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PAPER

Optimizing solar cell models: a multi-objective parameter estimation algorithm for improved photovoltaic system performance

Manish Kumar Singla[1,6], Mohammad Aljaidi[2], Jyoti Gupta[3], Murodbek Safaraliev[4], Ramesh Kumar[5,6,7], Ziad M Ali[8], Mohammed H Alsharif[9,*] and Mun-Kyeom Kim[10,*]

[1] Department of Biosciences, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Chennai-602 105, India
[2] Department of Computer Science, Zarqa University, Zarqa 13110, Jordan
[3] School of Engineering and Technology, K. R. Mangalam University, Haryana, Gurgaon, 122003, India
[4] Department of Automated Electrical Systems, Ural Federal University, 620002 Yekaterinburg, Russia
[5] Department of Interdisciplinary Courses in Engineering, Chitkara University Institute of Engineering & Technology, Chitkara University, Punjab, India
[6] Applied Science Research Center, Applied Science Private University, Amman 11931, Jordan
[7] Jadara University Research Center, Jadara University, Jordan
[8] College of Engineering at Wadi Addawaser, Prince Sattam Bin Abdulaziz University, KSA, 11991, Saudi Arabia
[9] Department of Electrical Engineering, College of Electronics and Information Engineering, Sejong University, 209 Neungdong-ro, Gwangjin-gu, Seoul 05006, Republic of Korea
[10] School of Energy System Engineering, Chung-Ang University, 84 Heukseok-ro, Dongjak-gu, Seoul 06974, Republic of Korea
[*] Authors to whom any correspondence should be addressed.

E-mail: msingla0509@gmail.com, mjaidi@zu.edu.jo, jg118207@gmail.com, murodbek_03@mail.ru, rameshkumarmeena@gmail.com, dr.ziad.elhalwany@aswu.edu.e.g, malsharif@sejong.ac.kr and mkkim@cau.ac.kr

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Abstract

Accurate models of solar cells are required to improve the performance of solar photovoltaic (PV) systems. Due to a lack of precise parameters in the manufacturer's datasheet, the solar cell model is often inaccurate. Estimating the parameters needed improperly makes it impossible to build up a reliable solar PV cell model. This paper proposes an algorithm for estimating cell parameters by multi-objective optimization to solve this issue. Several optimizers attempted to address the suboptimal results of optimization due to local minima and premature convergence. This work aims to evaluate the effectiveness of the proposed algorithm with those other popular algorithms to understand its reliability. The efficiency of this algorithm is proven using empirical results and statistical figures. It has important features, including simplicity and high accuracy, which imply that the algorithm is better suited to estimating solar PV models when compared with other algorithms. This algorithm is robust as it is computationally efficient and easy to use, which makes this method applicable for solving a wide variety of problems related to solar energy.

Introduction

Overall, with the advancement of PV cell technology, it has become more and more essential to simulate these solar photovoltaic (PV) devices. The modeling of solar cells is a two-step process in which researchers formulate mathematical expressions for the cell and estimate its parameters based on representative values from other sources [1, 2]. The most commonly used mathematical models discussing solar cells in the PV industry are single-diode (SD) [3] models, double-diode (DD) [4] models, and three-diode (TD) [5], among others. These models allow PV panel parameters to be calculated based on the characteristics of specific panels, such as the saturation current (Id), series resistance (Rse), shunt resistance (Rsh), ideality factor (a), and photocurrent (I), That requires estimates of which will determine the parameters. The different criteria of selection determine how many parameters should be estimated to build a specific SD, DD or TD model. So for PV models to deliver

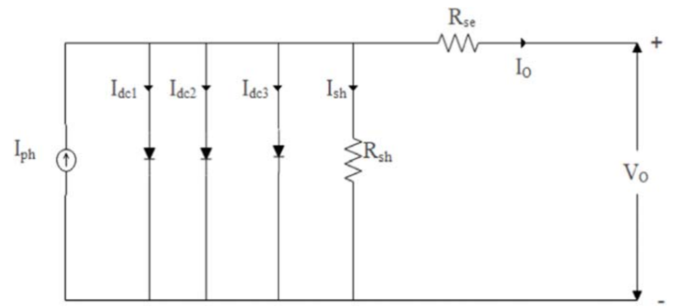


Figure 1. Simplified 3-diode PV circuit.

outputs in a way comparable with how physical solar cells perform, optimum values of these parameters should be identified such that they underpin outputs resembling those produced by the efficiencies expressed by their counterparts [6, 7].

The optimization of solar cell parameters has been revolutionized through heuristic methods. In contrast, the heuristic methods do not have any limitations concerning differentiability and convexity of parameters like traditional least squares curve fitting deterministic techniques [8, 9]. This type of analysis incorporates elements from natural phenomena and is supported by data relating to population, which makes their reliability and strength more powerful [10]. Such a system is known to be better at solving engineering problems than the classical deterministic approach [11]. Several algorithms are popular in this domain, such as particle swarm optimization (PSO), genetic algorithms (GA) [12], teaching–learning optimization (TLO) [13], cuckoo search (CS) [14], artificial bee colonies (ABCs) [15], Rao-1 [16], and the Jaya algorithm [17]. These methods have led to a calculation of solar PV cells in numerous manners so that the values for each cell layer can be evaluated about solar energy. Overall, there is no question that the use of heuristic methods game-changers as options to optimize solar cell parameters and can in addition provide considerable benefit over classical deterministic approaches on optimization.

