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Comparative Analysis of Metaheuristic Algorithms for Extracting Electrical Parameters of PV Modules

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Abstract. This paper presents a comparison of various metaheuristic algorithms used for extracting electrical parameters from specific photovoltaic (PV) panels. The focus lies on assessing and comparing the efficiency of eight chosen algorithms in precisely deriving electrical parameters from PV modules, selected for their novelty and widespread use. The ODM mathematical model was utilized due to its exceptional precision and simplicity to accomplish this aim. Next, a series of simulations were executed to establish the optimal electrical parameters with the best root mean square (RMS) values for each algorithm. The resulting dataset from these simulations was then analysed and compared to draw the final conclusions. The primary goal of this comparative analysis is to obtain valuable knowledge about the abilities of various new Metaheuristic algorithms in determining the electrical parameters of photovoltaic modules.

Keywords.Photovoltaic, One Diode Model,Metaheuristic Algorithms, Extracting Electrical Parameters.

INTRODUCTION

Electricity generation is widely recognized by the United Nations (UN) as a major contributor to global climate change, primarily due to the dominance of fossil fuels, which still account for more than 80% of global energy production (Halassa et al., 2023). As a result, governments around the world are increasingly prioritizing renewable energy sources because of their many advantages over traditional energy sources. Among these renewable options, solar energy, particularly solar photovoltaic (PV), has received particular attention and has emerged as a major player in the renewable energy market. The appeal of solar energy stems from its inherent advantages over fossil fuels, such as its abundance, sustainability, and minimal environmental impact (Aboagye et al., 2023). The information provided highlights the global trends and impressive growth of solar energy, positioning it as a promising solution to meet energy needs while mitigating the adverse effects associated with traditional fossil fuel power generation.

The cost of electricity produced by photovoltaic (PV) systems is primarily determined by the price and lifespan of PV modules. To ensure reliability and efficiency, PV modules undergo stringent qualification and design approval testing in controlled laboratory settings, adhering to International Electrotechnical Commission (IEC) standards(Aboagye et al., 2023). The critical role of photovoltaic (PV) module modelling lies in its contribution to understanding and optimizing the performance of PV systems, for improved energy generation and efficiency. Different mathematical models, such as the one-diode, two-diode, and multi-diode models, have been developed to accurately extract electrical parameters from measured data, each of these models includes a current source of photocurrent (Iph) which represents the total current generated by the incident light on the PV cell, a group of a parallels diodes models the effects of the PN junction within the PV cell, series resistance (Rs) represents the resistivity of the metal contacts and accounts for any ohmic losses in the circuit, and shunt resistance (Rsh) represents leakage currents in the cells and allows for modelling of the shunt effects. The one-diode model assumes a simplified equivalent circuit with one diode and is widely used due to its simplicity and computational efficiency. It provides a reasonable estimate of the behaviour of the module under normal operating conditions (Seghiour et al., 2022). However, its accuracy diminishes in certain scenarios like low light or partial shading. To address these limitations, the two-diode model introduces an additional diode and associated parameters to capture more non-linear effects. It improves accuracy, particularly under shading conditions and varying temperatures (Tifidat et al., 2022; Yaqoob et al., 2021). In advanced PV technologies, such as multi-junction or tandem cells, the multi-diode model further extends accuracy by incorporating multiple diodes, each representing different energy bandgaps or spectral responses. Although the multi-diode model increases complexity and parameter estimation efforts, it allows for precise modelling of specific PV technologies (Schuster et al., 2022).

The extraction of parameters in PV module modelling involves various methods aimed at accurately determining the values of key variables. Analytical methods use mathematical models and theoretical principles to establish physical relationships between extrinsic (measured) and intrinsic (desired) variables. These methods aim to derive parameter values through mathematical calculations and analytical expressions. On the other hand, numerical methods employ optimization techniques to minimize the quadratic error between measured and estimated variables, using iterative algorithms to refine the parameter estimates. These methods rely on numerical simulations and computational approaches to converge on the best-fit parameter values (Hamadiet al., 2021). Additionally, Metaheuristic algorithm methods, such as genetic algorithms or particle swarm optimization, offer alternative approaches by mimicking natural or social processes to search for optimal parameter values in a vast parameter space. These metaheuristic algorithms offer flexibility and can effectively explore complex, nonlinear relationships. The choice of parameter extraction method depends on the specific requirements, available data, and desired level of accuracy in PV module modelling. The main question posed by this research article is identifying which innovative novel metaheuristic algorithm can effectively tackle the problem of extracting photovoltaic (PV) electrical parameters in a more efficient manner.

