Photovoltaic parameters estimation using three metaheuristic algorithms: A comparative study

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Sunlight has served as the primary energy source since the inception of life on Earth. Despite the emergence of alternative energy sources like fossil and nuclear energy, solar energy remains the most environmentally friendly and cost-effective option. Harnessing this energy involves utilizing photovoltaic (PV) modules to generate electricity. Extensive research is dedicated to PV modules, with a primary emphasis on electrical modeling, which plays a crucial role in effectively controlling a PV system and determining its I-V characteristics. PV modules encompass various electrical models, including the single-diode model (SDM), double-diode model (DDM), and triple-diode model (TDM). The difficulty lies in precisely determining the unknown parameters associated with each model. This study sets out with a clear objective: to tackle the challenge of identifying the elusive parameters within the SDM. The primary aim is to compare the effectiveness of three metaheuristic algorithms namely, the Flower Pollination Algorithm (FPA), Teaching-Learning-Based Optimization (TLBO), and Honey Badger Algorithm (HBA) in identifying these unknown parameters. In practical terms, this study extends to the evaluation of these algorithms on specific PV modules such as the Photowatt-PWP201 module, Tata Solar Power TP240 module, and RTC France solar cell. The evaluation of results is based on the root mean square error (RMSE) values. Notably, HBA stands out as it demonstrates superior performance, achieving the lowest RMSE of 9.860218e-04 A for the RTC France solar cell. Conversely, FPA records the highest RMSE, reaching 9.458277e-03 A for the TP240 module.

Keywords: *solar energy; PV modeling; parameter estimation; metaheuristics algorithms.*
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1. Introduction

In contemporary times, climate change has emerged as a global concern primarily attributed to the emission of greenhouse gases, with carbon dioxide (CO_2) identified as the predominant contributor [1,2]. The combustion of fossil fuels such as coal, oil, and natural gas in various sectors, including electricity production, transportation, and industrial activities, is a significant source of CO_2 emissions. The global shift towards renewable energy sources, such as solar power, is gaining momentum as a crucial step in mitigating CO_2 emissions and combating climate change. A noteworthy example is Morocco, where, as per statistics from the Ministry of Energy Transition and Sustainable Development, the installed solar power capacity reached 830 MW in 2022 [3]. This capacity is further divided into thermal and photovoltaic energy sources [4], reflecting a substantial commitment to sustainable energy practices. This work primarily focuses on photovoltaic energy, with a specific emphasis on its electrical modeling [5]. It plays a pivotal role in the installation of a PV system, encompassing energy prediction and control. Moreover, it serves as the foundation for various research fields within PV energy, including

PV thermal modeling [6] and maximum power point tracking (MPPT) [7]. Numerous electrical models exist in literature, including the single-diode model (SDM), double-diode model (DDM), and PV module model (MM). Notably, the SDM and MM emerge as the most extensively utilized models. Figure 1 illustrates the corresponding equivalent circuits for these prominent models.