Scientific advancements have led to the development of several optimization algorithms for estimating solar cell efficiency. Nevertheless, heuristic algorithms have some limitations in this area. Due to their exclusive search mechanisms, PSO and GA can prematurely convergence in multi-modal systems due to their concentration on local minima. ABC and CS both perform well in the exploration phase, but they exhibit delays in convergence once this phase is over. A further issue is that most heuristic algorithms lack the ability to deal with multi-objective functions as well as noisy raw data, which limits their effectiveness. To address the challenge of balancing local and global search in parameter estimation for solar PV cells, researchers have proposed a heuristic approach. This method offers significant improvements in accuracy. The algorithm leverages both three-diode and four-diode models for solar PV cells (as described in [18–20]). Notably, it may gain most appropriate performance inspite of noisy facts. This is achieved by incorporating an additional series resistance parameter into a simplified, single-diode model that already accounts for series resistance. These scholarly papers contribute significantly in multiple aspects, including:

- Tested algorithm's performance using CEC2019 benchmarks (average & standard deviation calculated).
- Compared solar cell parameter estimation (RMSE) to other algorithms (at standard temperature).
- Used statistical tests (Friedman, Wilcoxon) to validate results.

Mathematical modeling of solar PV cells

Modeling a solar cell involves two key steps. First, we need to create a mathematical equation that reflects the cell's behavior. This equation is called a model. Second, we determine specific values for the variables in the model, which are called parameters. Among the most common models used to understand solar cell behavior are the single-diode (SD) and double-diode (DD) models. These models act as the foundation for analyzing how solar cells work.

Improving solar cell parameter estimation: a deep dive into 3-diode models

When compared to double diode models, three-diode models provide a more detailed picture of how solar cells work (as shown in figure 1). This model considers leakage currents (represented by Idc3) that flow through grain

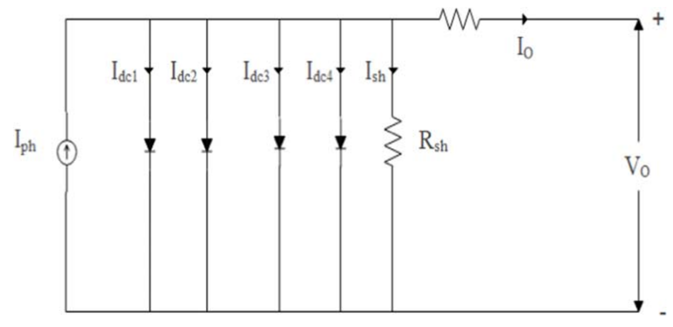


Figure 2. Simplified 4-diode PV circuit.

boundaries within the cell. Unlike a double-diode model, the three-diode model includes a shunt resistance path for this leakage current. Additionally, the series resistance within the main part of the cell is captured by the semiconductor-to-substrate resistance in the model. By including these extra details, the three-diode model offers a more accurate representation of solar cell behavior. Equation (1) shows the mathematical equation used in this model.

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

The three-diode model offers high accuracy in fitting the solar cell's current output (I–V curve). This allows us to calculate the contributions of various components within the cell. However, the model itself can be quite complex. This model is particularly useful for simulating the current–voltage behavior of large-area silicon solar cells.

Extracting solar parameters: deep dive into 4-diode models

Four-diode equivalent circuits offer several advantages over simpler models (single, double, and triple diode) for analyzing large industrial solar cells. This approach provides higher accuracy with minimal difference between real-world measurements and calculations. It also excels at fitting the cell's current–voltage curve (I-V curve) and performs well under standard test conditions (STC). However, this increased accuracy comes at a cost: the four-diode model is more complex.

For large industrial solar cells (exceeding 155.2 cm^2 and with efficiencies above 17.1%), simpler models like single or double diode might not capture all the important characteristics. Leakage currents within the cell (represented by Idc1 and Idc2) become more significant in larger cells, and a four-diode model better accounts for these effects. Figure 2 illustrates the four-diode equivalent circuit.

Four Diode Model equation (equation (2))

$$I_O = I_{ph} - I_{rsd1}\left[\exp\left(\frac{q(V_O + I_O R_{se})}{n_1 KT}\right) - 1\right] - I_{rsd2}\left[\exp\left(\frac{q(V_O + I_O R_{se})}{n_2 KT}\right) - 1\right] - I_{rsd3}\left[\exp\left(\frac{q(V_O + I_O R_{se})}{n_3 KT}\right) - 1\right] - I_{rsd4}\left[\exp\left(\frac{q(V_O + I_O R_{se})}{n_4 KT}\right) - 1\right] - \frac{V_O + I_O R_{se}}{R_{sh}} \tag{2}$$

This equation (shown elsewhere as equation (2)) represents the four-diode model for solar cells. Let's break down the variables:

Io: The electrical current produced by the cell.

Vo: The voltage output by the cell.

Iph: The current generated by light hitting the cell (photocurrent).

I_{rsd1}, I_{rsd2}, I_{rsd3}, I_{rsd}4: These represent tiny leakage currents that flow in the opposite direction of normal current flow (reverse saturation currents) for each of the four diodes.

n_1, n_2, n_3, n_4: These are factors related to how efficiently the diodes conduct current (ideality factors).

q: The fundamental unit of electric charge.

K: A constant value in science related to temperature and energy (Boltzmann's constant).

T: The temperature of the solar cell material (in Kelvin, a scientific temperature scale).