This study evaluates and compares the performance of several novel metaheuristic algorithms for the extraction of electrical parameters from specific photovoltaic (PV) panels. The algorithms examined include the Slime Mould Algorithm, Chernobyl Disaster Optimizer, Nutcracker Optimization Algorithm, Transit Search Algorithm, Young's Double-Slit Experiment Optimizer, Exponential Distribution Optimizer, and the two widespread algorithms namely Artificial Bee Colony (ABC) and the Bonobo Optimizer.

This article is structured as follows: Section 2 introduces the photovoltaic cell and its mathematical model, which is used for PV parameter extraction in this study. Section 3 showcases the suggested optimization algorithms for comparative analysis. Simulation results and a comparison of those results are discussed in Section 4. Lastly, Section 5 provides the conclusion of the article.

PV CELL MODELING

Solar Cells

The solar cell is a crucial component of the photovoltaic system, which is typically made of semiconductor material, mainly silicon. Introducing foreign atoms (doping) into the cell generates a p-n junction, which creates an electrical field in the crystal. When light hits a solar cell, it causes the release of charge carriers that move through the crystal and create a voltage of about 0.5V. The current produced by the solar cell is determined by factors such as radiation and cell area, typically ranging between 0 and 10A. To generate a usable voltage of 20-50V, multiple cells are connected in series within a solar module. Moreover, the solar cells in the modules are safeguarded against environmental factors like moisture by mechanical protection and sealing (Mertens, 2014).

Single diode model

Numerous methodologies have been proposed, providing different degrees of complexity and precision in modelling photovoltaic modules. Among these approaches, the single-diode model has been commonly used because of its notable accuracy and comparative simplicity (He et al., 2022).

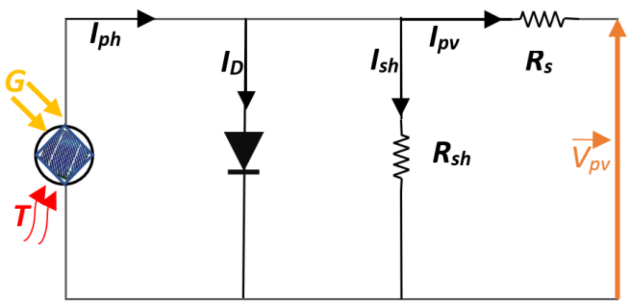

Fig. 1. ODM of PV cell.

The single model of a PV cell is shown in figure1, In this model, the output current of solar cell can be formulated as below:

$I_{pv} = I_{ph} - I_d - I_{sh}$ (1)

I_{pv} is the cell output, I_{ph} is the photocurrent, I_d is the diode current, and I_{sh} is the shunt resistor current. According to Shockley equation, the equation2 will be:

$$I_{pv} = I_{ph} - I_0\left(e^{\frac{V_{pv}+R_S I_{pv}}{nV_t}} - 1\right) - \frac{V_{pv}+R_S I_{pv}}{R_{sh}} \quad (2)$$

V_{pv} is the cell output voltage, I_0 is the reverse saturation current of the diode, R_s is the series resistance, R_{sh} is the shunt resistance, n is the diode ideal factor and V_t is the junction thermal voltage we can calculated by the equation 3:

$$V_t = \frac{K_B.T}{q} \quad (3)$$

q is constant and represents the absolute value of the electric charge of the electron $(1.6 \times 10^{-19}\,C)$, K_B is the Boltzmann constant $(1.3 \times 10^{-23} J/K)$, T is the absolute temperature of the PV cell. The process of extracting the electrical parameters (Iph, I0, n, Rs, Rsh) of the ODM can be viewed as an optimization problem, as it involves minimizing an objective function (Seghiour et al., 2022).The Root Mean Square Error (RMSE) is a measure used to quantify the difference between the measured and estimated currents, calculated using equation (2).

$$RMSE = \sqrt{\frac{1}{L}\sum_{i=1}^{L}\left[g_i\left(I_m, V_m, [I_{ph}, I_0, n, R_s, R_{sh}]\right)\right]} \quad (4)$$

Where:

$$g\left(I_m, V_m, [I_{ph}, I_0, n, R_s, R_{sh}]\right) = I_{ms} - I_{pv}(I_m\,, V_m\,) \quad (5)$$

Where:

$$I_{pv}(I_m\,, V_m\,) = I_{ph} - I_0\left(e^{\frac{V_m+R_S I_m}{nV_t}} - 1\right) - \frac{V_m+R_S I_m}{R_{sh}} (6)$$

With I_m is the measured current, V_m is the measured voltage of the PV module. Practical measurement of these variables is usually carried out using an I-V curve tracer. L represent the length of the experimental I-V curve of the PV module, which is employed during the PV module parameter extraction stage. $[I_{ph}, I_0, n, R_s, R_{sh}]$ represent the vectors of unknown parameters.

