	16.7987	-0.008	-0.0055	-0.0061	-0.0065	-0.0080	-0.0079	-0.0080
23	17.0499	-0.111	-0.0641	-0.0584	-0.0559	-0.1111	-0.1106	-0.1115
24	17.2793	-0.209	-0.1834	-0.1460	-0.1301	-0.2094	-0.2097	-0.2090
25	17.4885	-0.303	-0.2581	-0.2651	-0.2647	-0.3030	-0.3024	-0.3031

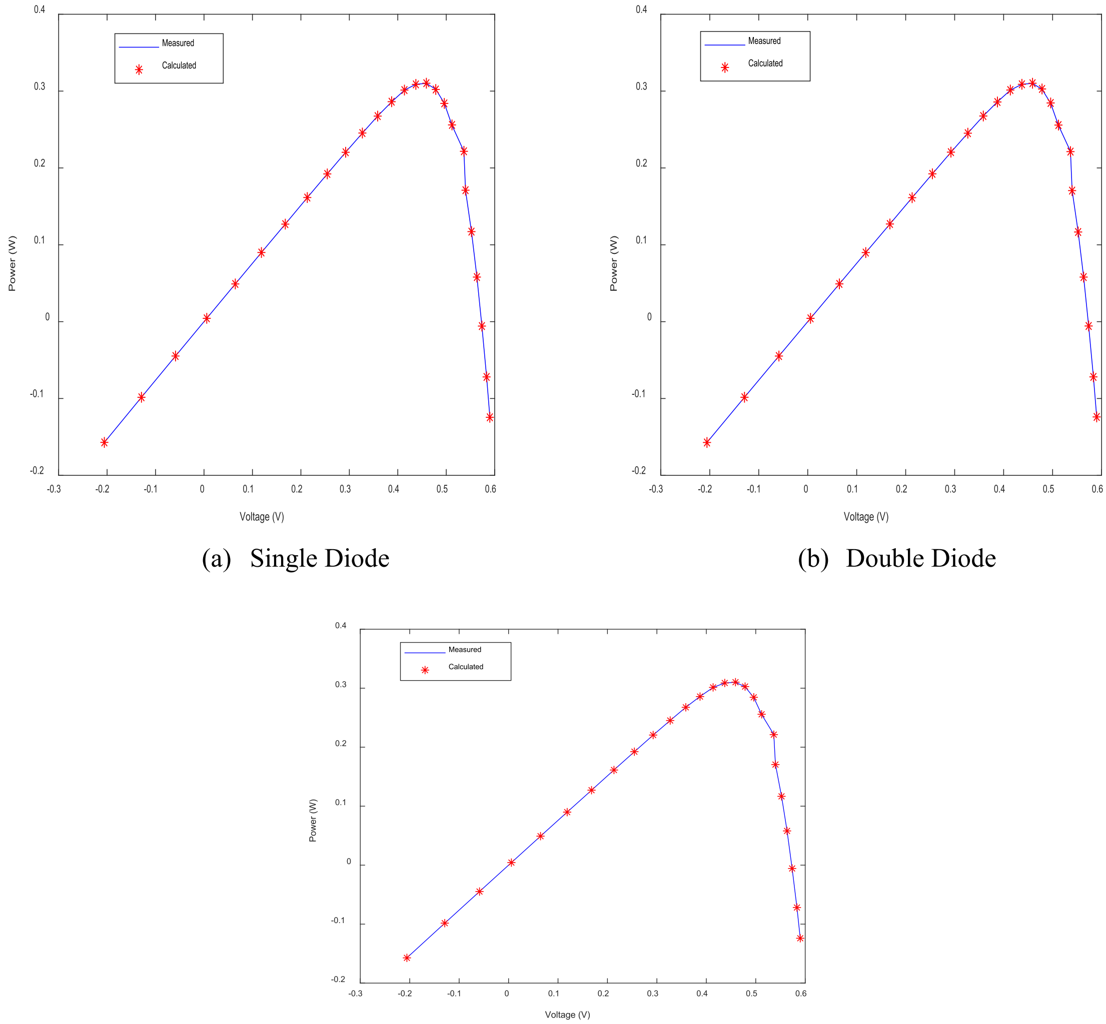
TABLE 11. Calculated power for different temperature variation of three diode model of solar.

