

Original Article

Parameter Estimation of Solar Photovoltaic Models with Honey Badger Algorithm and Newton-Raphson Method

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Abstract - In the field of solar Photovoltaic (PV) cells, extraction of parameters pertains to the ascertainment of the electrical properties of a PV cell, which are susceptible to perturbation by a multitude of factors, including cell configuration, irradiance, and temperature. It is crucial to precisely extract the parameters in order to model a cell's performance and optimize its design for constancy and efficiency. The objective is to obtain the parameters of a mathematical model that best describes the behaviour of a PV cell. In this study, a Honey Badger-based biologically inspired metaheuristic approach Newton-Raphson (N-R) method is applied to single and double-diode PV models. Conversely, when calculating objective functions, the N-R approach is employed to resolve nonlinear equations. Unfortunately, the majority of conventional techniques fail to take the nonlinearities of the I-V characteristics into account when estimating the parameters using the standard objective function. The suggested approach was validated by comparing the estimated parameters and Root Mean Square Error (RMSE) calculated among the estimated and experimental data with those obtained using various optimization approaches previously reported by researchers. The proposed approach has an RMSE of $7.73E-04$ for the Single Diode Model (SDM) and $7.68E-04$ for the Double Diode Model (DDM), which is less than most similar algorithms. In addition, the proposed method requires fewer control parameters for tuning than other methods, and extracted parameters closely match experimental data.

Keywords - Solar PV cell, Single diode model, Double Diode Model, Honey Badger Algorithm, Newton-Raphson method.

1. Introduction

The growing need for renewable energy sources is fueled by concerns surrounding environmental degradation and the limited availability of energy. Power plants that generate electricity via solar energy, especially large-scale Photovoltaic (PV) systems, are widely used. These PV systems were often placed in open spaces and can be exposed to harsh environmental conditions like heavy rainstorms and strong winds.

To tackle these challenges, an accurate data-driven model is much needed in the solar sector to evaluate the essential features of PV systems. An in-depth examination of the extraction of solar model parameters is crucial for assessing the performance of PV power plants, determining efficiency, pinpointing maximum power points, and optimizing the energy handling of the PV system [3].

The thorough modelling of a PV cell involves two essential phases: the establishment of a mathematical model and the estimation of parameters. The most widely utilized Single-Diode Model (SDM) and Double-Diode Model

(DDM) are applied in practical scenarios [5]. Nevertheless, the PV model performance is substantially impacted by unspecified parameters, which may result in instability and inaccuracies, especially as the equipment ages. Therefore, precise parameter estimation of photovoltaic cells is an essential aspect of simulation.

Furthermore, PV system installation and optimization must be more precise. Nonetheless, the photovoltaic model is viewed as a non-convex system with nonlinear parameters, posing several hurdles and constraints. The search for techniques to accurately estimate unknown parameters has been ongoing recently. Deterministic methods, analytical methods, and metaheuristic methods are the three main methodologies that have been identified [6].

Analytical techniques, known for their simplicity, speed, and uniqueness, analyze each data point on the I-V characteristics curve to minimize error between anticipated and measured values. However, these methods, relying on mathematical formulations with assumptions, may not achieve complete accuracy [3]. Deterministic approaches operate on



the principle of using all true measured data for the whole approach. They extract unspecified parameters through an objective function, representing the variance between experimental and estimated data points. Despite their comprehensive approach, deterministic methods using gradient information may converge only to locally optimal solutions [8].

Metaheuristic methods, also utilizing all actual measured data, stand out as universal optimization algorithms owing to their simplicity, robustness, reliability, and application-friendliness [25-28]. Inspired by biological processes, these methods, including Evolutionary-Based Algorithms (e.g., GA, DEA, ESA) and Swarm-Based Algorithms (e.g., PSO, ACO, GWO, WOA, Social-Spider Optimization, SSA), offer effective solutions to real-world problems [15-19].

When seeking precise modelling of PV cells and modules, researchers often employ analog electrical circuits. Photovoltaic researchers commonly choose the SDM and DDM for their modelling endeavors [29, 30]. There are five parameters in the SDM, the accurate determination of which is imperative for simulating its behavior. Similarly, seven parameters need to be carefully determined to simulate the double-diode PV model effectively. The key to achieving a faithful representation of the P-V and I-V characteristics in the physical system lies in the accurate estimation of these five or seven parameters. The ultimate objective is to reduce the absolute error between the assessed and estimated currents of photovoltaic cell/module systems.

As a result, the objective function plays an important role in the extraction of optimal parameters. The most often used goal function for extracting solar PV system parameters is Root Mean Square Error (RMSE). Most research papers estimate the current using a simple function that disregards the nonlinear nature of I-V characteristics. This leads to erroneous estimated parameters obtained with the traditional method.

To address nonlinearity, researchers have developed a variety of strategies, including the Newton-Raphson (N-R) method, Taylor series expansion, Lambert W function, and others [7]. This article proposes a novel strategy that integrates the Honey Badger Algorithm (HBA) with the N-R method to estimate the unknown parameters of SDM and DDM models of PV cells.

The paper is organized as Section 2 provides details on the mathematical modelling of the photovoltaic models utilized in this paper, section 3 outlines objective function based on RMSE, Section 4 provides a detailed description of the suggested approach, with a flow chart and mathematical model. Section 5 examines and presents results on typical standard functions and PV models for cells and modules. The last section includes concluding observations and future scope.

2. Modelling of Solar PV System

Photovoltaic modelling involves the use of mathematical models to explain the functionality and performance of photovoltaic cells. The SDM and the DDM are two of the most popular models [7].

2.1. SDM

The Single Diode Model has gained popularity for its balanced blend of moderate complexity and high accuracy in delivering results. This model conceptualizes an ideal PV cell as one diode operating in parallel with a current source. Nonetheless, acknowledging the non-ideal nature of actual solar cells, the SDM incorporates a shunt resistance to accommodate leakage current and a series resistance to symbolize material resistivity and the ohmic losses associated with contacts. The equivalent circuit for the SDM is shown in Figure 1.

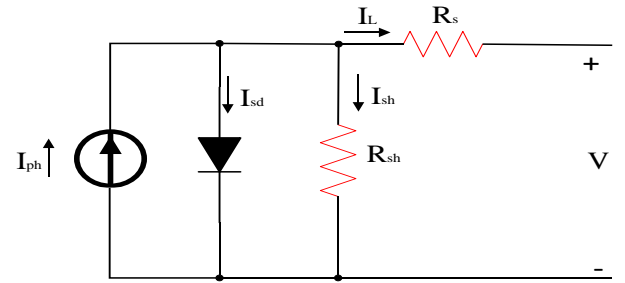


Fig. 1 SDM of solar PV cell

The output current of the solar cell is,

$$I_L = I_{ph} - I_d - I_{sh} \quad (1)$$

Where, I_d is the diode current, I_L is solar cell output current, I_{ph} is photo-generated current and I_{sh} is shunt resistance current.

$$I_d = I_{sd} \left(e^{\frac{q(V_L + I_L R_s)}{nkT}} - 1 \right) \quad (2)$$

$$I_{sh} = \frac{V_L + I_L R_s}{R_{sh}} \quad (3)$$

Where, I_{sd} is reverse saturation current of diode, q is electron charge, k is Boltzmann constant, V_L is solar cell output voltage, R_s is series resistance, n is diode ideality factor, T is temperature and shunt resistance R_{sh} . PV cell output current can be obtained by substituting current expressions (3) and (2) in (1) as follows:

$$I_L = I_{ph} - I_{sd} \left(e^{\frac{q(V_L + I_L R_s)}{nkT}} - 1 \right) - \frac{V_L + I_L R_s}{R_{sh}} \quad (4)$$

To precisely model the behavior of the PV cells, the unknown parameters of SDM $\{I_{ph}, I_{sd}, R_{sh}, R_s, n\}$ must be estimated using an optimization approach.