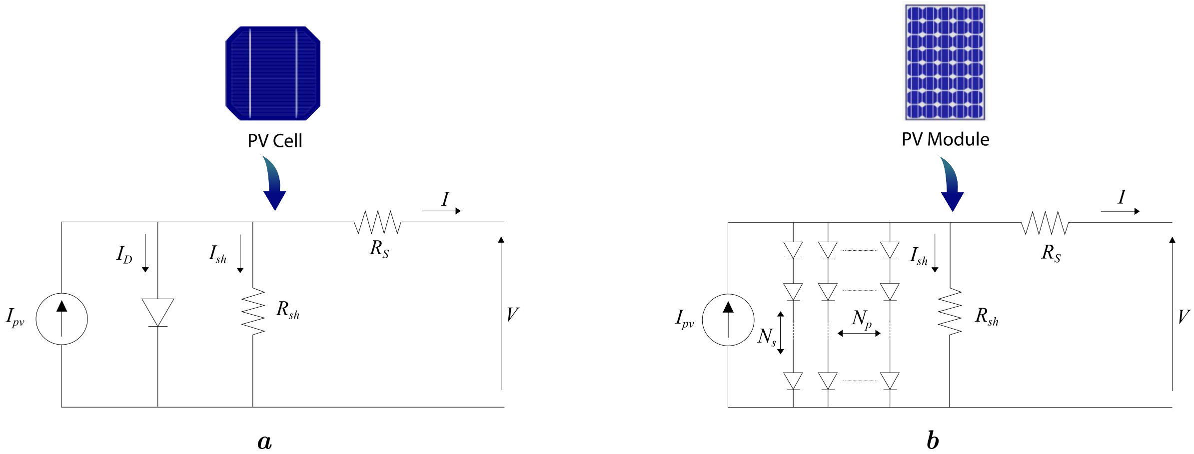

Fig. 1. The electrical circuits: (***a***) of SDM and (***b***) of MM.

The distinction between SDM and MM lies in the inclusion of the number of cells connected in series and parallel in the latter. The MM represents a comprehensive modeling approach for a PV module, while SDM is specifically designed for a PV cell. Both models share five unidentified parameters: the light-generated current I_{pv}, the reverse saturation current I_0, the series resistance R_s, the shunt resistance R_{sh}, and the diode ideality factor a. The characteristic equations for SDM and MM are articulated in (1) and (2), respectively,

$$I = I_{pv} - I_0 \left[e^{\frac{q(V+R_sI)}{akT}} - 1 \right] - \frac{V + R_sI}{R_{sh}}, \tag{1}$$

$$I = I_{pv}N_p - I_0N_p \left[e^{\frac{q(VN_p+R_sIN_s)}{akTN_sN_p}} - 1 \right] - \frac{VN_p + R_sIN_s}{R_{sh}N_s}. \tag{2}$$

The main challenge revolves around precisely identifying the model's unknown parameters. The methods employed for parameter determination can be broadly classified into three categories: analytical, numerical, and metaheuristic approaches [8,9]. Analytical methods are typically straightforward and simple to implement [10]. They often involve several mathematical operations that do not require iterative processes. However, its functionality relies heavily on the module's data-sheet, limiting its operation to standard test conditions (STCs). On the other side, numerical approaches involve creating equations that can be resolved through numerical or iterative methodologies [11]. Some approaches integrate both analytical and numerical methods to determine PV parameters [12,13].

Metaheuristic methods can be employed across a spectrum of problems to discover approximate solutions that optimize a specified objective function [14]. Examples include the Genetic algorithm (GA) [15], utilizing the inherent principle of survival of the fittest, the differential evolution (DE) [16], the flower pollination algorithm (FPA) [17], the teaching-learning-based optimization (TLBO) [18], and the honey badger algorithm (HBA) [19]. Many other metaheuristic algorithms draw inspiration from natural phenomena, mirroring the behaviors of swarms and animals engaged in food searching.

The objective of this research is to assess the effectiveness of three metaheuristic algorithms FPA, TLBO, and HBA in determining the parameters of photovoltaic models (SDM and MM). These algorithms aim to optimize the Root Mean Square Error (RMSE) as the objective function, with the goal of estimating PV parameters by minimizing the error between estimated and experimental currents,

$$f(X) = \mathrm{RMSE}(X) = \sqrt{\frac{1}{N}\sum_{i=1}^{N} g(X)^2}, \tag{3}$$

X is the unknown parameters vector, N is the number of measured data, and $g(X)$ is the difference between the estimated and experimental current for the SDM and MM display in (4) and (5);

$$g_{\mathrm{SDM}}(X) = X_1 - X_2\left[e^{\frac{q(V+X_3I)}{X_5kT}} - 1\right] - \frac{V+X_3I}{X_4} - I_{\mathrm{exp}}, \tag{4}$$

$$g_{\mathrm{MM}}(X) = X_1N_p - X_2N_p\left[e^{\frac{q(VN_p+X_3IN_s)}{X_5kTN_sN_p}} - 1\right] - \frac{VN_p+X_3IN_s}{X_4N_s} - I_{\mathrm{exp}}. \tag{5}$$

The upcoming sections of this paper are arranged as follows: in the second section, we will introduce the three metaheuristic algorithms, followed by a thorough evaluation and comparison of their precision in estimating PV model parameters across three modules and cells. The concluding section provides a summary of the results and outlines the conclusions derived from the study.