Celsius (Degree cent.)			0	10	15	20	25	30
Kelvin (Degree Kelv.)			273.15	283.15	288.15	293.15	298.15	303.15
S.NO	V_L (V)	P_L Measured (A)	P_L Calculated (A)	P_L Calculated (A)	P_L Calculated (A)	P_L Calculated (A)	P_L Calculated (A)	P_L Calculated (A)
1	0.1248	0.1287	0.1275	0.1284	0.1283	0.1287	0.1286	0.1288
2	1.8093	1.8636	1.8576	1.8553	1.8587	1.8627	1.8634	1.8757
3	3.3511	3.4382	3.4030	3.4030	3.4185	3.4409	3.4359	3.4366
4	4.7622	4.8670	4.8208	4.8422	4.8446	4.8713	4.8741	4.8684
5	6.0538	6.1628	6.1918	6.2269	6.1852	6.1731	6.1597	6.1918
6	7.2364	7.3486	7.4354	7.4209	7.3804	7.3486	7.3862	7.3486
7	8.3189	8.4354	8.5344	8.5161	8.4869	8.4270	8.4653	8.4354
8	9.3097	9.4028	9.5089	9.5248	9.4819	9.4289	9.4205	9.4028
9	10.2163	10.2521	10.2623	10.2653	10.2572	10.2510	10.2357	10.2521
10	11.0449	10.9124	11.3542	11.3984	11.0563	10.9068	10.8847	10.9322
11	11.8018	11.3651	11.7935	11.5658	11.5115	11.3640	11.3285	11.3687
12	12.4929	11.5622	12.3367	12.1169	11.9570	11.5609	11.5259	11.5609
13	13.1231	11.4499	12.5024	12.4945	11.9446	11.3987	11.4407	11.4368
14	13.6983	11.0614	11.8394	11.6710	11.3244	11.0600	11.0422	11.0408
15	14.2221	10.3324	11.3563	11.1814	10.7420	10.3053	10.3423	10.3324
16	14.6995	9.3268	10.0280	10.2353	9.7443	9.3298	9.3518	9.3254
17	15.1346	8.0894	9.1231	9.1322	9.0111	8.1031	8.1091	8.0894
18	15.5311	6.6395	7.6926	7.5186	7.1490	6.6846	6.6722	6.6395
19	15.8929	5.0619	5.9662	5.7961	5.4624	5.1032	5.0762	5.0619
20	16.2229	3.3825	4.6105	4.4289	4.3039	3.4165	3.3792	3.3825
21	16.5241	1.6689	2.7777	2.5695	2.4885	1.6805	1.6888	1.6689
22	16.7987	-0.1344	-0.0924	-0.1025	-0.1092	-0.1344	-0.1327	-0.1344
23	17.0499	-1.8925	-1.0929	-0.9957	-0.9531	-1.8942	-1.8857	-1.9011
24	17.2793	-3.6114	-3.1690	-2.5228	-2.2480	-3.6183	-3.6235	-3.6114
25	17.4885	-5.2990	-4.5138	-4.6362	-4.6292	-5.2990	-5.2885	-5.3008

TABLE 12. Friedman ranking test of solar pv cells.

Algorithms	Friedman Ranking			Actual Ranking
	Single Diode	Double Diode	Three Diode	
DOX	298.879	298.501	298.110	3
GWO	454.852	454.456	454.217	4
PSO	550.958	550.874	550.654	5
PO	119.547	119.436	119.210	2
Proposed Algorithm	111.987	111.354	111.214	1

F_{10} (k), all of which have a dimension of 40 as represented in Table 1. To assess the performance of the proposed algorithm, we compared it against four other meta-heuristic algorithms, namely PSO, DOX, GWO, and PO. Each algorithm was independently run 20 times using MATLAB 2020a, an Intel CPU 2.50GHz processor, and 8GB of RAM. To ensure a fair assessment of the ten benchmark functions and their comparison with other meta-heuristic algorithms, a limit of



(a) Single Diode (b) Double Diode

(c) Three Diode

FIGURE 10. P-V curve of all models.

1000 feature evaluations was set. Upon comparison of the mean and Standard Deviation (SD) values of the benchmark test functions obtained using the various algorithms, it is evident that the proposed algorithm provides better values than the other algorithms as shown in Table 2. These results indicate that the proposed algorithm is the most efficient of the four algorithms studied, providing better values for the benchmark test functions. In conclusions, the results of this study highlight the efficiency of the proposed algorithm compared to other meta-heuristic algorithms. The use of a fair assessment approach in evaluating the ten benchmark test functions, coupled with multiple independent runs of each algorithm, provides reliable and credible results. The findings of this study hold the potential to provide substantial advantages to scholars and professionals engaged in the domain of optimization, specifically those with a focus on meta-heuristic algorithms. Further studies could explore the application of the proposed algorithm in solving other optimization problems, as well as the optimization of its parameters to improve its efficiency and performance. The benchmark test functions used in this study could also be expanded to include more complex functions, thereby providing a more comprehensive evaluation of the algorithm's performance.