2.2. DDM

The Double Diode Model incorporates a more intricate structure by introducing the current source in parallel with two diodes. This model also has a shunt and series resistance. The dual diodes serve to elucidate the polarization phenomena occurring at the PN junction, adding a layer of complexity to capture the nuanced behavior of real-world solar cells. Figure 2 shows the DDM's equivalent circuit.

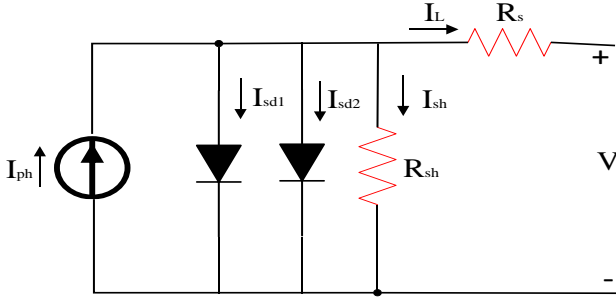


Fig. 2 DDM of solar PV cell

In the DDM, the solar PV cell's output current may be computed using KCL and the following equations:

$$I_L = I_{ph} - I_{d1} - I_{d2} - I_{sh} \quad (5)$$

The output current may be expressed as follows,

$$I_L = I_{ph} - I_{sd1} \left(e^{\frac{q(V_L + I_L R_s)}{n_1 k T}} - 1 \right) - I_{sd2} \left(e^{\frac{q(V_L + I_L R_s)}{n_2 k T}} - 1 \right) - \frac{V_L + I_L R_s}{R_{sh}} \quad (6)$$

Where I_{sd1}, I_{sd2} were the reverse saturation currents of diodes and n_1, n_2 were the diode ideality factors.

The unknown parameters of DDM $\{I_{ph}, I_{sd1}, I_{sd2}, R_{sh}, R_s, n_1, n_2\}$ that need to be estimated in addition to the known values.

2.3. PV Module

The PV module output current is expressed as follows:

$$I_L = I_{ph} N_p - I_{sd} N_p \left(e^{\left\{ \frac{q(V_L + I_L R_s N_s)}{n N_s k T} \right\}} - 1 \right) - \frac{V_L + \frac{I_L R_s N_s}{N_p}}{\frac{R_{sh} N_s}{N_p}} \quad (7)$$

Where N_s is the number of series cells, N_p is the number of parallel cells. The PV cells are typically connected in series, thus $N_p = 1$. Consequently, the PV module output current :

$$I_L = I_{ph} - I_{sd} \left(e^{\left\{ \frac{q(V_L + I_L R_s N_s)}{n N_s k T} \right\}} - 1 \right) - \frac{V_L + I_L R_s N_s}{R_{sh} N_s} \quad (8)$$

3. Proposed Objective Function

The main objective is to minimize the disparity between experimental and simulated outcomes while assessing solar PV cell parameters. To accomplish this, the root mean square error serves as the objective function for optimizing the parameters of the solar PV model. The main objective of this research is to precisely determine the solar PV cell parameters by utilizing voltage and current measurements through the use of metaheuristic optimization approaches. In this paper, objective function [7], denoted as F_{obj} which is used for estimating the parameters.

$$F_{obj} = \sqrt{\frac{1}{N} (\sum_{i=1}^N [I_{L.meas} - I_{L.calc}]^2)} \quad (9)$$

The basic approach involves calculating the RMSE between the calculated and measured current values using the Equation (9). This is achieved by solving the Equations (10) to (12) and equating them to zero to obtain the estimated current.

For SDM,

$$f(x) = I_{ph} - I_{sd} \left(e^{\frac{q(V_L + I_L R_s)}{n k T}} - 1 \right) - \frac{V_L + I_L R_s}{R_{sh}} - x \quad (10)$$

For DDM,

$$f(x) = I_{ph} - I_{sd1} \left(e^{\frac{q(V_L + I_L R_s)}{n_1 k T}} - 1 \right) - I_{sd2} \left(e^{\frac{q(V_L + I_L R_s)}{n_2 k T}} - 1 \right) - \frac{V_L + I_L R_s}{R_{sh}} - x \quad (11)$$

For PV Panel,

$$f(x) = I_{ph} - I_{sd} \left(e^{\left\{ \frac{q(V_L + I_L R_s N_s)}{n N_s k T} \right\}} - 1 \right) - \frac{V_L + I_L R_s N_s}{R_{sh} N_s} - x \quad (12)$$

The current (I_L) is determined by solving Equations (10) to (12) at a given voltage using the N-R method.

- It is important to note the following remarks regarding the objective functions and their implications:
- The highly nonlinear nature of the current equation may result in a discrepancy between the error function value and the actual current error. Therefore, the error function alone may not accurately replicate the current error.
- The reduction of the error function value does not guarantee a corresponding reduction in the current RMSE error. Many metaheuristic algorithms suggested in the literature operate under this assumption, yet its application may not consistently yield the desired results.
- By considering these objective functions and approaches, The study seeks to precisely estimate the PV system parameters using measurements of voltage and current.

- This optimization process will not only advance our comprehension of the system's performance but also elevate its overall efficiency.

4. Honey Badger Algorithm

4.1. The Inspiration behind HBA

The Honey Badger Algorithm is a new metaheuristic optimization technique. The method is inspired by the hunting behaviour of Honey Badger (HB) and is intended to address optimization challenges. It mimics two foraging behaviors used by honey badgers: digging and honey. In digging mode, it utilizes its sniffing skills to assess the position of its prey. Upon reaching the approximate location, the honey badger navigates round its prey to identify the best spot for digging. During honey mode, it depends on the assistance of honeyguide birds to accurately pinpoint the whereabouts of prey.

4.2. Mathematical Model

HBA's mathematical model consists of digging and honey phases. The method includes both the exploration and exploitation stages, establishing its position as a universal optimization algorithm. In HBA, the possible solutions are organized into a matrix. Every row of this matrix corresponds to the location of a honey badger.

4.2.1. Initialization Phase

The initialization step establishes the placements of the honey badgers inside the search zone. This initialization is done based on the below equation.

$$x_i = lb_i + r_1 \cdot (ub_i - lb_i) \quad (13)$$

r_1 is random number (0 to 1)

In this equation, x_i denotes the position of the i^{th} HB. The values ub_i and lb_i represent the upper and lower bounds of the considered space, respectively. r_1 contributing to the introduction of randomness in the initialization process.