Problem formulation

Scientists use an optimization technique to identify unknown properties within a mathematical model of a solar cell. This technique is based on the four-diode model, where, $x = [R_{se}\, R_{sh} I_{ph} I_{rsd1} I_{rsd2} I_{rsd3} I_{rsd4} n_1 n_2 n_3 n_4]$. The goal is to minimize the difference between the actual electrical current produced by the solar cell (measured I-V data) and the current calculated by the model. To achieve this, the optimization technique adjusts these unknown values in the model. Mathematically, equations are reformulated (from 1 & 2 to 3 & 4) to define a function that needs to be minimized (objective function). Finally, the technique calculates an average value based on the experimental data.

$$f(V_O,\ I_O,\ x) = I_O - I_{ph} + I_{rsd1}\left[\exp\left(\frac{q(V_O + I_O R_{se})}{n_1 KT}\right) - 1\right] + I_{rsd2}\left[\exp\left(\frac{q(V_O + I_O R_{se})}{n_2 KT}\right) - 1\right] + I_{rsd3}\left[\exp\left(\frac{q(V_O + I_O R_{se})}{n_3 KT}\right) - 1\right] - \frac{V_O + I_O R_{se}}{R_{sh}} \tag{3}$$

$$f(V_O,\ I_O,\ x) = I_O - I_{ph} + I_{rsd1}\left[\exp\left(\frac{q(V_O + I_O R_{se})}{n_1 KT}\right) - 1\right] + I_{rsd2}\left[\exp\left(\frac{q(V_O + I_O R_{se})}{n_2 KT}\right) - 1\right] + I_{rsd3}\left[\exp\left(\frac{q(V_O + I_O R_{se})}{n_3 KT}\right) - 1\right] + I_{rsd4}\left[\exp\left(\frac{q(V_O + I_O R_{se})}{n_4 KT}\right) - 1\right] - \frac{V_O + I_O R_{se}}{R_{sh}} \tag{4}$$

To assess how closely the model's calculated currents match the real-world measurements, scientists use a metric called RMSE. This is a standard way to quantify errors between predicted and actual values. You can find the specific formula for RMSE in equation (5).

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum\nolimits_{i=1}^{N}(f_i(V_O,\ I_O,\ x))} \tag{5}$$

The equation for RMSE considers N measurements from the real solar cell. It also factors in the solution values determined by the optimization algorithm (represented by x vector). The lower the RMSE value, the better the model aligns with real-world data. Therefore, minimizing RMSE is crucial for accurately estimating the solar cell's parameters.

Proposed algorithm

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. In fact, they boast the largest brain size when compared to their physical dimensions. It is worth noting, however, that their brain-to-body ratio is actually 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 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 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 [21].

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 in order to safeguard their precious caches from theft [22].

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

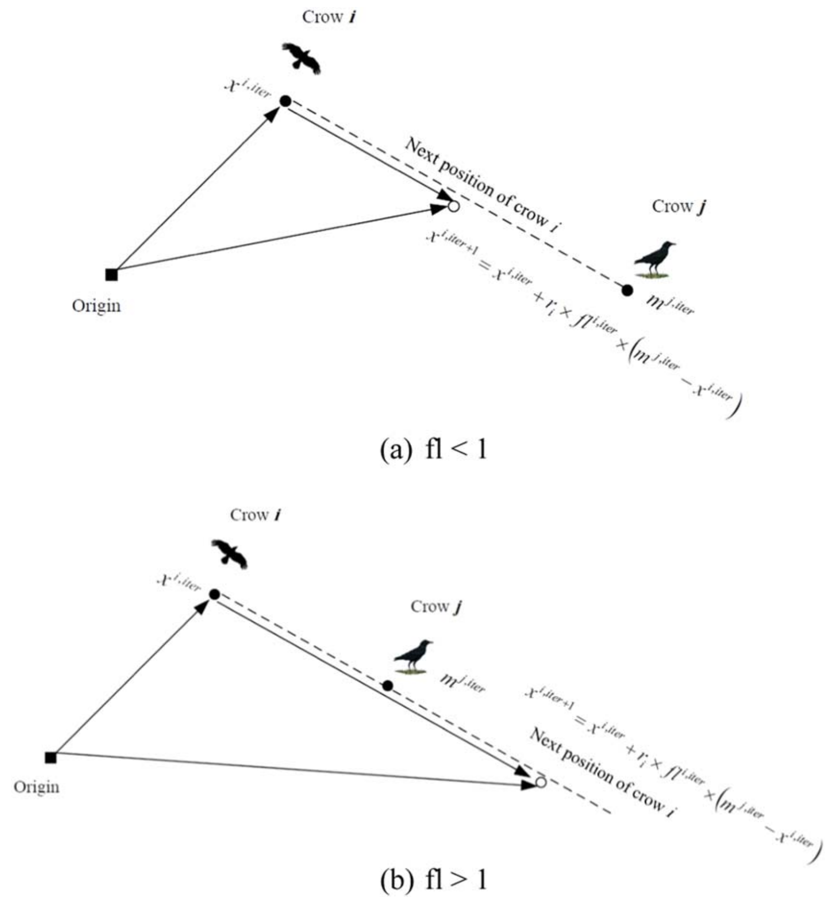


Figure 3. Schematic of CS in State 1.

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.
- In order to protect their stockpiles from thieves, crows guard their nests.

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 (6):

$$x^{i,iter+1} = x^{i,iter} + r_i \times fl^{i,iter} \times (m^{j,iter} - x^{i,iter}) \tag{6}$$

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 3 illustrates the state schematic and the impact of the parameter fl on search capabilities. Lower fl values lead to localized search around a specific point $x^{i,iter}$, while higher values facilitate broader, global search.

In figure 3(a), when fl is below 1, the crow's next position lies along the dashed line between points $x^{i,iter}$ and $m^{j,iter}$. Conversely, in figure 3(b), for fl values exceeding 1, the crow's next position extends $m^{j,iter}$ beyond the dashed line.

Stage 2: Crow *j* knows that crow *i* is subsequent it. As a result, in order to protect its cache from being pilfered, crow *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 (7):

$$x^{i,iter+1} = \begin{cases} x^{i,iter} + r_i \times fl^{i,iter} \times (m^{j,iter} - x^{i,iter}) & r_j \geqslant AP^{j,iter} \\ a\ random\ position & otherwise \end{cases} \tag{7}$$

where r_j is a random number between 0 and 1 and $AP^{j,iter}$ denotes the awareness probability.