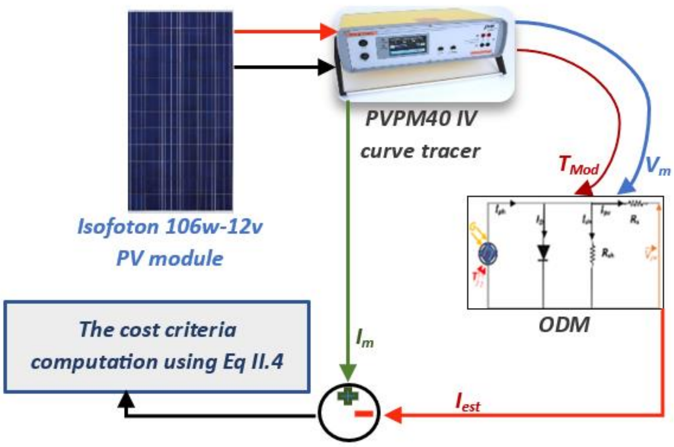

Fig.2 .The ODM parameters extraction procedure.

The aim purpose of this process is to identify the most favourable values for the unknown parameters of the ODM, which minimize the RMSE as defined in equation 5, the proposed procedure is defined in figure 2.

METAHEURISTIC ALGORITHMS

To address the objective function 6 and extract the electrical parameters of a PV module, we propose a comparative analysis of the following optimization algorithms:

Slime Mould Algorithm

The SMA is a type of algorithm inspired by the behaviour of an organism called the Slime Mould, specifically the acellular slime mould Physarumpolycephalum. The Slime Mould has a complex structure made up of interconnected tubes that transport cytoplasm. This unique anatomy allows the Slime Mould to create networks of veins that connect multiple food sources, enabling it to feed on all of them simultaneously. When the Slime Mould finds a food source, its biochemical oscillator triggers contraction waves that cause cytoplasm to flow through the veins. The speed of this flow depends on the thickness of the veins' walls. The SMA mimics this behaviour by using positive and negative input to navigate towards food sources. This abstract briefly introduces the SMA, its inspiration from the Slime Mould, and its use of mathematical models and procedures (Gharehchopogh et al., 2023).

Chernobyl Disaster Optimizer (CDO)

This algorithm is inspired by the Chernobyl disaster, which resulted from the explosion of a nuclear reactor. Generally, nuclear explosions release three types of radiation particles: beta, gamma, and alpha. These particles travel at different speeds through various mediums. The proposed algorithm aims to efficiently explore and search any domain of search space while easily avoiding local minima.[9]

The Nutcracker Optimization Algorithm

The Nutcracker Optimization Algorithm is inspired by how nutcrackers search for good food and store it for later. Researchers noticed the unique behaviour of birds, especially nutcrackers, in finding and retrieving stored food. This inspired them to create an optimization algorithm that solves different problems. By mimicking the clever strategies of nutcrackers, this algorithm aims to find the best solutions just like how nutcrackers find and store their food (Abdel-Basset et al., 2023).

Artificial Bee Colony (ABC):

The Artificial Bee Colony (ABC) algorithm, inspired by honeybee foraging behaviour, is a swarm-based meta-heuristic optimization approach. It initializes a population of potential solutions called food source positions, each representing a solution to the optimization problem. The nectar amount associated with each food source indicates its quality. Employed bees, onlooker bees, and scout bees perform different roles within the algorithm. Employed bees select high-quality food sources, onlooker bees choose based on nectar amount probabilities, and scout bees search for new food sources to replace abandoned ones. The ABC algorithm has demonstrated its efficacy in solving various practical problems, both in mathematical functions and real-world business scenarios (Ji et al., 2019).

Transit search: An optimization algorithm

Transit search (TSO) is an astrophysics-inspired meta-heuristic optimization algorithm that leverages the transit method for detecting exoplanets. By analysing light curves and identifying periodic dips in star brightness, the algorithm explores for potential exoplanetsignals, replicating the observation of dimming when a planet passes in front of a star (Mirrashid and Naderpour, 2022).