The parameter estimation for the solar PV cell diode model involves a search within the specified range. The Photovoltaic Current (I_{pv}) has a lower bound of 0 and an upper bound of 1 ampere. The Reverse Saturation Currents of Diodes 1, 2, and 3 (I_{rsd1}, I_{rsd2}, I_{rsd3}) fall within the range of 0 to 1 microampere. The Series Resistance (R_{se}) varies between 0 and 0.5 ohms. The Shunt Resistance (R_{sh}) ranges from 0 to 500 ohms. The ideality factors n1, n2, and n3 are set between 1 and 2. The data sheet from R.T.C. France for reference, short-circuit current (I_{sc}) measures 0.7603 amperes, while the open-circuit voltage (V_{oc}) stands at 0.5728 volts. The maximum power voltage (V_{mp}) is

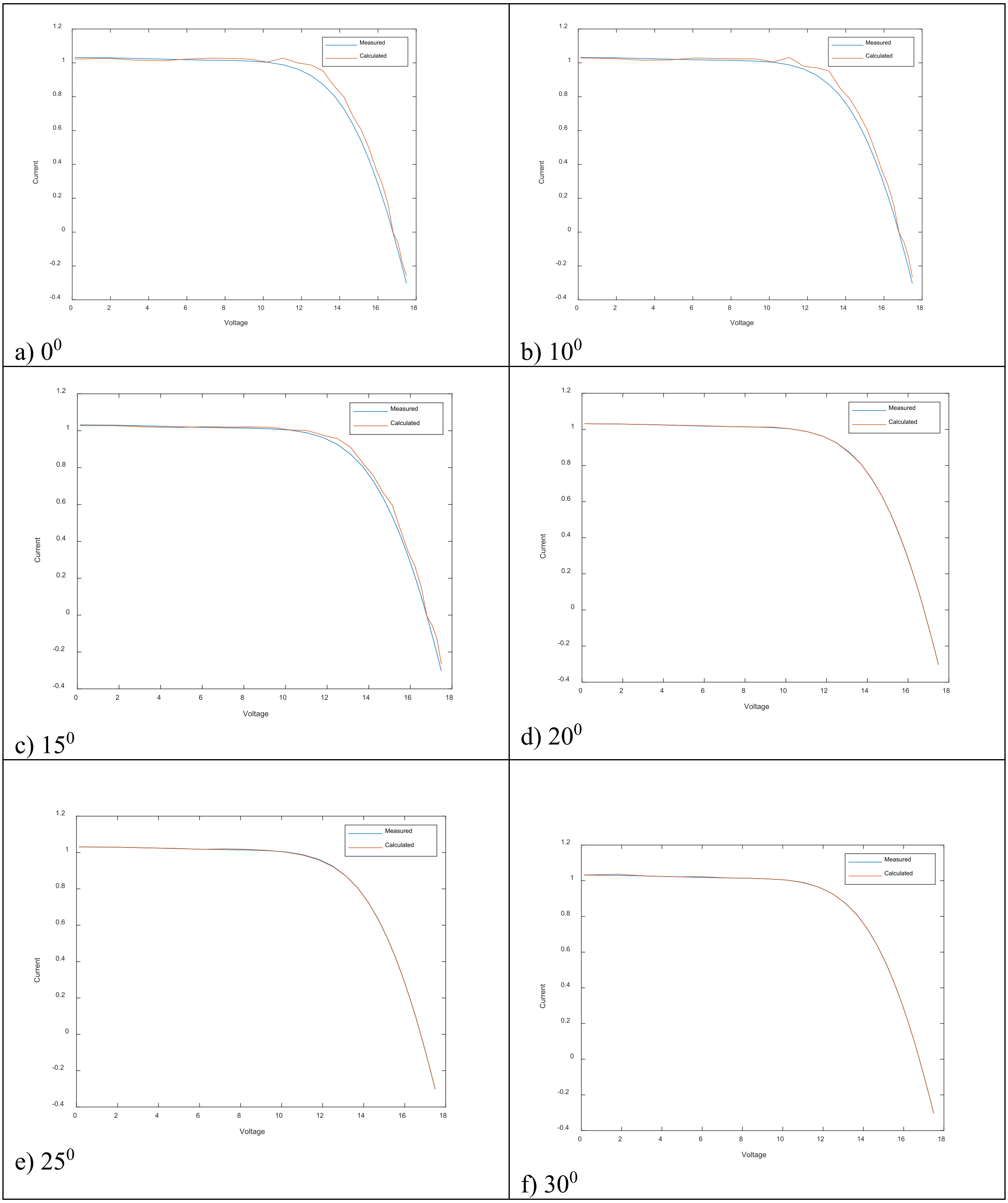


FIGURE 11. V-I curve of triple diode at different temperature.