2. Metaheuristic algorithms

Metaheuristic algorithms are designed to work with a suite of heuristics or problem-solving strategies. These high-level strategies are engineered to discover approximate solutions for intricate optimization problems by navigating the solution space intelligently and in a guided manner. Many metaheuristic algorithms draw inspiration from nature, human society, or artificial phenomena [20].

2.1. Flower pollination algorithm (FPA)

The fundamental concept underlying the flower pollination algorithm (FPA) involves emulating the natural process of flower pollination to address intricate optimization problems [17]. This emulation is guided by four rules that encapsulate the key characteristics of the pollination process:

- Global pollination processes involve biotic and cross-pollination, with pollinators executing Levy flights while carrying pollen.
- Abiotic and self-pollination fall under the category of local pollination.
- Flower constancy is defined as the likelihood of reproduction, directly linked to the similarity between two flowers.
- A switch parameter, represented as $p \in [0,1]$, regulates the occurrence of both local and global pollination processes. The influence of local pollination, constituting a significant fraction p of the overall pollination activity, is affected by factors like the wind.

Within the realm of global pollination, pollen can traverse extensive distances, aided by the substantial mobility of flying insects capable of covering considerable geographic ranges. This phenomenon can be mathematically articulated by the following equation:

$$X_i^{t+1} = X_i^t + L(X_i^t - g_*). \tag{6}$$

During iteration t, the representation of pollen for type i is X_i^t, and the optimal solution among all solutions discovered in the present generation is symbolized as g_*. The intensity of pollination, encapsulated by the parameter L, can be expressed using the Levy distribution,

$$L \sim \frac{\lambda\,\Gamma(\lambda)\sin\frac{\pi\lambda}{2}}{\pi}\frac{1}{s^{1+\lambda}}. \tag{7}$$

In numerous optimization problems, the conventional gamma function $\Gamma(\lambda)$ is utilized with a value of $\lambda = 1.5$.

The second rule, pertaining to local pollination, can be mathematically represented as follows,

$$X_i^{t+1} = X_i^t + \varepsilon(X_i^t - X_k^t). \tag{8}$$

Most flowers have the capacity for both local and global pollination. To facilitate this, a switch probability denoted as p (Rule 4) is employed to transition between global and local pollination. In the context of many optimization problems, a value of $p = 0.8$ often yields superior performance.

Algorithm 1 Flower Pollination Algorithm (FPA)

Set initial parameters $p \in [0,1]$
Generate initial population of flowers
Find the current best solution g_*
Start
while (stopping criterion not satisfied) **do**
  for each flower **do**
    if rand() $< p$ **then**
      Global pollination Eq. (6)
    else
      Select two random solutions X_j^t and X_k^t
      Local pollination Eq. (8)
  Keep the current best solution
End FPA

2.2. Teaching-Learning-Based Optimization (TLBO)

The TLBO algorithm is an optimization technique inspired by the dynamics of teaching and learning observed in human society. It consists of two primary phases: the teaching phase and the learning phase [18]. During the teaching phase, the algorithm pinpoints the optimal solution within the population and labels it as the teacher X_{teacher}. Subsequently, the other solutions in the population are revised by assimilating the information imparted by the teacher, aiming to enhance their performance as students,

$$X_{i,\text{new}} = X_i + \text{rand}(X_{\text{teacher}} - T_F X_{\text{mean}}), \tag{9}$$

$$X_{\text{mean}} = \frac{1}{P} \sum_{i=1}^{P} X_i. \tag{10}$$

Considering a population of size P, where each member is represented as X_i, and denoting the updated version of learner X_i as $X_{i,\text{new}}$. The average solution within the population is denoted by X_{mean}. The teaching factor T_F, determining the magnitude of change in the mean level, is introduced. Specifically, T_F is computed by rounding up the sum of 1 and a randomly generated number within the range of 0 to 1, expressed as $T_F = \text{round}(1 + \text{rand}(0,1))$.