4.2.2. Intensity (I)

In HBA, the intensity (I) represents the strength of the prey's concentration and the distance between the prey and the i^{th} HB. It signifies the smell intensity, where a higher intensity implies a stronger smell. The intensity is calculated based on the below equation.

$$I_i = r_2 \cdot \frac{s}{4\pi d_i^2} \quad (14)$$

r_2 is a random number between 0 and 1

$$S = (x_i - x_{i+1})^2$$

$$d_i = x_{\text{prey}} - x_i$$

In this equation, S is the source or concentration strength, which corresponds to the location of prey. The term d_i denotes the distance between the i^{th} HB and prey, calculated as the difference between the positions of the prey (x_{prey}) and the i^{th} badger (x_i).

4.2.3. Density Factor Update

In HBA, the crucial density factor (α) serves as a key player in regulating time-varying randomization, facilitating a smooth transition from exploration to exploitation. It undergoes continuous updates during the algorithm's execution, gradually decreasing with iterations to temper randomization over time.

The update of α is determined by the following equation:

$$\alpha = C \cdot \exp\left(\frac{-t}{t_{\max}}\right) \quad (15)$$

t_{\max} = maximum number of iterations

In this equation, C is a constant value that is more than or equal to 1, by default value is set to 2. The current iteration is denoted by a variable t . This update aims to balance exploration and exploitation throughout the search space.

By gradually decreasing α , the algorithm reduces randomization and focuses more on exploiting promising portions of the search area. This helps the algorithm converge towards optimal solutions while avoiding getting trapped in local optima.

4.2.4. Position Update

In HBA position update (x_{new}) process splits into two parts: the "digging phase" and the "honey phase" Let us delve into each phase for a better understanding:

Digging Phase

In this phase, HB moves in a cardioid pattern. The Cardioid movement can be simulated using the following equation.

$$x_{\text{new}} = x_{\text{prey}} + F \cdot \beta \cdot I \cdot x_{\text{prey}} + F \cdot r_3 \cdot \alpha \cdot d_i \cdot \frac{1}{|\cos(2\pi r_4) \times [1 - \cos(2\pi r_5)]|} \quad (16)$$

In this equation, x_{prey} represents the prey's position, and β denotes the HB's ability to obtain food (≥ 1 , default = 6).

The flag F determines the search direction and is determined using the below method.

$$F = \begin{cases} 1, & \text{if } r_6 \leq 0.5 \\ -1, & \text{else} \end{cases}$$

r_6 = random number between 0 and 1

Honey Phase

In this phase, the simulation replicates a situation where a beehive is located by a honey badger following a honeyguide bird. The following equation provides an accurate representation of this phase.

$$x_{new} = x_{prey} + F \cdot r_7 \cdot \alpha \cdot d_i \quad (17)$$

r_7 is a random number between 0 and 1

Where x_{new} is the updated position of the honey badger, while x_{prey} is the location of the prey. The HBA method effectively changes the locations of its agents by combining the digging and honey phases, resulting in a balanced blend of exploration and exploitation throughout the optimization process.

4.3. Key Features of the HBA

HBA is a robust algorithm that effectively balances exploration and exploitation. It incorporates several key features that enhance its robustness and increase the chances of finding high-quality solutions. These features include:

- **Exploitation Behaviour with Intensity Parameter (I):** The HBA ensures exploitation behaviour by utilizing the

intensity parameter (I). This parameter guides the population individuals towards promising regions that have already been identified, allowing the algorithm to exploit their potential and improve the quality of solutions.

- **Dynamic Time-Varying Randomization with Density Factor (α):** The HBA uses a density factor (α) that enables dynamic time-varying randomization. This element ensures a seamless transition from the phase of exploration to the phase of exploitation, maintaining a delicate balance between exploring new regions and exploiting the potential of already identified promising areas.
- **Preventing Trapping in Local Regions with Flag F:** The HBA uses a flag F to prevent population candidates from getting trapped in local regions. This flag directs the search towards new regions, increasing the chances of finding even better solutions.
- **Balancing Exploration and Exploitation with Digging and Honey Phases:** The HBA incorporates digging and honey phases, which balance the exploitation and exploration properties of the search mechanism. The digging phase allows for exploration by searching for new regions, while the honey phase focuses on exploiting the potential of already identified promising regions.

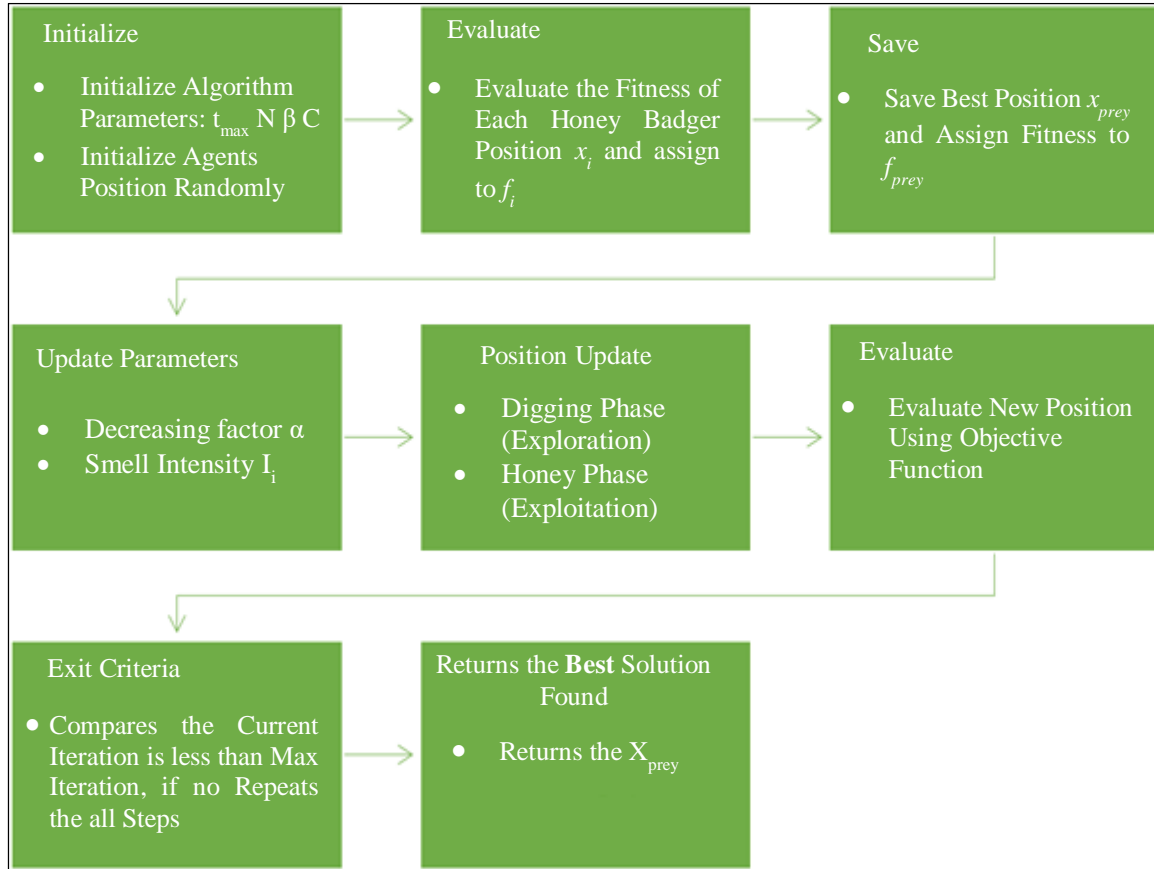


Fig. 3 Honey Badger Algorithm overview

5. Results and Discussion

In this work, the HBA technique is leveraged to derive the optimal parameters for the SDM and DDM models. The validity of the HBA approach is confirmed by comparing its findings with the latest research in the area, ensuring both accuracy and efficiency. To evaluate the efficacy of the parameter extraction technique utilizing HBA, we employ experimental data presented by [1]. Two types of PV models are considered for testing: SDM and DDM for various case studies, which include Photo Watt-PWP 201 PV module (irradiance set at 1000 W/m², & T= 45°C) and RTC France silicon solar cell (irradiance set at 1000 W/m² & T= 33°C). The PV model's parameters are determined by configuring the suggested HBA method with the following values: population set = 50, maximum number of iterations = 1000, parameter β = 0.01, and Constant C = 2. The settings were optimized using the random search approach.