Young's double-slit experiment optimizer

The YDSE Optimizer is a distinctive metaheuristic algorithm inspired by Young's double-slit experiment. It creates a random population representing monochromatic light waves and simulates their behaviour as they pass through two slits. The algorithm forms interference patterns based on wavefront points, leading to bright and dark fringes on a projection screen. Population solutions move through the search space according to their order number, leveraging the bright fringe regions for potential optimal solutions and examining the dark regions to evade local optima. By emulating the principles of light interference, the YDSE Optimizer strikes a delicate balance between exploitation and exploration strategies, facilitating efficient and effective search processes (Abdel-Basset et al., 2023).

Exponential Distribution Optimizer

EDO, a novel metaheuristic algorithm, draws inspiration from the exponential probability distribution (EPD) and employs an exponential distribution curve for position updates during the exploitation and exploration phases. The algorithm begins by generating a random population representing a collection of EPDs. Each solution is treated as a series of exponential random variables. In the exploitation phase, EDO integrates three key concepts from EPD: the memoryless property, guiding solution, and exponential variance. To embody the memoryless property, successful individuals in the original population are considered winners and stored in a memoryless matrix alongside newly generated solutions, regardless of their relative fitness. This approach ensures that past failures, classified as losers, do not hinder future updates, allowing them to contribute to the improvement of subsequent solutions (Abdel-Basset et al., 2023).

Bonobo Optimization

The Bonobo Optimization (BO) algorithm is a smart and adaptive optimization technique inspired by the social behaviour and reproductive strategies of bonobos. It mimics their interesting reproductive behaviours, such as social hierarchy and mating strategies. BO adjusts its parameters in continuous spaces, making it well-suited for solving real-parameter optimization problems. The BO algorithm has been successfully applied to various engineering problems (Das and Pratihar, 2019).

EXPERIMENTAL RESULTS

The procedure of the unknown PV module electrical parameters extraction is presented in the figure 2. The objective function of the extraction parameters is presented in equation 6. The upper and lower bound is presented in the table1.

Table 1. The lower and Upper bounds of the PV electrical parameter.

Parameters	I_{ph}	I_0	n	R_s	R_{sh}
Lower Bound	0	10^{-6}	1	0	0
Upper Bound	7	10^{-4}	2	1	100

Among the algorithms evaluated, it is evident that the best RMS value achieved is 0.0170613, with PV module parameter value: Table 3 presents the simulation results of the selected metaheuristic algorithms, including the population size, iteration number, and simulation cycle required to obtain the best Root Mean Square (RMS) for each algorithm.

The exceptional result was obtained by three algorithms namely: Exponential Distribution Optimizer (EDO), Young's double-slit experiment optimizer (YDSE), and Bonobo

Optimization (BO). These algorithms showcased superior performance in minimizing the RMS value, underscoring their effectiveness in optimizing the given problem.

Table 2.PV module parameter value.

I_{ph}	I_0	A	R_s	R_{sh}
5.44307	$1.06864*10^{-5}$	1.6792	0.00380605	2.50697

When comparing these three algorithms in terms of population size and the number of iterations, it is noteworthy that YDSE required a population size of 300 with 10^4 iterations to achieve the result. In contrast, EDO and BO achieved the same result with population sizes of 30 and 100, respectively, along with 10^4 iterations for EDO and 10^4 iterations for BO. Consequently, the EDO and BO algorithms demonstrated greater efficiency in resolving this electrical problem. Furthermore, it is worth mentioning that the BO algorithm achieved the best result in just one simulation cycle. This outcome highlights the algorithm's remarkable speed and efficacy in resolving the problem compared to the other algorithms.
In summary, the EDO, YDSE, and BO algorithms delivered exceptional results in minimizing the RMS value, with the latter two demonstrating greater efficiency in terms of population size and iteration requirements. Additionally, the BO algorithm exhibited unparalleled speed, resolving the problem in a single cycle. These findings emphasize the significance of these algorithms in effectively addressing and optimizing the given electrical problem.

Table 3.Electrical Parameters extracted using the various algorithms from the solar PV module.