0.4507 volts with a corresponding current at maximum power (I_{mp}) of 0.6894 amperes. The shunt resistance under standard conditions (R_{sh}) is calculated at 246.80 ohms, and the series resistance (R_{se}) is 0.0907 ohms. The temperature (T) considered for these measurements is 306.15 Kelvin, with an ideality factor (N) of 1. The new proposed algorithm, CSO, is developed and utilized to estimate parameters for single, double, and three diode models of the solar PV cell. The evaluation is based on the Root Mean Square Error (RMSE), which is then compared with other algorithms, namely PSO,

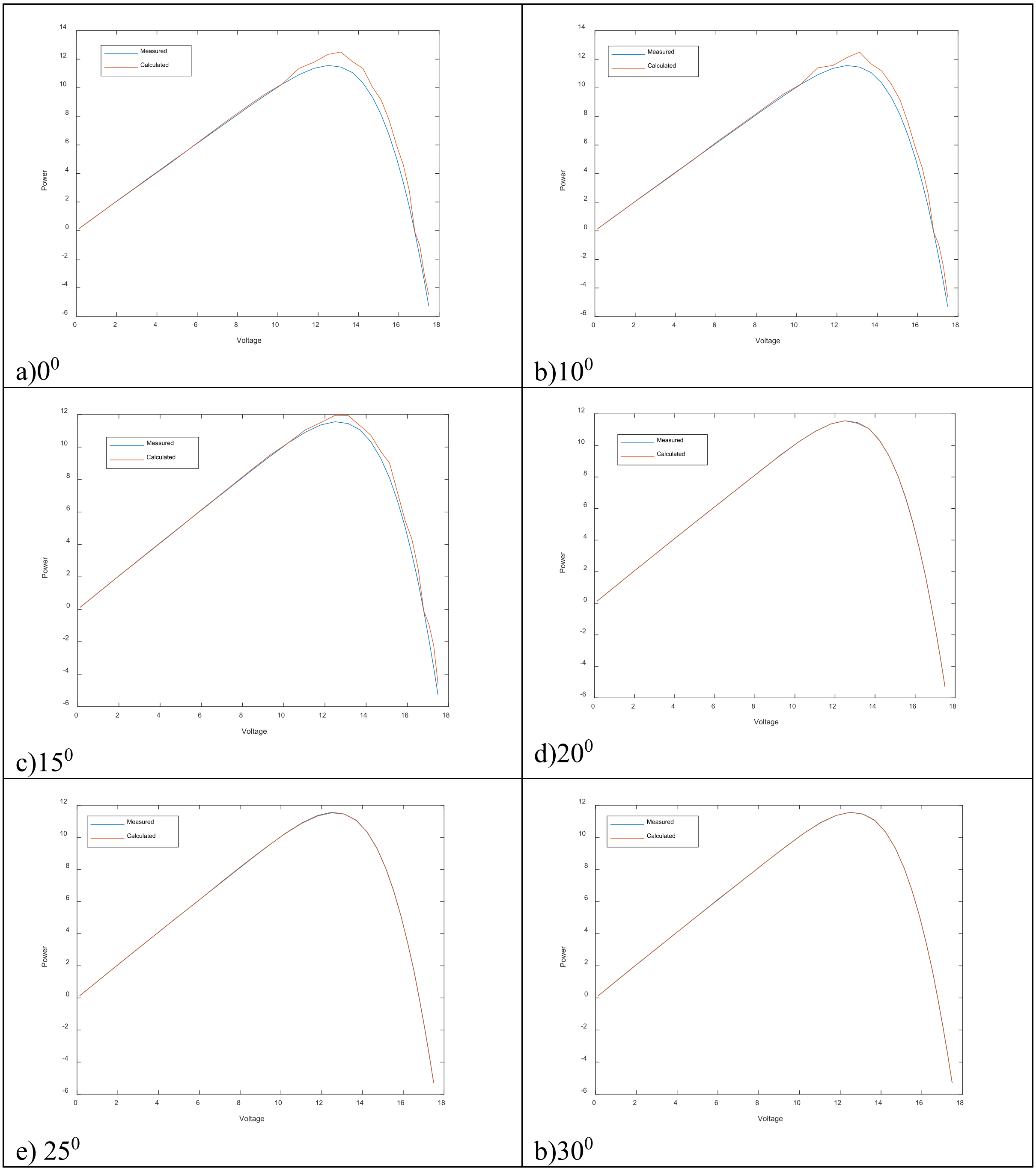


FIGURE 12. **V-P curve of triple diode at different temperature.**

GWO, DOX, PO. All the programs are coded in MATLAB 2020a and executed on a Windows 10 platform with 8 GB RAM and an Intel CPU 2.50GHz processor. Each algorithm undergoes 30 independent runs with the same limit of feature evaluations, set at 1000.