The HBA algorithm suggested in this study works in collaboration with the Newton-Raphson (N-R) approach. While the optimization process is underway, the HBA algorithm exchanges information about the PV cell parameters with the N-R approach while also calculating the objective function's value. Subsequently, the N-R approach addresses the nonlinear function defined in Equation (4) for a specified voltage, generating corresponding output current values.

The N-R method is a popular iterative technique for solving non-linear equations. This method builds on the traditional successive approximation method for determining function roots. The technique starts with an initial root estimate (x_0) and refines it with the function's derivative at that point. The iteration procedure is continued until there is little variation in the estimations or the iteration count reaches its limit. The objective function value is obtained through the utilization of the NR technique in the optimization process. The optimization algorithm directs the PV parameters to the N-R approach for the computation. The proposed approach is illustrated in Figure 4.

5.1. Single-Diode Model

The SDM unknown parameters are $\{I_{ph}, I_{sd}, R_{sh}, R_s, n\}$. The upper and lower bounds of these parameters are presented in Table 1, and Table 2 presents estimated parameters. Figure 5 illustrates the P-V and I-V curves of a PV cell, showcasing both practical measurements and those derived from estimated parameters. Table 3 shows that the proposed method outperforms its peers in terms of all metrics of RMSE values, indicating that the HBA could demonstrate reliable and steady efficacy when compared to others.

Table 8 displays the estimated currents, experimentally measured currents, absolute and estimated power, and current error values. The robustness of the proposed approach for the SDM is checked with other standard algorithms available in the literature. The HBA algorithm demonstrates outstanding performance with the proposed objective function. The current RMSE obtained with HBA is 7.7299E-04 which is less when compared to its peers mentioned in Table 3, which validates the accuracy of the estimated parameters.

Table 1. Ranges of the parameters of PV Cells

Parameter	PV Module		Single /Double Diode	
	Upper Bound	Lower Bound	Upper Bound	Lower Bound
$I_{ph}(A)$	2	0	1	0
$I_{sd}, I_{sd1}, I_{sd2} (\mu A)$	50	0	1	0
n	50	1	2	1
$R_{sh}(\Omega)$	2000	0	100	0
$R_s(\Omega)$	2	0	0.5	0

Table 2. Estimated parameters for SDM-based RTC france silicon with different algorithms

Algorithm	I_{ph}	I_{sd}	n	R_{sh}	R_s
GOTLBO [14]	0.76078	0.331552	1.48382	54.1154	0.036265
EOTLBO [13]	0.760776	0.323021	1.481184	53.71853	0.036377
IJAYA [12]	0.7608	0.3228	1.4811	53.7595	0.0364
EJAYA [9]	0.76078	0.32302	1.48118	53.71852	0.03638
SMA [10]	0.76076	0.32314	1.48114	53.71489	0.03637
WLCSODGM [11]	0.760776	0.323021	1.481184	53.71852	0.036377
Proposed Method	0.760787	0.310535	1.477221	52.884157	0.0365490

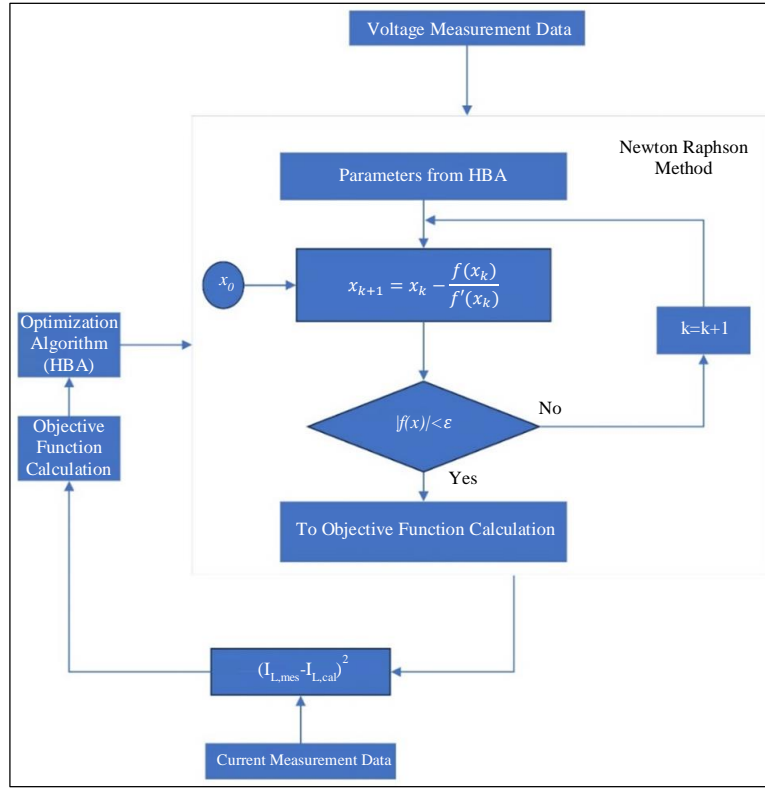


Fig. 4 Parameter extraction using the proposed approach

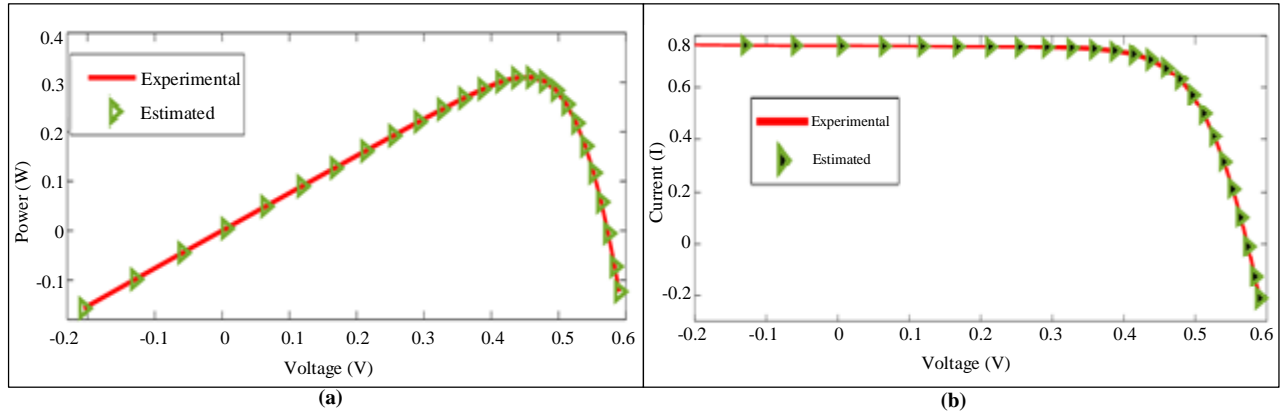


Fig. 5 Measured and estimated data of SDM (a) P-V characteristic, and (b) I-V characteristic.