Algorithm 2 Teaching-Learning-Based Optimization (TLBO)

Generate initial population
Start
while (stopping criterion not satisfied) **do**
  Calculate the X_{mean} Eq. (10)
  Select the best solution X_{teacher}
  Teacher phase
  for each learner **do**
    Generate $X_{i,\text{new}}$ Eq. (9)
    if $f(X_{i,\text{new}}) < f(X_i)$ **then**
      $X_i = X_{i,\text{new}}$
  Learner phase
  for each learner **do**
    Select a random learner X_j $(j \neq i)$
    Generate $X_{i,\text{new}}$ Eq. (11)
    if $f(X_{i,\text{new}}) < f(X_i)$ **then**
      $X_i = X_{i,\text{new}}$
  Keep the current best solution
End TLBO

In the learning phase, learners engage in skill enhancement by randomly selecting peers for group discussions and formal communication. The learning process for each individual can be articulated as follows:

$$L = \begin{cases} X_i + \mathrm{rand}(X_i - X_j) & \text{if} \quad f(X_i) < f(X_j), \\ X_i + \mathrm{rand}(X_j - X_i) & \text{otherwise}, \end{cases} \tag{11}$$

where $f(X_i)$ and $f(X_j)$ represent the objective function values of X_i and X_j, respectively.

2.3. Honey Badger Algorithm (HBA)

HBA takes inspiration from the foraging behavior of the honey badger, a creature renowned for its aggression and tenacity [19]. Emulating the honey badger's approach, the algorithm incorporates elements such as utilizing its keen sense of smell to locate food sources, adept digging for underground resources, and the ability to follow the honey-guide bird to discover beehives. The primary goal of the algorithm is to mirror the honey badger's efficiency in locating food sources, applying this concept to optimization problems for finding the optimal solution. The HBA comprises two distinct phases: the digging phase and the honey phase. During the digging phase, the HBA emulates the search behavior of a honey badger,

$$X_{\text{new}} = X_{\text{prey}} + F\beta I_i X_{\text{prey}} + F r_1 \alpha d_i \big[\cos(2\pi r_2)(1 - \cos(2\pi r_3))\big], \tag{12}$$

$$I_i = r_4 \frac{(X_i - X_{i+1})^2}{4\pi d_i^2}, \tag{13}$$

$$\alpha = C \exp \frac{-t}{t_{\max}}, \tag{14}$$

where C is a constant ($C = 2$) and $t_{\max}$ is the maximum iteration.

Algorithm 3 Honey Badger Algorithm (HBA)

Generate initial population
Evaluate the fitness f_i for each X_i
Save best position X_{prey} and assign fitness to f_{prey}
Start
while (stopping criterion not satisfied) **do**
  Update the decreasing factor α Eq. (14)
  for each honey badger position **do**
    Calculate the intensity I_i Eq. (13)
    if $r < 0.5$ **then**
      Update the position X_{new} Eq. (12)
    else
      Update the position X_{new} Eq. (15)
    Evaluate new position and assign to f_{new}
    if $f_{\text{new}} \leqslant f_i$ **then**
      Set $X_i = X_{\text{new}}$ and $f_i = f_{\text{new}}$
    if $f_{\text{new}} \leqslant f_{\text{prey}}$ **then**
      Set $X_{\text{prey}} = X_{\text{new}}$ and $f_{\text{prey}} = f_{\text{new}}$
  Keep the current best solution
End HBA

Within the framework of honey badger foraging behavior, the following variables are established: X_{prey} signifies the prey's position, denoting the optimal location for food acquisition. The honey badger's prowess in gathering food is denoted by $\beta \geqslant 1$. The distance between the prey and the ith honey badger is expressed as $d_i = X_{\text{prey}} - X_i$. The prey's intensity, denoted by I_i, is influenced by both the prey's concentration and the distance between it and the ith honey badger. The parameter α governs the density factor, ensuring a smooth and time-varying transition from exploration to exploitation.