Algorithm	Iph	I0	A	Rs	Rsh	RMS	Pop size	Iterations	Cycle
SMA	5.48855	$9.29715*10^{-5}$	2	0	31.2612	0.14684	3000	103	1
CDO	5.35693	$4.97236*10^{-5}$	1.89784	0.00246	32.8398	0.02481	300	104	1
NOA	5.41628	$2.79405*10^{-5}$	1.81026	0.00313	4.16909	0.01931	300	$3*10^5$	10
ABC	5.42345	$1.51499*10^{-5}$	1.7244	0.00358	3.201	0.01741	300	30000	10
TSO	5.43651	$1.20903*10^{-5}$	1.69494	0.00372	2.68911	0.0171	200	$2*10^3$	5
YDSE	5.44307	$1.06864*10^{-5}$	1.6792	0.00381	2.50697	0.01706	300	104	5
EDO	5.44307	$1.06864*10^{-5}$	1.6792	0.00381	2.50697	0.01706	30	104	5
BO	5.44307	$1.06864*10^{-5}$	1.6792	0.00381	2.50697	0.01706	100	103	1

The convergence curves depicted in the following figures illustrate the performance of each algorithm during the simulation. These curves align closely with the data presented in Table 3. Focusing on the three algorithms (YDSE, EDO, and BO) that exhibit the best RMS values. For YDSE and BO, they require approximately 80 iterations to initiate convergence towards the optimal RMS value. This suggests a longer exploration phase before reaching a stable solution. However, BO stands out with faster convergence, taking only 20 iterations to begin converging towards the optimal value. This indicates its superior ability to efficiently explore the solution space and quickly identify promising regions. The observed convergence behaviour indicates the effectiveness of the BO algorithm in rapidly approaching the optimal solution. Its capacity to adapt and self-adjust parameters over continuous spaces likely contributes to its accelerated convergence.

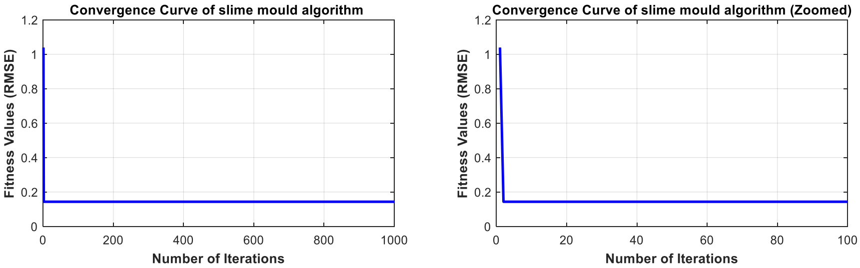

Fig.3.SMA algorithm convergence curve.

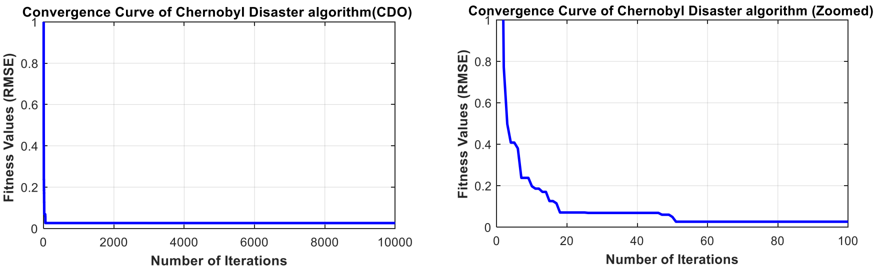

Fig.4.CDO algorithm convergence curve.

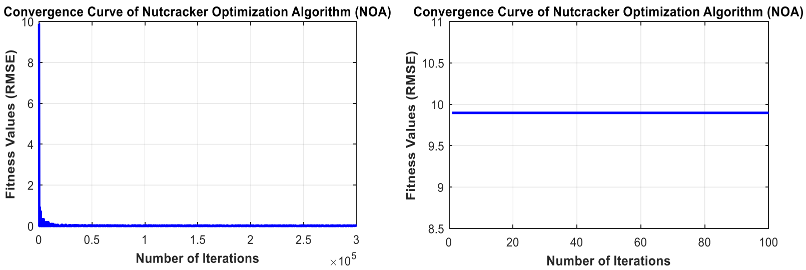

Fig.5.NOA algorithm convergence curve.

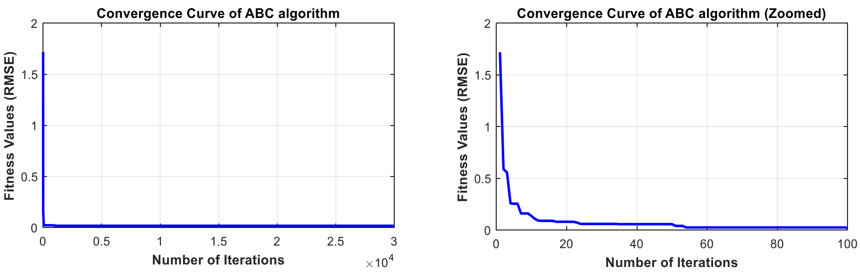

Fig.6.ABC algorithm convergence curve.