B. PARAMETER ESTIMATION

The parameter estimation is done of solar diode models, i.e., single, double and three diode model. In the single diode model five unknown parameters are calculated as shown in Table 3. The RMSE value is also calculated from that it is seen that the proposed algorithm is far better than the rest of the compared algorithms. In the double diode model seven unknown parameters are calculated as shown in Table 4. The RMSE value of this model is also calculated and seen that the proposed algorithm is better than the compared algorithm. In the three-diode model nine parameters are calculated as shown in Table 5. In this also RMSE is calculated and

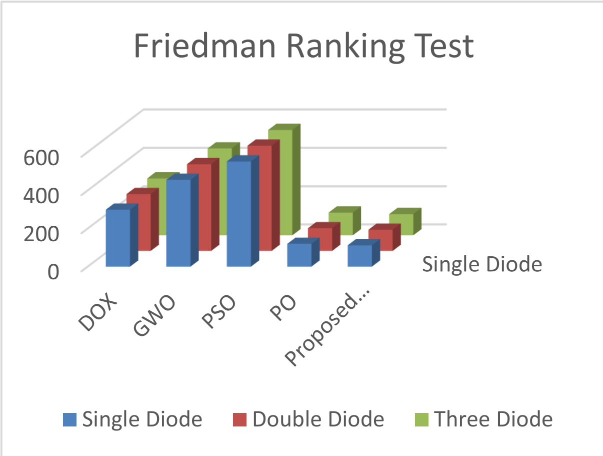


FIGURE 13. Friedman ranking of all models.

seen that the proposed algorithm is better than the compared algorithm. From the table and Figure 7 it is concluded that the proposed algorithm is better than the rest of the compared algorithms in all three models of the solar diode.

C. SOLUTION ACCURACY

As illustrated in Table 6, the proposed algorithm demonstrates a computational time (Secs) in contrast to PSO, DOX, GWO, and PO algorithms. The proposed algorithm displays a good computational time than other algorithms in all the three models as shown in Figure 8. The Table 7, Table 8, Figure 9, and Figure 10 represents the I-V and P-V curves for the solar PV cells are obtained, respectively. The Table 9 shows the all three diodes at different operating temperature. The Table 10, Table 11, Figure 11 and Figure 12 shows the three diode I-V and P-V curve at different operating temperature. The results clearly reveal that the proposed algorithm performs better and more accurately than the other algorithms. Therefore, it can be concluded that the proposed algorithm is more effective and efficient in solving complex optimization problems. Furthermore, this algorithm has promising potential for application in various fields, including renewable energy systems, manufacturing, and logistics.

D. STATISTICAL ANALYSIS

The test outcomes for Friedman's ranking rank sum [31], [32], [33], [34], [35] are laid out in Table 12 respectively. The Friedman ranking test shows that proposed algorithm secured the topmost rank, followed by PO, DOX, GWO, and PSO. The proposed algorithm performs superior to other meta-heuristic algorithms in parameter estimation for all the three diode models, as evidenced by the results obtained from both experimental tests. The algorithm is more accurate, efficient, and performs better. Furthermore, additional Friedman ranking test results are presented in Figure 13. In conclusion, the data suggests that the proposed algorithm is a promising approach for parameter estimation of all three diode solar PV cells.

VII. CONCLUSION

A. DISCUSSION

The main aim of this study is to determine the parameters of a single diode, double diode and three diode model for PV cell using the data sheet provided by R.T.C France. The current investigation utilizes the proposed meta-heuristic optimization method to assess the parameters of a single, double, three diode solar PV cell model built by a crow employing a circular design. The estimated parameters in the study are five, seven and nine, which include the incorporation of additional series and parallel resistances that enhance the estimation process. The findings of this study have the potential to contribute to improving solar photovoltaic (PV) cell performance.