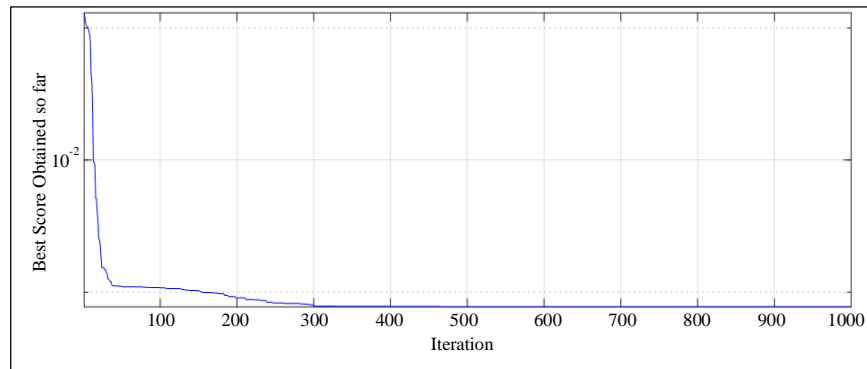


Fig. 6 Convergence curve for SDM model

Table 3. Comparative statistical analysis of SDM results obtained using various methods

Algorithm	RMSE		
	Min	Mean	STD
GOTLBO [14]	9.87E-04	1.21E-03	4.70E-04
EOTLBO [13]	9.86E-04	9.86E-04	4.13E-17
IJAYA [12]	9.86E-04	9.86E-04	1.40E-05
EJAYA [9]	9.86E-04	9.86E-04	6.80E-17
SMA [10]	9.80E-04	1.93E-03	7.26E-04
WLCSODGM [11]	9.86E-04	9.86E-04	2.64E-17
Proposed Method	7.73E-04	7.73E-04	4.61E-09

5.2. Double Diode Model

The seven unknown parameters of the DDM are $\{I_{ph}, I_{sd1}, I_{sd2}, R_{sh}, R_s, n_1, n_2\}$. Table 1 displays the lower and upper boundaries for these parameters. The P-V and I-V characteristics of a PV cell under practical and estimated parameters are shown in Figure 5. In Figure 8, the convergence curve is shown. Table 6 displays the estimated parameters, and Table 5 shows that the proposed method (HBA) outperforms other similar approaches in terms of all metrics of RMSE values, indicating that the HBA can

demonstrate reliable and steady efficacy when compared to others.

Table 9 displays the power errors and absolute current for each measurement relating to the estimated and measured values. The robustness of the proposed approach for the DDM is compared with the literature and found to be superior to the other algorithms. The current error is 7.48E-04 (RMSE) which is less when compared to its peers mentioned in Table 5, which confirms the precision of the estimated parameters.

Table 4. Estimated parameters for DDM with different algorithms

Algorithm	I_{ph}	I_{sd1}	I_{sd2}	R_{sh}	R_s	n_1	n_2
GOTLBO [14]	0.760752	0.800195	0.220462	56.0753	0.036783	1.999973	1.448974
EOTLBO [13]	0.760781	0.225975	0.749344	55.48544	0.03674	1.451017	0.749344
IJAYA [12]	0.7601	0.005045	0.75094	77.8519	0.0376	1.2186	1.6247
EJAYA [9]	0.76078	0.22597	0.74934	55.48509	0.03674	1.45102	2
SMA [10]	0.76076	0.74874	0.22652	55.71456	0.03677	2	1.45463
WLCSODGM [11]	0.760781	0.749202	0.225992	55.48504	0.03674	2	1.451023
Proposed Method	0.760766	0.199898	0.892283	55.430845	0.037017	1.440212	1.999741

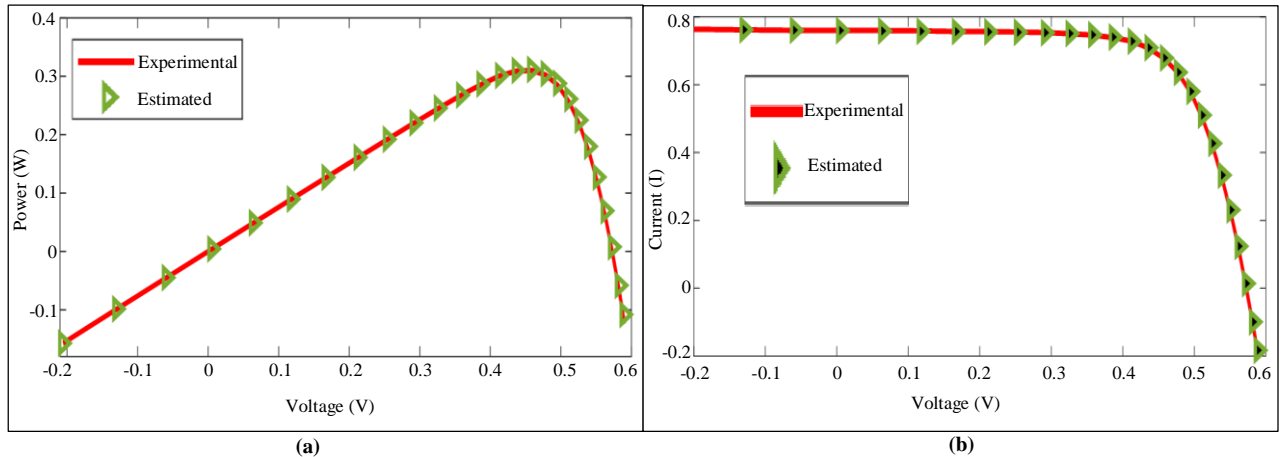


Fig. 7 Measured and estimated for DDM (a) P-V characteristic, and (b) I-V characteristic.

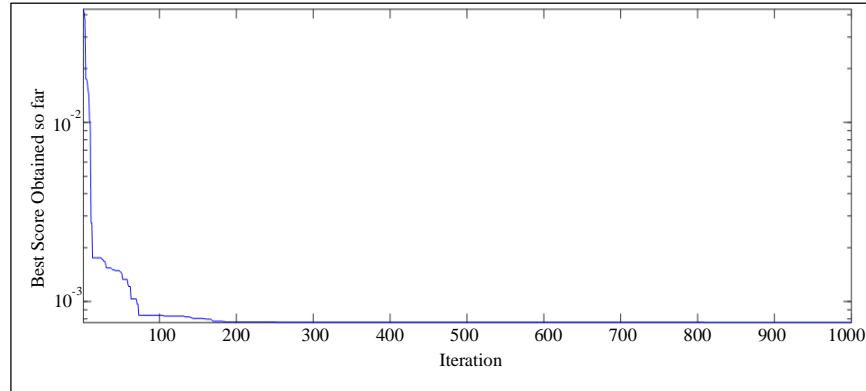


Fig. 8 Convergence curve for DDM Model

Table 5. Comparative statistical analysis of DDM results obtained using various methods