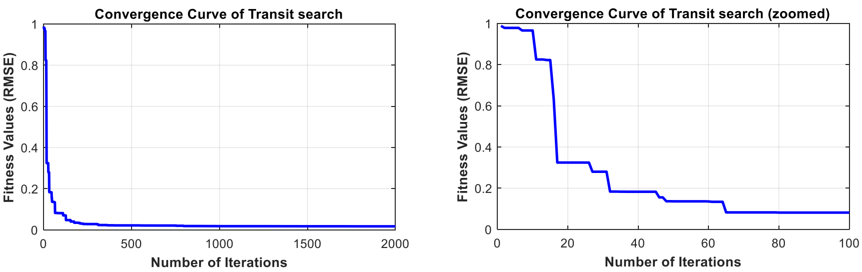

Fig.7.TSO algorithm convergence curve.

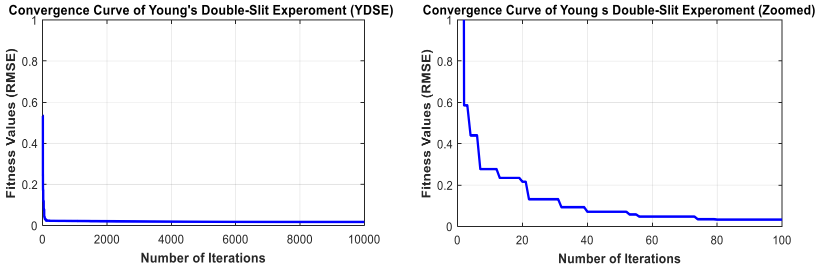

Fig. 8.YDSE algorithm convergence curve.

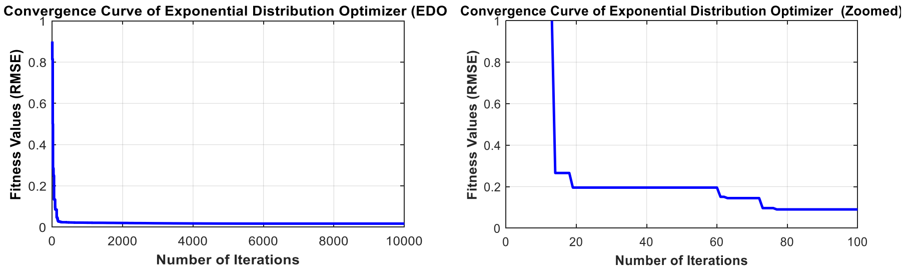

Fig.9.EDO algorithm convergence curve.

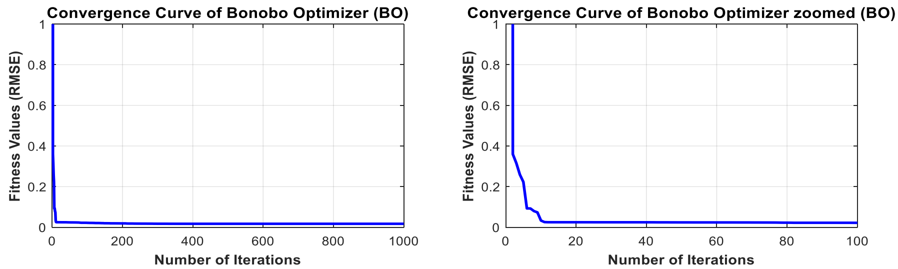

Fig. 10.EDO algorithm convergence curve.

CONCLUSION

In summary, this research paper explores metaheuristic algorithms in the context of extracting electrical parameters from photovoltaic (PV) panels. A detailed comparison is carried out to evaluate the effectiveness of eight selected algorithms based on their novelty and popularity. Through a series of simulations, the optimal electrical parameters with the best root mean square (RMS) values were determined for each algorithm. The top-performing algorithms include F. Young's double-slit experiment optimizer (YDSE), Exponential Distribution Optimizer (EDO), and Bonobo Optimizer (BO). Notably, BO demonstrates quick convergence, making it an efficient choice for optimization. This research provides valuable insights into the potential of metaheuristic algorithms in resolving challenges related to PV parameter extraction. Such information can guide researchers and professionals in selecting suitable algorithms for optimizing PV systems.

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