SUMMARY

In conclusion, the proposed algorithm demonstrates efficacy and efficiency in parameter estimation of a single, double and three diode PV cell model. The algorithm's excellent performance in terms of error minimization and rapid convergence sets it apart from other metaheuristic algorithms. The results of benchmark test functions and comparisons with other algorithms indicate that proposed algorithm is an effective algorithm for solving optimization problems and can be used for various applications with excellent outcomes. The findings based on the results obtained so far are listed below:

- The proposed algorithm offers an efficient approach for accurately estimating parameters within single, double, and three diode PV cell models. Its effectiveness stems from minimizing the disparity between predicted and observed PV cell values, ensuring both speed and precision. Moreover, its versatility enables successful application across diverse conditions.
- To showcase the efficency of the proposed algorithm, a series of ten benchmark test functions were executed, yielding mean and Standard Deviation (SD) values. Results substantiate the superiority of the proposed algorithm over alternative methods, establishing its proficiency in optimization problem-solving. These findings underscore its potential for widespread application with consistently favorable outcomes.
- Employing the proposed algorithm for parameter estimation within single, double, and three diode PV cell models under standard temperature conditions, comparisons were made with other metaheuristic algorithms such as PSO, DOX, GWO, and PO. The results demonstrate the proposed algorithm's remarkable performance, evident in its notably low Root Mean Square Error (RMSE) values: 1.01E-07 for single diode, 2.1E-07 for double diode, and 1.89E-07 for three diode. Furthermore, through Friedman Ranking Test and Wilcoxon's rank sum test, the proposed algorithm emerged as the top-ranked method, confirming its superiority. Convergence curves further underscore its faster convergence rate compared to other algorithms.

According to the research, the utilization of proposed algorithm offers an effective and efficient technique for parameter estimation of single, double and three diode model of solar photovoltaic (PV) cell. Not only can this method improve the accuracy of the model, but it can also reduce the time required for parameter estimation. Furthermore, it is possible to explore its usage in other domains such as machine learning and control systems. Another advantage of this method is that it can be utilized for the development of more efficient solar cell models. As a result, the proposed algorithm method has a promising future in the field of renewable energy. It is recommended that further research be conducted to determine the full potential and efficacy of this technique in various applications.

REFERENCES

[1] M. Arshad, "Clean and sustainable energy technologies," in *Clean Energy for Sustainable Development*. Washington, DC, USA: Academic, 2017, pp. 73–89.

[2] S. Mekhilef, R. Saidur, and M. Kamalisarvestani, "Effect of dust, humidity and air velocity on efficiency of photovoltaic cells," *Renew. Sustain. Energy Rev.*, vol. 16, no. 5, pp. 2920–2925, Jun. 2012.

[3] (2017). *REN 21. Renewables 2017: Global Status Report*. [Online]. Available: https://doi.org/10.1016/j.rser.2016.09.082

[4] V. Lo Brano, A. Orioli, G. Ciulla, and A. Di Gangi, "An improved five-parameter model for photovoltaic modules," *Sol. Energy Mater. Sol. Cells*, vol. 94, no. 8, pp. 1358–1370, Aug. 2010.

[5] V. Khanna, B. K. Das, D. Bisht, Vandana, and P. K. Singh, "A three diode model for industrial solar cells and estimation of solar cell parameters using PSO algorithm," *Renew. Energy*, vol. 78, pp. 105–113, Jun. 2015.

[6] T. Easwarakhanthan, J. Bottin, I. Bouhouch, and C. Boutrit, "Nonlinear minimization algorithm for determining the solar cell parameters with microcomputers," *Int. J. Sol. Energy*, vol. 4, no. 1, pp. 1–12, Jan. 1986.

[7] P. Sharma and T. S. Bhatti, "A review on electrochemical double-layer capacitors," *Energy Convers. Manage.*, vol. 51, no. 12, pp. 2901–2912, Dec. 2010.

[8] A. Ortizconde, F. Garciasanchez, and J. Muci, "New method to extract the model parameters of solar cells from the explicit analytic solutions of their illuminated characteristics," *Sol. Energy Mater. Sol. Cells*, vol. 90, no. 3, pp. 352–361, Feb. 2006.

[9] D. S. H. Chan, J. R. Phillips, and J. C. H. Phang, "A comparative study of extraction methods for solar cell model parameters," *Solid-State Electron.*, vol. 29, no. 3, pp. 329–337, Mar. 1986.

[10] W. Liu, C. Wang, and A. P. J. Mol, "Rural public acceptance of renewable energy deployment: The case of Shandong in China," *Appl. Energy*, vol. 102, pp. 1187–1196, Feb. 2013.

[11] J. Appelbaum and A. Peled, "Parameters extraction of solar cells—A comparative examination of three methods," *Sol. Energy Mater. Sol. Cells*, vol. 122, pp. 164–173, Mar. 2014.

[12] Y. Li, W. Huang, H. Huang, C. Hewitt, Y. Chen, G. Fang, and D. L. Carroll, "Evaluation of methods to extract parameters from current–voltage characteristics of solar cells," *Sol. Energy*, vol. 90, pp. 51–57, Apr. 2013.

[13] A. A. Elbaset, H. Ali, and M. Abd-El Sattar, "Novel seven-parameter model for photovoltaic modules," *Sol. Energy Mater. Sol. Cells*, vol. 130, pp. 442–455, Nov. 2014.