Values for r_1, r_2, r_3, and r_4 are random numbers generated within the range of 0 to 1. The flag F controls the search direction and can assume either the value of 1 or -1.

The mathematical representation of the scenario in which a honey badger follows a honey-guide bird to find a beehive during the honey phase can be expressed by the following equation,

$$X_{\text{new}} = X_{\text{prey}} + F r_5 \alpha d_i, \tag{15}$$

r_5 denote a random variable uniformly distributed over the unit interval $[0, 1]$.

3. Results and discussions

The three algorithms are employed to extract the PV parameters from three distinct PV modules and cells. In this research field, the RTC France solar cell and the Photowatt PWP201 module are extensively employed in PV characterisation, their experimental data collected at temperatures of $T = 33°\text{C}$ and $T = 45°\text{C}$, respectively [21]. Another module is the Tata Solar Power TP240 module, which consists of 60 poly-crystalline PV cells connected in series, and its data is obtained under standard test conditions (STCs) [22]. Table 1 provides a comprehensive overview of the parameter ranges for the three panels. Consistently, the population size P is fixed at 100, and the maximum iteration limit $t_{\max}$ is standardized at 10000 iterations for all three algorithms to ensure a fair comparison and equitable decision-making.

Table 1. The parameters range for the different modules and cell.

	RTC France		PWP201		TP240	
	Lb	***Ub***	***Lb***	***Ub***	***Lb***	***Ub***
$I_{pv}(A)$	0	1	0	2	0	9
$I_0(A)$	0	1e-6	0	50e-60	0	1e-6
$R_s(\Omega)$	0	0.5	0	2	0	0.6
$R_{sh}(\Omega)$	0	100	0	2000	0	100
a	1	2	1	2	1	2

Table 2 offers a thorough summary of the extracted parameters and RMSE values for each PV system. Remarkably, the HBA exhibits the lowest RMSE among all three tested panels, as highlighted in the table. Moreover, three algorithms consistently deliver smaller RMSE values, indicative of their efficacy. The validation of these RMSE results is visually depicted in Figures 2–4, illustrating the I-V curves of the experimental dataset juxtaposed with the estimated values for three panels. Notably, the estimated current from all three algorithms closely mirrors the experimental data, affirming their accuracy in extracting the PV parameters.

Table 2. Values of the five parameters and the RMSE for the different algorithms.

Module/cell	Algorithm	I_{pv} (A)	I_0 (A)	R_s (Ω)	R_{sh} (Ω)	a	RMSE(A)
RTC France	FPA	0.760774	3.214607e-07	3.640172e-02	53.675235	1.480693	9.861049e-04
	TLBO	0.760780	3.232425e-07	3.637263e-02	53.644478	1.481254	9.860364e-04
	HBA	0.760775	3.230205e-07	3.637709e-02	53.718438	1.481183	**9.860218e-04**
PWP201	FPA	1.028604	4.917640e-06	1.164628	1589.273	50	2.608133e-03
	TLBO	1.030363	3.498403e-06	1.201378	1003.682	48.660815	2.429985e-03
	HBA	1.030026	3.621041e-06	1.198060	1066.449	48.791193	**2.429595e-03**
TP240	FPA	8.683310	1.165333e-08	3.718959e-03	6.573485	1.159582	9.458277e-03
	TLBO	8.684124	9.260328e-09	3.796484e-03	6.483112	1.146746	9.150916e-03
	HBA	8.687114	8.129722e-09	3.812287e-03	5.840245	1.139565	**8.753808e-03**

In the remainder of this study, we will assess three algorithms using the absolute error (AE), defined as the absolute difference between the estimated and experimental currents. Table 3 provides a statistical analysis of AE, including the minimum (Min), maximum (Max), and average (Mean) values for three algorithms and three tested panels. The results show that HBA produces the lowest mean