Algorithm	RMSE		
	Min	Mean	STD
GOTLBO [14]	9.87E-04	1.15E-03	1.13E-04
EOTLBO [13]	9.82E-04	9.85E-04	1.69E-06
IJAYA [12]	9.83E-04	1.03E-03	9.83E-05
EJAYA [9]	9.82E-04	9.84E-04	1.51E-06
SMA [10]	9.81E-04	2.00E-03	7.84E-04
WLCSODGM [11]	9.82E-04	9.84E-04	1.54E-06
Proposed Method	7.68E-04	7.48E-04	1.01E-05

5.3. Solar PV Module

This analysis primarily focused on a single standard experimental measurement for extracting parameters from a solar photovoltaic module, specifically the Photowatt-PWP201. The objective is to extract five parameters: $\{I_{ph}, I_{sd}, R_{sh}, R_s, n\}$ for the PV module. The upper and lower bounds for these parameters can be found in Table 1. Figure 10 illustrates the convergence curve for the PV module Photowatt-PWP201. Table 6 displays the estimated parameter values obtained from 30 runs using the proposed approach. Additionally, Table 10 provides an overview of the results. To

further analyse the characteristics of the PV module PWP201, we have included the P-V and I-V characteristics in Figure 9, respectively.

To evaluate the effectiveness of the proposed approach, it is compared with existing methods mentioned in the literature. The results of this comparison for the Photowatt-PWP201 PV module are presented in Table 7. The table demonstrates that the proposed method surpasses the other algorithms in performance. It achieves a minimum current error of 2.2953E-03 (RMSE) which is less when compared to its peers.

Table 6. Estimated parameters for PV module PWP201 with different algorithms

Algorithm	I_{ph}	I_{sd}	R_{sh}	R_s	n
GOTLBO [14]	1.03005	3.484181	1038.34	1.202289	48.64271
EOTLBO [13]	1.030514	3.482263	981.9822	1.201271	48.64283
IJAYA [12]	1.030451	3.483344	987.8993	1.20134	48.64389
EJAYA [9]	1.03051	3.48226	981.9824	1.20127	48.64283
SMA [10]	1.03422	1.32143	559.45	1.25644	45.19925
WLCSODGM [11]	1.030514	3.482263	981.9822	1.201271	48.64283
Proposed Method	1.03143	2.639659	22.8142	0.034319	1.322236

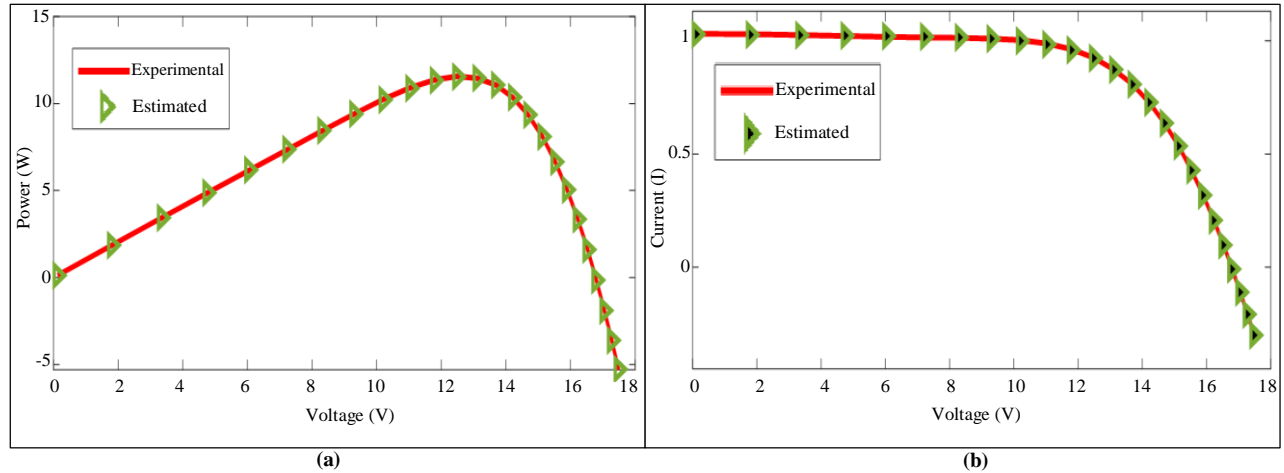


Fig. 9 Measured and estimated data for PV Module (Photowatt-PWP201) (a) P-V characteristic, and (b) I-V characteristic.

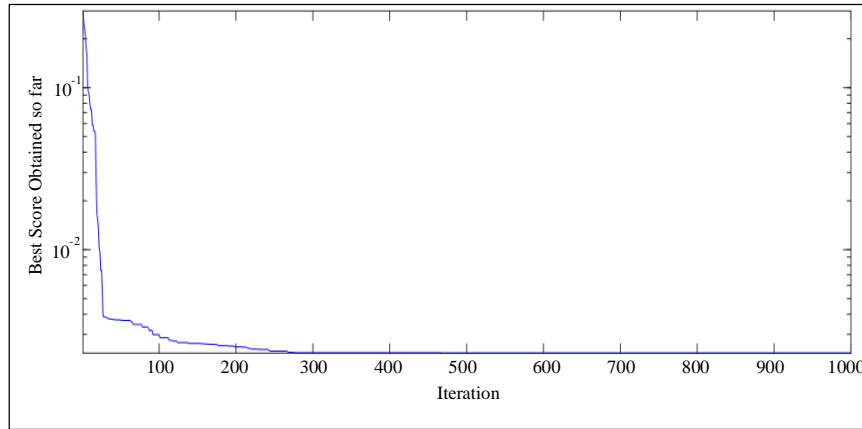


Fig. 10 Convergence curve for PV module (Photowatt-PWP201)

Table 7. Comparative statistical analysis of PV Module (Photowatt-PWP201) results obtained using various methods

Algorithm	RMSE		
	Min	Mean	STD
GOTLBO [14]	2.43E-03	2.48E-03	2.94E-05
EOTLBO [13]	2.43E-03	2.43E-03	3.62E-17
IJAYA [12]	2.43E-03	2.43E-03	3.78E-06
EJAYA [9]	2.43E-03	2.43E-03	6.39E-17
SMA [10]	2.81E-03	3.35E-03	6.25E-03
WLCSODGM [11]	2.43E-03	2.43E-03	3.03E-17
Proposed Method	2.29E-03	2.47E-03	4.12E-04

The proposed approach outperforms competing methods [9-14], as seen by its curves in Figures 6, 8, and 10 which exhibit a curve of quick convergence right from the start and complete a fast convergence around 300 iterations. Based on

the results so far, it appears that the proposed approach achieves both rapid convergence and correct solutions. Table 11 presents the parameter settings for all examined methods derived from recommendations mentioned in the literature.