A metaheuristic algorithm should be used in order to achieve a good balance between diversification and intensification [23]. 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.

CSA implementation for optimization

A flowchart for the CSA, which is a computational algorithm used for solving a specific problem, has been visually displayed in figure 4. The primary intent of this pseudocode is to clearly represent the numerous actions that take place in the process of implementing the CSA. It provides a roadmap for programmers and researchers who want to use the CSA in their software or research projects, helping them understand the linear progression that characterizes the implementation process. However, in this particular part of the work, a systematic and methodical description of the steps that are needed to implement the CSA successfully is provided. Each step is clearly described, which enables one to have a thorough understanding of the implementation process. Following these steps, individuals can apply the CSA algorithm successfully and get the required outcomes.

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

This approach, called Crow Search Algorithm (CSA), works like a simulation of crows searching for food. Imagine a flock of N crows scattered randomly across a vast area with d dimensions. Each crow represents a potential solution to the problem we're trying to solve. The possible solution (d) reflects the number of variables we're considering. Equation (8) defines how each crow's position is represented in this d- possible solution.

$$Crows = \begin{bmatrix} y_1^1\ y_2^1 \ldots \ldots y_n^1 \\ y_1^2\ y_2^2 \ldots \ldots y_n^2 \\ y_1^M\ y_2^M \ldots \ldots y_n^M \end{bmatrix} \tag{8}$$

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 (9):

$$Memory = \begin{bmatrix} z_1^1\ z_2^1 \ldots \ldots z_n^1 \\ z_1^2\ z_2^2 \ldots \ldots z_n^2 \\ z_1^M\ z_2^M \ldots \ldots z_n^M \end{bmatrix} \tag{9}$$

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

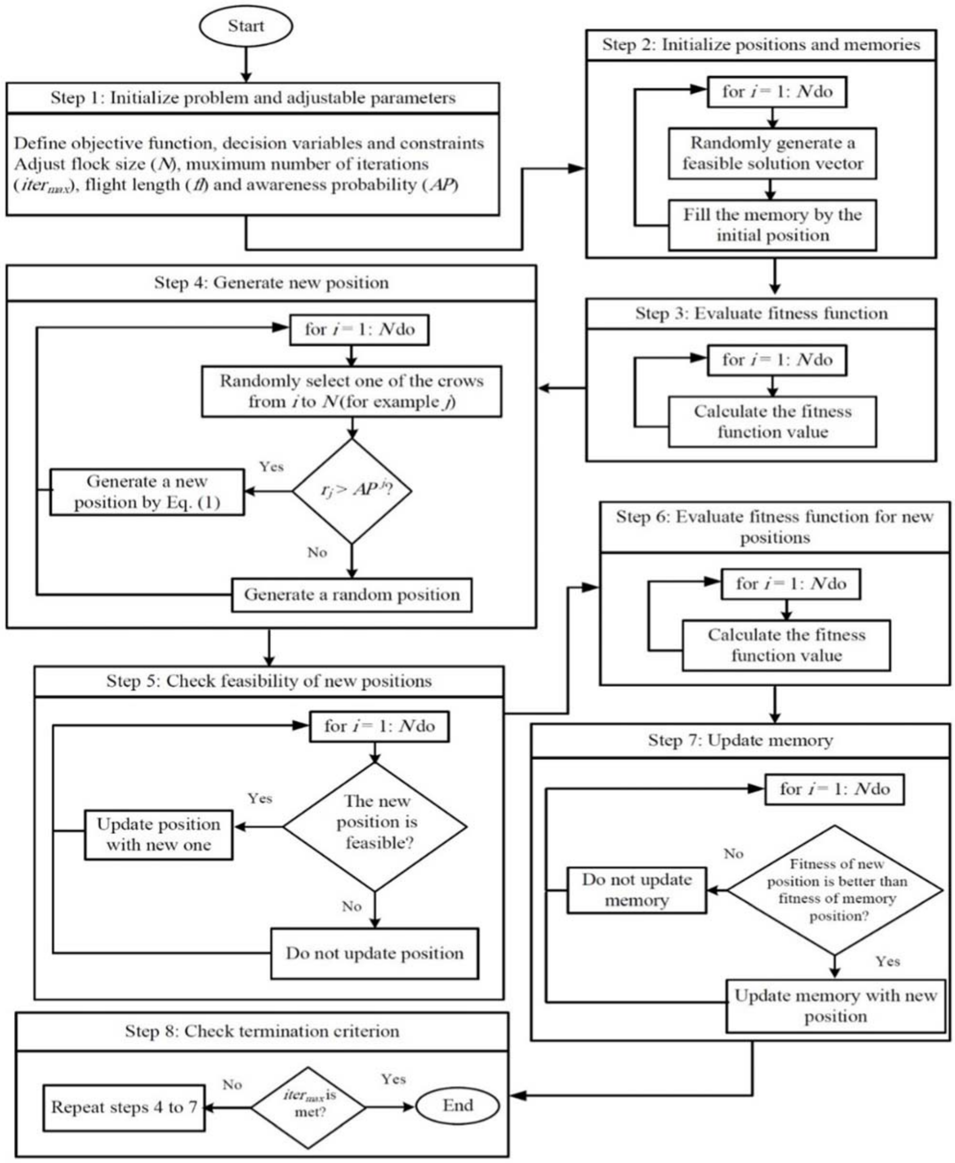


Figure 4. Flow Chart of CS.

crow has hidden (n^i). 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 (10):

$$n^{j,iter+1} = \begin{cases} y^{j,iter+1}\, f(y^{j,iter+1}) \textit{ is better than } f(n^{j,iter}) \\ n^{j,iter} \quad o.w. \end{cases} \tag{10}$$

If a crow finds a spot with a better outcome (higher fitness value) than its previous location, it remembers this new spot. Here, 'fitness value' refers to how well a solution works for the problem we're trying to solve. Basically, crows learn from each other and keep moving towards areas with better results.