[14] D. F. Alam, D. A. Yousri, and M. B. Eteiba, "Flower pollination algorithm based solar PV parameter estimation," *Energy Convers. Manage.*, vol. 101, pp. 410–422, Sep. 2015.

[15] J. A. Jervase, H. Bourdoucen, and A. Al-Lawati, "Solar cell parameter extraction using genetic algorithms," *Meas. Sci. Technol.*, vol. 12, no. 11, pp. 1922–1925, Nov. 2001.

[16] M. Ye, X. Wang, and Y. Xu, "Parameter extraction of solar cells using particle swarm optimization," *J. Appl. Phys.*, vol. 105, no. 9, pp. 1–8, May 2009.

[17] K. M. El-Naggar, M. R. AlRashidi, M. F. AlHajri, and A. K. Al-Othman, "Simulated annealing algorithm for photovoltaic parameters identification," *Sol. Energy*, vol. 86, no. 1, pp. 266–274, Jan. 2012.

[18] L. Guo, Z. Meng, Y. Sun, and L. Wang, "Parameter identification and sensitivity analysis of solar cell models with cat swarm optimization algorithm," *Energy Convers. Manage.*, vol. 108, pp. 520–528, Jan. 2016.

[19] N. Rajasekar, N. K. Kumar, and R. Venugopalan, "Bacterial foraging algorithm based solar PV parameter estimation," *Sol. Energy*, vol. 97, pp. 255–265, Nov. 2013.

[20] A. Askarzadeh and A. Rezazadeh, "Parameter identification for solar cell models using harmony search-based algorithms," *Sol. Energy*, vol. 86, no. 11, pp. 3241–3249, Nov. 2012.

[21] Q. Niu, H. Zhang, and K. Li, "An improved TLBO with elite strategy for parameters identification of PEM fuel cell and solar cell models," *Int. J. Hydrogen Energy*, vol. 39, no. 8, pp. 3837–3854, Mar. 2014.

[22] D. Oliva, M. A. El Aziz, and A. E. Hassanien, "Parameter estimation of photovoltaic cells using an improved chaotic whale optimization algorithm," *Appl. Energy*, vol. 200, pp. 141–154, Aug. 2017.

[23] D. Oliva, A. A. Ewees, M. A. E. Aziz, A. E. Hassanien, and M. Peréz-Cisneros, "A chaotic improved artificial bee colony for parameter estimation of photovoltaic cells," *Energies*, vol. 10, no. 7, p. 865, Jun. 2017.

[24] A. Valdivia-González, D. Zaldívar, E. Cuevas, M. Pérez-Cisneros, F. Fausto, and A. González, "A chaos-embedded gravitational search algorithm for the identification of electrical parameters of photovoltaic cells," *Energies*, vol. 10, no. 7, p. 1052, Jul. 2017.

[25] M. Chegaar, Z. Ouennoughi, F. Guechi, and H. Langueur, "Determination of solar cells parameters under illuminated conditions," *J. Electron Devices*, vol. 2, no. 2003, pp. 17–21, 2003.

[26] M. K. Mat Desa, S. Sapeai, A. W. Azhari, K. Sopian, M. Y. Sulaiman, N. Amin, and S. H. Zaidi, "Silicon back contact solar cell configuration: A pathway towards higher efficiency," *Renew. Sustain. Energy Rev.*, vol. 60, pp. 1516–1532, Jul. 2016.

[27] H.-G. Beyer, "Evolutionary algorithms in noisy environments: Theoretical issues and guidelines for practice," *Comput. Methods Appl. Mech. Eng.*, vol. 186, nos. 2–4, pp. 239–267, Jun. 2000.

[28] H. Prior, A. Schwarz, and O. Güntürkün, "Mirror-induced behavior in the magpie (Pica pica): Evidence of self-recognition," *PLoS Biol.*, vol. 6, no. 8, p. e202, Aug. 2008.

[29] C. A. F. Wascher, V. Dufour, and T. Bugnyar, "Carrion crows cannot overcome impulsive choice in a quantitative exchange task," *Frontiers Psychol.*, vol. 3, p. 118, Aug. 2012.

[30] X. S. Yang, "Metaheuristic optimization," *Scholarpedia*, vol. 6, no. 8, p. 11472, 2011.

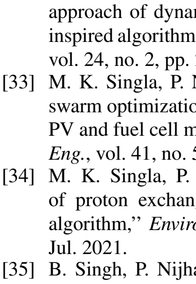
[31] D. P. Mahato, J. K. Sandhu, N. P. Singh, and V. Kaushal, "On scheduling transaction in grid computing using cuckoo search-ant colony optimization considering load," *Cluster Comput.*, vol. 23, no. 2, pp. 1483–1504, Jun. 2020.