Table 8. Absolute current and power errors of SDM-based RTC France silicon solar cell

Voltage	Actual Current	Estimated Current	Absolute Current Error	Power	Absolute Power Error
-0.2057	0.764	0.76414959	0.00014959	-0.15715	3.07707E-05
-0.1291	0.762	0.762702122	0.00070212	-0.09837	9.06439E-05
-0.0588	0.7605	0.761373602	0.0008736	-0.04472	5.13678E-05
0.0057	0.76	0.760154205	0.00034579	0.004335	1.97103E-06
0.0646	0.76	0.759038634	0.00096137	0.049096	6.21042E-05
0.1185	0.759	0.758010232	0.00098977	0.089942	0.000117288
0.1678	0.757	0.757045083	4.5083E-05	0.127025	-7.565E-06
0.2132	0.757	0.756084144	0.00091586	0.161392	0.000195261
0.2545	0.7555	0.755021635	0.00047837	0.192275	0.000121744
0.2924	0.754	0.753596673	0.00040333	0.22047	0.000117933
0.3269	0.7505	0.751326704	0.0008267	0.245338	-0.00027025
0.3585	0.7465	0.747305048	0.00080505	0.26762	-0.00028861
0.3873	0.7385	0.740084763	0.00158476	0.286021	-0.00061378
0.4137	0.728	0.727426839	0.00057316	0.301174	0.000237117
0.4373	0.7065	0.707027109	0.00052711	0.308952	-0.0002305
0.459	0.6755	0.67540187	9.813E-05	0.310055	4.50417E-05
0.4784	0.632	0.630999777	0.00100022	0.302349	0.000478507
0.496	0.573	0.57217598	0.00082402	0.284208	0.000408714
0.5119	0.499	0.499539572	0.00053957	0.255438	-0.00027621
0.5265	0.413	0.413484653	0.00048465	0.217445	-0.00025517
0.5398	0.3165	0.317160637	0.00066064	0.170847	-0.00035661
0.5521	0.212	0.212015312	1.5312E-05	0.117045	-8.4539E-06
0.5633	0.1035	0.102635391	0.00086461	0.058302	0.000487034
0.5736	-0.01	-0.00929934	0.00070066	-0.00574	-0.0004019
0.5833	-0.123	-0.124361272	0.00136127	-0.07175	0.00079403
0.59	-0.21	-0.209101001	0.000899	-0.1239	-0.00053041

Table 9. Absolute current and power errors of DDM-based RTC France silicon solar cell

Voltage	Actual Current	Estimated Current	Absolute Current Error	Power	Absolute Power Error
-0.2057	0.764	0.763991	9.30315E-06	-0.15715	-1.91366E-06
-0.1291	0.762	0.762602	-0.000601691	-0.09837	7.76783E-05
-0.0588	0.7605	0.761327	-0.000826586	-0.04472	4.86033E-05
0.0057	0.760	0.760155	0.000344509	0.004335	1.9637E-06
0.0646	0.7600	0.759082	0.000917787	0.049096	5.9289E-05
0.1185	0.7590	0.758088	0.000911599	0.089942	0.000108025
0.1678	0.7570	0.757147	-0.00014667	0.127025	-2.46112E-05
0.2132	0.7570	0.756193	0.000807329	0.161392	0.000172123
0.2545	0.7555	0.755114	0.000385857	0.192275	9.82005E-05
0.2924	0.7540	0.753645	0.000354656	0.22047	0.000103701
0.3269	0.7505	0.751306	-0.000805722	0.245338	-0.00026339
0.3585	0.7465	0.747203	-0.00070255	0.26762	-0.000251864
0.3873	0.7385	0.739922	-0.001421695	0.286021	-0.000550622
0.4137	0.7280	0.727276	0.000724348	0.301174	0.000299663
0.4373	0.7065	0.707019	-0.000518554	0.308952	-0.000226764
0.4590	0.6755	0.675721	-0.000221012	0.310055	-0.000101445
0.4784	0.6320	0.631843	0.000157187	0.302349	7.51984E-05
0.4960	0.5730	0.573725	-0.000725082	0.284208	-0.000359641
0.5119	0.4990	0.501927	-0.002926951	0.255438	-0.001498306
0.5265	0.4130	0.416802	-0.003801818	0.217445	-0.002001657
0.5398	0.3165	0.321445	-0.004944505	0.170847	-0.002669044
0.5521	0.2120	0.217283	-0.005283036	0.117045	-0.002916764
0.5633	0.1035	0.108867	-0.005366598	0.058302	-0.003023005
0.5736	-0.0100	-0.00213	-0.007871817	-0.00574	-0.004515274
0.5833	-0.1230	-0.11626	-0.006740854	-0.07175	-0.00393194
0.5900	-0.2100	-0.20033	-0.009670797	-0.1239	-0.00570577

Table 10. Absolute current and power errors of PV module (Photowatt-PWP201)

Voltage	Actual Current	Current Estimated	Absolute Current Error	Power	Absolute Power Error
0.1248	1.0315	1.023794	0.007705722	0.128731	0.000962
1.809	1.03	1.023716	0.006284286	1.863579	0.01137
3.351	1.026	1.02358	0.00242041	3.438229	0.008111
4.762	1.022	1.023292	-0.001292101	4.866968	-0.00615
6.054	1.018	1.022652	-0.004652414	6.162768	-0.02816
7.236	1.0155	1.021268	-0.005767806	7.348564	-0.04174
8.319	1.014	1.018437	-0.004437003	8.435365	-0.03691
9.31	1.01	1.013013	-0.0030131	9.402797	-0.02805
10.22	1.0035	1.003289	0.000210581	10.25206	0.002151
11.04	0.988	0.986997	0.001003219	10.91236	0.01108
11.8	0.963	0.961472	0.001527732	11.36513	0.01803
12.49	0.9255	0.924081	0.001418769	11.56218	0.017725
13.12	0.8725	0.872877	-0.00037718	11.4499	-0.00495
13.7	0.8075	0.807011	0.000488773	11.06138	0.006695
14.22	0.7265	0.727316	-0.000815679	10.33236	-0.0116
14.7	0.6345	0.635727	-0.001227139	9.326833	-0.01804
15.14	0.5345	0.535047	-0.000547327	8.089444	-0.00828
15.53	0.4275	0.428363	-0.000862952	6.639545	-0.0134
15.89	0.3185	0.318442	5.82288E-05	5.061889	0.000925
16.22	0.2085	0.207833	0.000666828	3.382475	0.010818
16.52	0.101	0.098478	0.002521917	1.668934	0.041672
16.8	-0.008	-0.00797	-3.31171E-05	-0.13439	-0.00056
17.05	-0.111	-0.11076	-0.000241693	-1.89254	-0.00412
17.28	-0.209	-0.20897	-3.45476E-05	-3.61137	-0.0006
17.49	-0.303	-0.30198	-0.001015426	-5.29902	-0.01776

Table 11. The algorithms' parameter settings

Algorithm	Parameters
GOTLBO [14]	NP = 50 Jr = 1.0
EOTLBO [13]	NP = 50 SP is Random Real Number (0,1)
IJAYA [12]	NP = 50
EJAYA [9]	NP = 30, rate Ra = 0.3
SMA [10]	NP = 50, Vb=-1 to 1, Vc = 1 to 0, W = Adaptive
WLCSODGM [11]	NP= 50, E=1.5, S=1.2

6. Conclusion

Modelling a PV system accurately is crucial for maximizing performance and guaranteeing reliable operation. To attain this objective, extracting optimal parameters for the PV model which influence its performance necessitates the application of a well-suited optimization technique. In this work, HBA with N-R method is employed to resolve nonlinear equations, specifically designed for extracting optimal parameters for both the SDM and DDM of RTC France silicon solar cell and PV module (Photowatt-PWP201). This comprehensive approach ensures that the algorithm is validated using a diverse range of data sources. The validation of the proposed method entails a comparison of its results with those obtained through various optimization techniques reported by previous researchers.