Stage 8: Check termination criterion

Table 1. CEC 2019 benchmark test function.

Name of function	Function	Range
l_1 = CEC1	$f1, f2, f3 \ldots f10 = Sphere\ function$ $\delta1, \delta2, \delta3 \ldots \delta10 = [1, 1, 1, \ldots 1]$ $\lambda1, \lambda2, \lambda3 \ldots \lambda10 = \left[\frac{5}{100}, \frac{5}{100}, \frac{5}{100}, \ldots \frac{5}{100}\right]$	[−5, 5]
l_2 = CEC2	$f1, f2, f3 \ldots f10 = Griewanks' sfunction$ $\delta1, \delta2, \delta3 \ldots \delta10 = [1, 1, 1, \ldots 1]$ $\lambda1, \lambda2, \lambda3 \ldots \lambda10 = \left[\frac{5}{100}, \frac{5}{100}, \frac{5}{100}, \ldots \frac{5}{100}\right]$	[−5,5]
l_3 = CEC3	$f1, f2, f3 \ldots f10 = Griewanks' sfunction$ $\delta1, \delta2, \delta3 \ldots \delta10 = [1, 1, 1, \ldots 1]$ $\lambda1, \lambda2, \lambda3 \ldots \lambda10 = [1, 1, 1, \ldots 1]$	[−5,5]
l_4 = CEC4	$f1, f2 = Ackely' sfunction$ $f3, f4 = Rastrigin' sfunction$ $f5, f6 = Weierstrass\ function$ $f7, f8 = Griewanks' sfunction$ $f9, f10 = Sphere\ function$ $\delta1, \delta2, \delta3 \ldots \delta10 = [1, 1, 1, \ldots 1]$ $\lambda1, \lambda2, \lambda3 \ldots \lambda10 = \left[\frac{5}{32}, \frac{5}{32}, 1, 1, \frac{5}{0.5}, \frac{5}{0.5}, \frac{5}{100}, \frac{5}{100}, \frac{5}{100}, \frac{5}{100}\right]$	[−5,5]
l_5 = CEC5	$f1, f2 = Rastrigin' sfunction$ $f3, f4 = Weierstrass\ function$ $f5, f6 = Griewanks' sfunction$ $f7, f8 = Ackely' sfunction$ $f9, f10 = Sphere\ function$ $\delta1, \delta2, \delta3 \ldots \delta10 = [1, 1, 1, \ldots 1]$ $\lambda1, \lambda2, \lambda3 \ldots \lambda10 = \left[\frac{1}{5}, \frac{1}{5}, \frac{5}{0.5}, \frac{5}{0.5}, \frac{5}{100}, \frac{5}{100}, \frac{5}{32}, \frac{5}{32}, , \frac{5}{100}, \frac{5}{100}\right]$	[−5,5]

Table 2. CEC 2019 benchmark statistical test with dimension (20).

Algorithm	Functions	CEC1	CEC2	CEC3	CEC4	CEC5
Proposed Algorithm	Mean	5.00E+08	8.84E-19	6.73E-19	1.72E+08	4.45E-19
	S.D.	2.88E+08	1.00E-19	7.32E-20	1.05E+08	2.76E-20
PSO	Mean	1.52E+01	1.53E-01	3.42E-01	2.79E+01	2.26E-01
	S.D.	1.45E+01	5.78E-02	3.67E-02	2.05E+01	1.87E-01
RSA	Mean	1.75E+05	5.13E-14	4.87E-13	1.40E+05	5.16E-14
	S.D.	1.43E+05	2.85E-15	1.22E-13	4.19E+04	8.10E-15
CSA	Mean	2.03E+03	2.40E-06	3.33E-06	1.91E+04	3.03E-06
	S.D.	8.40E+02	3.63E-06	2.34E-06	9.51E+03	2.92E-06
PO	Mean	4.36E+02	3.77E-05	4.66E-05	3.89E+03	5.27E-05
	S.D.	2.90E+02	3.05E-05	3.61E-05	3.51E+03	2.47E-05

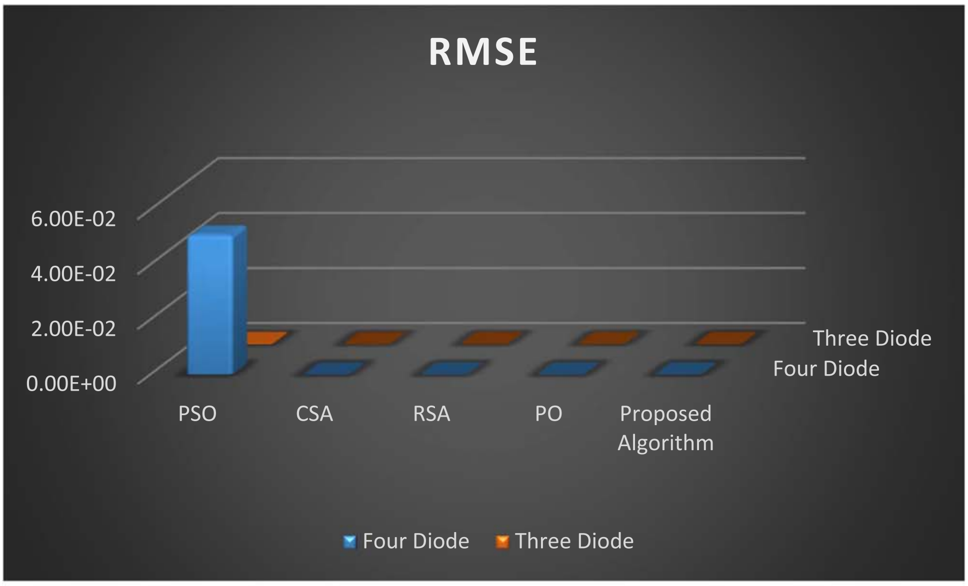
Table 3. Unknown parameters of three diode model.