[32] S. Rani, H. Babbar, P. Kaur, M. D. Alshehri, and S. H. Shah, "An optimized approach of dynamic target nodes in wireless sensor network using bio inspired algorithms for maritime rescue," *IEEE Trans. Intell. Transp. Syst.*, vol. 24, no. 2, pp. 2548–2555, Feb. 2023.

[33] M. K. Singla, P. Nijhawan, and A. S. Oberoi, "A novel hybrid particle swarm optimization rat search algorithm for parameter estimation of solar PV and fuel cell model," *COMPEL Int. J Comput. Math. Electr. Electron. Eng.*, vol. 41, no. 5, pp. 1505–1527, Aug. 2022.

[34] M. K. Singla, P. Nijhawan, and A. S. Oberoi, "Parameter estimation of proton exchange membrane fuel cell using a novel meta-heuristic algorithm," *Environ. Sci. Pollut. Res.*, vol. 28, no. 26, pp. 34511–34526, Jul. 2021.

[35] B. Singh, P. Nijhawan, M. K. Singla, J. Gupta, and P. Singh, "Hybrid algorithm for parameter estimation of fuel cell," *Int. J. Energy Res.*, vol. 46, no. 8, pp. 10644–10655, Jun. 2022.



MANISH KUMAR SINGLA received the B.E. degree in electrical engineering from Punjab Technical University, the M.E. degree in electrical engineering from the Thapar Institute of Engineering and Technology, India, and the Ph.D. degree from the Electrical and Instrumentation Engineering Department, Thapar Institute of Engineering and Technology, India. He is currently an Assistant Professor with the Department of Interdisciplinary Courses in Engineering, Chitkara University, Rajpura, India. He has published more than 40 manuscripts in good journals and granted more than seven patents. He is serving as an academic editor for some well-known journals. His current research interests include power systems, artificial intelligence, machine learning, renewable energy, and fuel cell.

JYOTI GUPTA received the B.E. degree in electrical engineering from Punjab Technical University, the M.E. degree in electrical engineering from the Thapar Institute of Engineering and Technology, India, and the Ph.D. degree from the Electrical and Instrumentation Engineering Department, Thapar Institute of Engineering and Technology. She is currently an Assistant Professor with the Department of Electrical Engineering, K. R. Mangalam University, Gurugram, India. She has published more than 40 manuscripts in good journals and granted more than six patents. She is serving as an academic editor for some well-known journals. Her current research interests include power systems, optimization, artificial intelligence, machine learning, renewable energy, and fuel cell.

MURODBEK SAFARALIEV received the B.S. and M.S. degrees in electrical engineering from Tajik Technical University named after academic M. S. Osimi, Tajikistan, in 2014 and 2016, respectively, and the Ph.D. degree in electrical power engineering from Ural Federal University, Russia, in 2022. Currently, he is a Senior Researcher with the Department of Automated Electrical Systems Department, Ural Energy Institute, Ural Federal University, Yekaterinburg, Russia. His research interests include optimization of the development, modes of power systems, and planning of hybrid renewable energy systems.

HAMED ZEINODDINI-MEYMAND (Member, IEEE) was born in Shahrebabk, Kerman, Iran, in 1986. He received the B.S. degree in electrical power engineering from the Ferdowsi University of Mashhad, in 2008, the M.S. degree in electrical power engineering from the Shiraz University of Technology, in 2011, and the Ph.D. degree in electrical power engineering from the Amirkabir University of Technology, Iran, in 2016.

Since 2017, he has been a Research Associate and a Lecturer with the Department of Electrical and Computer Engineering, Graduate University of Advanced Technology, Kerman. His research interests include power transformer condition evaluation, high voltage, optimization, microgrids, and distribution networks.

AHMAD JAVID GHANIZADEH was born in Herat, Afghanistan, in 1981. He received the B.S. degree in electrical engineering from the Sahand University of Technology, in 2003, the M.S. degree in electrical engineering from the Ferdowsi University of Mashhad, in 2009, and the Ph.D. degree in electrical engineering from the Amirkabir University of Technology, Iran, in 2014.

He has several years of teaching experience in Iran and Afghanistan universities. He has published more than 25 articles in reputable international journals. His main research interests include renewable energies and electrical power systems and related areas, such as power system modelling, optimization and development, and power transformer. In addition to his rich academic record, he has more than ten years of experience in the energy sector in the government and private sectors of Afghanistan. He was a Senior Energy Adviser to the Minister at the Ministry of Energy and Water, Kabul, Afghanistan. Currently, he is the President of Danial Javid Electrical Engineering Company, Afghanistan.