The results of the proposed method were compared with techniques such as GOTLBO, EOTLBO, IJAYA, EJAYA, SMA, and WLCSDGM. The findings show that the suggested approach achieves the best RMSE between the experimental and estimated data. Additionally, it showcases

the fastest conversion to optimal solutions, achieving less convergence time. Additionally, HBA requires fewer control parameters for adjustment compared to other techniques. Furthermore, the (P-V and I-V) curves assessed using the proposed method extracted parameters closely align with those derived from experimental data. This underscores the algorithm's capability to accurately extract optimal parameters across the entire spectrum of irradiance and temperature, even under low irradiance levels.

Given these observations, the proposed method stands out as the recommended choice due to its superior speed and accuracy in PV system modelling. Precise modelling of PV modules contributes to an overall increase in PV system efficiency, translating to enhanced performance and cost reduction. Future research in solar PV parameter estimation holds promise in developing novel hybrid approaches, enhancing robustness to uncertainties, and advancing real-time adaptive algorithms. Standardization efforts can ensure reliability, while scalable and efficient techniques will cater to large-scale systems.

References

- [1] T. Easwarakhantan et al., "Nonlinear Minimization Algorithm for Determining the Solar Cell Parameters with Microcomputers," *International Journal of Solar Energy*, vol. 4, no. 1, pp. 1-12, 1986. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [2] Erik Cuevas, Jorge Gálvez, and Omar Avalos, "Comparison of Solar Cells Parameters Estimation Using Several Optimization Algorithms," *Recent Metaheuristics Algorithms for Parameter Identification*, pp. 51-95, 2019. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [3] Efstratios I. Batzelis, and Stavros A. Papathanassiou, "A Method for the Analytical Extraction of the Single-Diode PV Model Parameters," *IEEE Transactions on Sustainable Energy*, vol. 7, no. 2, pp. 504-512, 2016. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [4] I. Nassar-Eddine et al., "Parameter Estimation of Photovoltaic Modules Using Iterative Method and the Lambert W Function: A Comparative Study," *Energy Conversion & Management*, vol. 119, pp. 37-48, 2016. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [5] Sameh I. Selem, Hany M. Hasanien, and Attia A. El-Fergany, "Parameters Extraction of PEMFC's Model Using Manta Rays Foraging Optimizer," *International Journal of Energy Research*, vol. 44, no. 6, pp. 4629-4640, 2020. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [6] D.F. Alam, D.A. Yousri, and M.B. Eteiba, "Flower Pollination Algorithm Based Solar PV Parameter Estimation," *Energy Conversion and Management*, vol. 101, pp. 410-422, 2015. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [7] Tummalala S.L.V. Ayyarao, and Polamarasetty P. Kumar, "Parameter Estimation of Solar PV Models with a New Proposed War Strategy Optimization Algorithm," *International Journal of Energy Research*, pp. 1-24, 2022. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [8] Papul Changmai, Sisir Kumar Nayak, and Sanjeev Kumar Metya, "Estimation of PV Module Parameters from the Manufacturer's Datasheet for MPP Estimation," *IET Renewable Power Generation*, vol. 14, no. 11, pp. 1988-1996, 2020. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [9] Xi Yang, and Wenying Gong, "Opposition-Based JAYA with Population Reduction for Parameter Estimation of Photovoltaic Solar Cells and Modules," *Applied Soft Computing*, vol. 104, 2021. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [10] C. Kumar et al., "A New Stochastic Slime Mould Optimization Algorithm for the Estimation of Solar Photovoltaic Cell Parameters," *Optik*, vol. 223, 2020. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [11] Guojiang Xiong et al., "Winner-Leading Competitive Swarm Optimizer with Dynamic Gaussian Mutation for Parameter Extraction of Solar Photovoltaic Models," *Energy Conversion and Management*, vol. 206, 2020. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [12] Kunjie Yu et al., "Parameters Identification of Photovoltaic Models Using an Improved JAYA Optimization Algorithm," *Energy Conversion and Management*, vol. 150, pp. 742-753, 2017. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [13] Guojiang Xiong et al., "Parameter Extraction of Solar Photovoltaic Models with an Either-or Teaching Learning Based Algorithm," *Energy Conversion and Management*, vol. 224, 2020. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [14] Xu Chen et al., "Parameters Identification of Solar Cell Models Using Generalized Oppositional Teaching Learning Based Optimization," *Energy*, vol. 99, pp. 170-180, 2016. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [15] J. Kennedy, and R. Eberhart, "Particle Swarm Optimization," *Proceedings of ICNN'95 - International Conference on Neural Networks*, Perth, Australia, vol. 4, pp. 1942-1948, 1995. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]

- [16] Marco Dorigo, Mauro Birattari, and Thomas Stutzle, "Ant Colony Optimization," *IEEE Computational Intelligence Magazine*, vol. 1, no. 4, pp. 28-39, 2006. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [17] Seyedali Mirjalili, Seyed Mohammad Mirjalili, and Andrew Lewis, "Grey Wolf Optimizer," *Advances in Engineering Software*, vol. 69, pp. 46-61, 2014. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [18] Seyedali Mirjalili et al., "Salp Swarm Algorithm: A Bio-Inspired Optimizer for Engineering Design Problems," *Advances in Engineering Software*, vol. 114, pp. 163-191, 2017. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [19] Seyedali Mirjalili, and Andrew Lewis, "The Whale Optimization Algorithm," *Advances in Engineering Software*, vol. 95, pp. 51-67, 2016. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [20] Fatma A. Hashim et al., "Honey Badger Algorithm: New Metaheuristic Algorithm for Solving Optimization Problems," *Mathematics and Computers in Simulation*, vol. 192, pp. 84-110, 2022. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [21] Shanshan Chen, Saeid Gholami Farkoush, and Sebastian Leto, "Photovoltaic Cells Parameters Extraction Using Variables Reduction and Improved Shark Optimization Technique," *International Journal of Hydrogen Energy*, vol. 45, no. 16, pp. 10059-10069, 2020. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [22] Ibrahim Anwar Ibrahim et al., "An Adaptive Wind Driven Optimization Algorithm for Extracting the Parameters of a Single-Diode PV Cell Model," *IEEE Transactions on Sustainable Energy*, vol. 11, no. 2, pp. 1054-1066, 2020. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [23] Bidyadhar Subudhi, and Raseswari Pradhan, "Bacterial Foraging Optimization Approach to Parameter Extraction of a Photovoltaic Module," *IEEE Transactions on Sustainable Energy*, vol. 9, no. 1, pp. 381-389, 2018. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [24] Jing Jun Soon, and Kay-Soon Low, "Photovoltaic Model Identification Using Particle Swarm Optimization with Inverse Barrier Constraint," *IEEE Transactions on Power Electronics*, vol. 27, no. 9, pp. 3975-3983, 2012. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [25] M.F. AlHajri et al., "Optimal Extraction of Solar Cell Parameters Using Pattern Search," *Renewable Energy*, vol. 44, pp. 238-245, 2012. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]