Parameter/ Algorithms	I_{pv}	n_1	n_2	n_3	R_s	R_{sh}	I_{o1}	I_{o2}	I_{o3}	RMSE	SSE
PSO	5.2835	0.5	0.668	0.580	0.001	97.451	0	1.16E-07	7.70E-09	1.57E-02	2.46E-04
CSA	6.9159	0.714	0.701	0.947	0.017	155.13	2.91E-08	4.51E-07	2.82E-09	3.31E-04	1.10E-07
RSA	5.8224	1.650	1.213	1.135	0.096	273.09	7.31E-08	2.78E-07	6.28E-08	4.33E-06	1.87E-11
PO	4.9012	1.511	1.400	0.925	0.001	73.37	0	0	1.00E-06	3.75E-09	1.40E-17
Proposed Algorithm	5.8587	1.081	1.161	1.261	0.077	158.20	2.69E-07	3.80E-07	6.28E-07	3.47E-16	1.20E-31

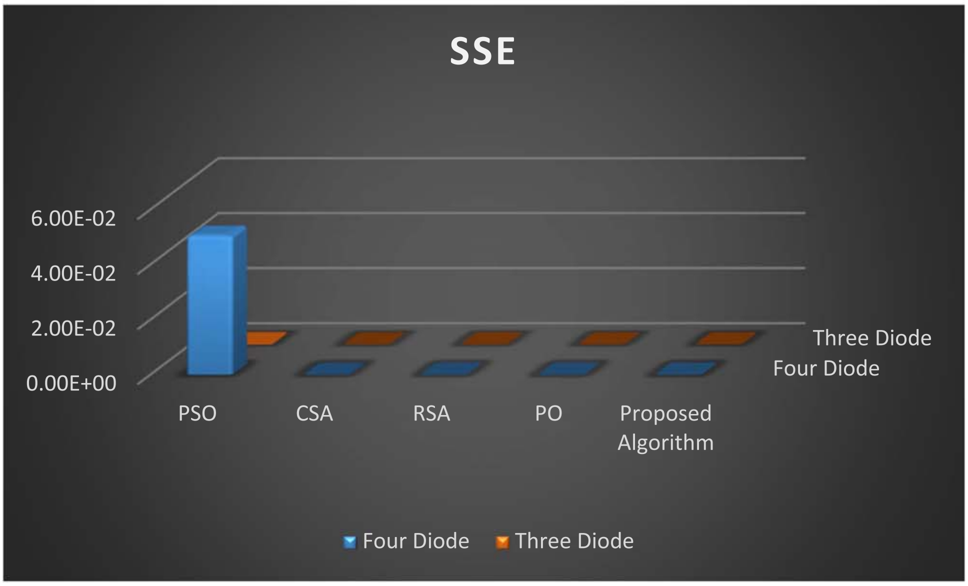
This process is repeated until the $iter_{max}$ has been reached, at which point stages 4 through 7 will be repeated. After the termination requirement is satisfied, the optimization problem's solution is the optimal memory location that occupies the highest percentage of the objective function value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

Table 4. Unknown parameters of four diode model.

Parameter/Algorithms	I_{pv}	n_1	n_2	n_3	n_4	R_s	R_{sh}	I_{o1}	I_{o2}	I_{o3}	I_{o4}	RMSE	SSE
PSO	6.1342	0.538	0.584	0.5	0.545	0.024	222.80	4.86E-09	2.48E-08	0	3.58E-08	2.25E-01	5.06E-02
CSA	6.8896	1.567	1.072	0.612	0.849	0.020	153.43	2.10E-07	0	6.60E-07	0	2.97E-04	8.82E-08
RSA	3.8102	0.760	1.026	1.286	1.598	0.023	301.84	5.24E-07	3.12E-07	3.97E-07	4.21E-07	5.97E-06	3.56E-11
PO	4.8691	1.231	0.925	1.044	1.324	0.002	104.84	0	1.00E-06	0	0	2.36E-09	5.59E-18
Proposed Algorithm	7.8285	1.085	1.214	1.089	1.053	0.087	220.96	2.55E-07	4.87E-07	3.72E-07	2.65E-07	5.06E-16	2.56E-31



(a)



(b)

Figure 5. (a) RMSE (b) SSE.

Table 5. Computational time (Secs) of both models.

Algorithms	Three diode model	Four diode model
PSO	3.154	3.297
RSA	2.698	2.852
CSA	2.154	2.197
PO	1.887	1.745
Proposed Algorithm	1.023	1.325

Experiment and results

Benchmark test functions

Among the test functions available in CEC 2019, five have been selected to assess the performance of the algorithm as shown in table 1. CEC1 through CEC5 are all derived from the CEC, which has 20 dimensions

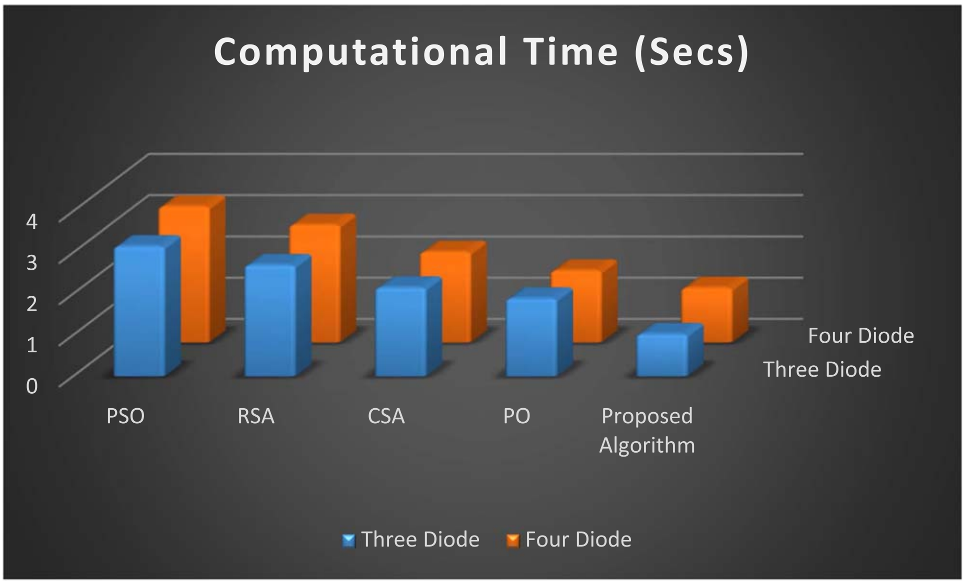


Figure 6. Computational time of both diode.

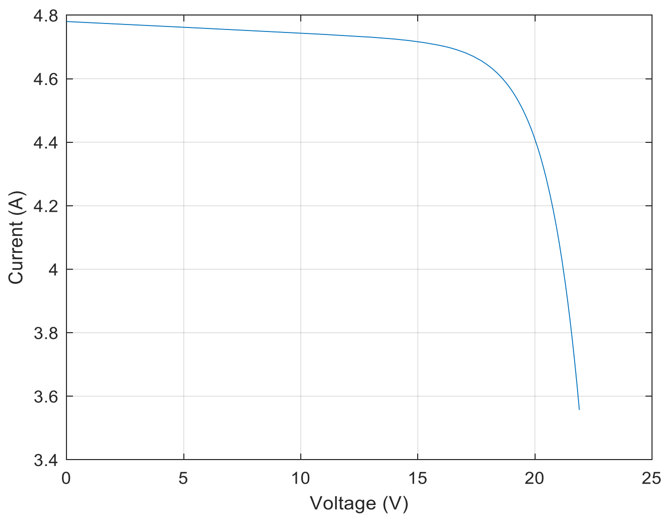


Figure 7. (V)-I curve of solar model.

respectively, with the dimensions corresponding to the dimensions of each characteristic. The purpose of this study is to present a comparative analysis between the PSO [20], RSA [24], CSA [25], PO [26] and proposed algorithm. Benchmark test functions were tested using other algorithms, where each was limited to 1000 feature evaluations per test function. This constraint was used to maintain the unbiasedness of the five benchmark test functions and algorithms analyzed. In this study, MATLAB 2018b was used to program the algorithms, which were executed independently for 30 iterations for each algorithm, with a total of 30 iterations for each algorithm.

This study estimates the statistical measures of the mean and standard deviation of five benchmark tests whose dimension is ten respectively, based on the formulated algorithm. This can be accomplished within the confines of table 2 as a result of the algorithm. A detailed analysis and an all-round assessment of the results and findings recorded in table 2 as a consequence of the in-depth analysis and comprehensive evaluation can confidently be said that the proposed algorithm is both more efficient and effective than the rest algorithms because of its in-depth analysis and comprehensive evaluation. The comparison has also strengthened this claim, as after careful consideration of the comparative analysis of the proposed algorithm with its counterparts, it is evident that the proposed algorithm has a considerably lower mean and standard deviation value compared with the other algorithms, especially when it comes to studying five benchmark test functions as a whole. As a result, the reference result derived from the standard check function appreciably enhances the above-mentioned hybrid algorithm. It in reality outshines all current algorithms in phrases of convergence quotes, stability,

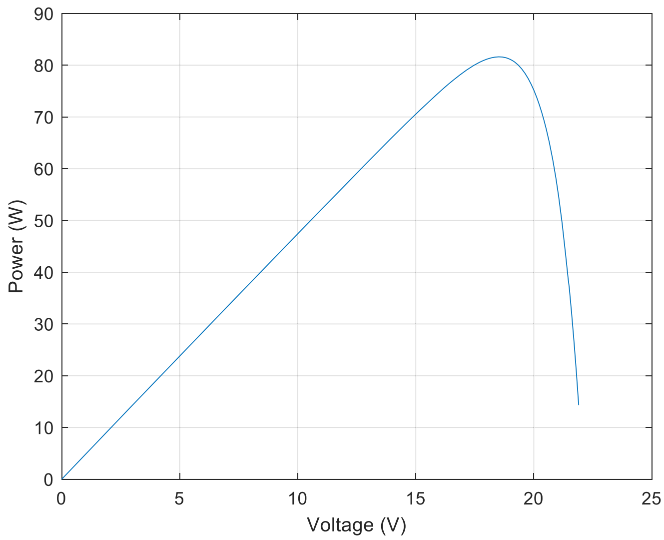


Figure 8. (P)-V curve of solar model.

Table 6. Friedman ranking test.

Algorithms	Friedman ranking test
PSO	5
RSA	3
CSA	4
PO	2
Proposed Algorithm	1

Table 7. Wilcoxon's rank sum test.

Algorithms	PSO	RSA	CSA	PO
Proposed Algorithm versus (Three Diode Model)	8.78E-13	7.52E-13	8.74E-13	7.54E-13
Proposed Algorithm versus (Four Diode Model)	8.41E-13	7.85E-13	8.12E-13	7.95E-13

accuracy, and usual performance when as compared to the algorithms presently employed. The proposed hybrid set of rules surpasses present ones in phrases of convergence charge, robustness, precision, and standard effectiveness. The obvious conclusion is that hybrid algorithms are more effective than any other algorithm, making them an optimal choice for optimization applications. The many merits this algorithm possesses are imperative to emphasize, including its dependability, efficiency, and ability to effectively handle intricate problems.

Engineer problem

This section addresses the parameter extraction challenges associated with individual solar PV models, with the aim of facilitating a thorough performance analysis. The solar system under consideration is a solar universe, characterized by polycrystalline cells as the SW80RNA prototype. Its main specifications include V_m of 17.90 V, I_m of 4.49A, V_{oc} of 21.90 V, and I_{sc} it is 4.78A Like the Nemy panel, it has 60 cells, 25 degrees and operates at a rated Celsius temperature. Parameter extraction is performed for three and four diode models. The first parameter, Ipv, ranges from 0 to 1 amp. The next four parameters Irsd1, Irsd2, Irsd3, and Irsd4 are measured in microamperes (μA) and range from 0 to 1. The Rse and Rsh parameters are measured in ohms (Ω), where Rse ranges from 0 to 0.5, and Rsh from 0 to 100. The final parameters n1, n2, n3, n4 are dimensionless and vary from 1 to 2. This section provides a detailed discussion of polycrystalline solar panels.

Case 1: Poly-Crystalline Solar Panel: In this condition, the solar panel beneath attention is from Solar World and makes use of poly-crystalline era. The parameter extraction procedure for both three diode and four diode models is targeted right here. Tables 3 and 4 show the unknown parameters of each solar models alongside

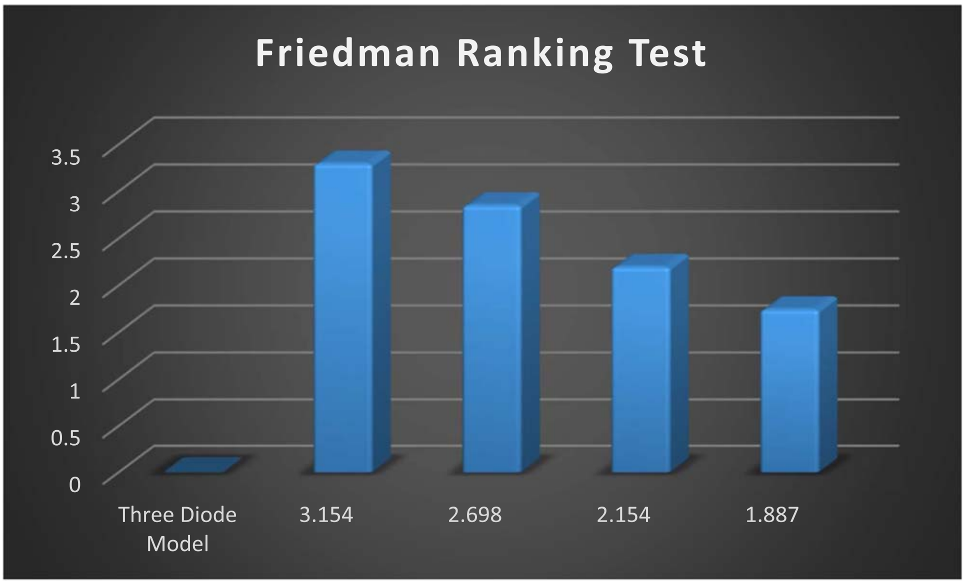


Figure 9. Friedman ranking test of poly-crystalline solar panel.

their respective mistakes (RMSE). Figure 5 illustrates the RMSE and SSE errors for both approaches. Additionally, table 5 and figure 6 gift the computational time for the 3 and 4 diode approaches. Analysis of those tables and figures indicates that the proposed hybrid algorithm is better than the compared algorithms. Specifically, it excels in terms of convergence time, reliability, and memory usage as compared to standalone algorithms. The figures 7 and 8 shows the I–V and P-V graphs which shows the simulated result. Following the extraction of each models, the Friedman ranking test (table 6, figure 9) and Wilcoxon's rank sum test (table 7) have been carried out. Results from these tests similarly affirm that the proposed hybrid algorithm surpasses the other standalone algorithms in overall performance.

Conclusion

This study proposes a new algorithm to introduce the global optimization problems in solar cell parameter extraction. This approach is essentially a method to explore a wider range of possibilities. This test the algorithm on a single-diode solar cell model, which is a simplified but mathematically accurate representation of real-world solar cells with three or four diodes, like the Solar World-SW80RNA model. The results of the investigation that have been carried out so far can be summarized as follows:

- The proposed algorithm outperforms other algorithms in global optimization by delivering more precise solutions and faster convergence rates.
- In comparison to Friedman ranking and Wilcoxon's rank-sum tests, proposed algorithm shows a better performance with regard to consistency and efficiency than any other technique
- Proposed algorithm is a more effective method for managing both PV models statistically than obtaining parameters by means of regression analysis.

The findings of the study highlight the promise and practicality of the proposed algorithm for parameter estimation for solar PV cells. In addition to optimizing solar PV cells, this system demonstrates versatility in solving a variety of energy production projects, making it invaluable for solving various energy challenges. Its role in power systems extends to optimized distributed generation systems, economical load dissipation and energy systems. It offers a variety of opportunities like distributed generation configurations, economic load dispatch, and energy scheduling.

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Conflicts of interest

'The authors declare no conflict of interest.'

Data availability statement

All data that support the findings of this study are included within the article (and any supplementary files).

ORCID iDs

Manish Kumar Singla https://orcid.org/0000-0003-1028-2729
Jyoti Gupta https://orcid.org/0000-0001-7558-7334
Ziad M Ali https://orcid.org/0000-0002-6959-9686
Mohammed H Alsharif https://orcid.org/0000-0001-8579-5444
Mun-Kyeom Kim https://orcid.org/0000-0002-0901-7816

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