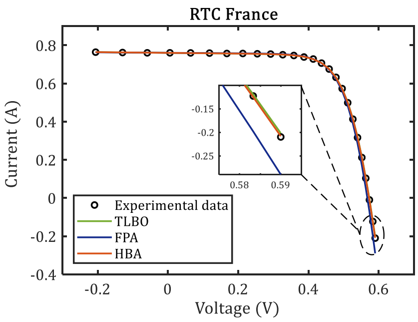

Fig. 2. I-V characteristics of both the experimental and the estimated data for RTC France cell.

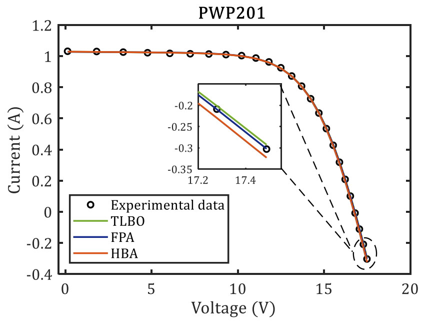

Fig. 3. I-V characteristics of both the experimental and the estimated data for PWP201 module.

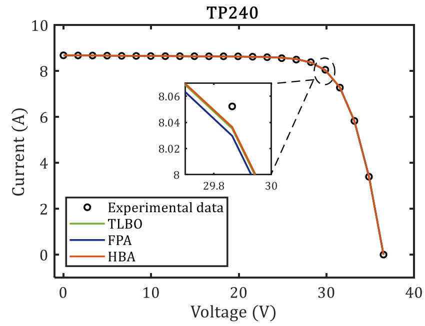

Fig. 4. I-V characteristics of both the experimental and the estimated data for TP240 module.

absolute error for PWP201 and TP240 modules. For the RTC France cell, FPA yields the minimum mean absolute error, closely rivaling HBA's performance. To offer a comprehensive view of AE results, we illustrate the fluctuation of AE concerning voltage in Figures 5–7, confirming previous findings and revealing a consistent pattern across all three algorithms. This uniformity is particularly evident in Figure 5 for the RTC France cell.

Table 3. Statistical result of absolute error (AE) for the different algorithms.

	AE (A)								
	RTC France			PWP201			TP240		
	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean
FPA	8.6971e-05	2.5077e-03	**8.2609e-04**	6.5102e-05	5.5255e-03	2.1272e-03	1.6108e-03	2.2546e-02	7.0405e-03
TLBO	9.1150e-05	2.5143e-03	8.2846e-04	7.8253e-05	4.6363e-03	1.9740e-03	1.0845e-03	2.2543e-02	6.7003e-03
HBA	8.7178e-05	2.5122e-03	8.2765e-04	6.7921e-05	4.7896e-03	**1.9696e-03**	1.5887e-04	1.9641e-02	**6.2603e-03**

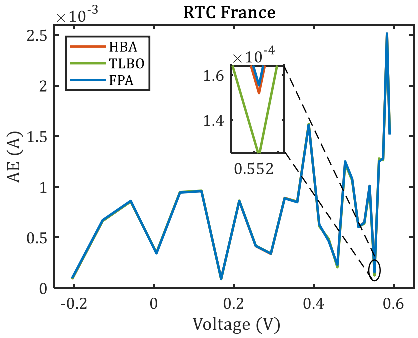

Fig. 5. The curves of the absolute error for RTC France cell.

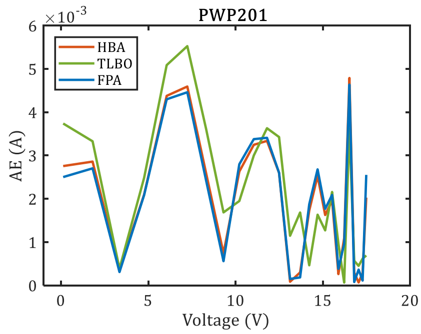

Fig. 6. The curves of the absolute error for PWP201 module.

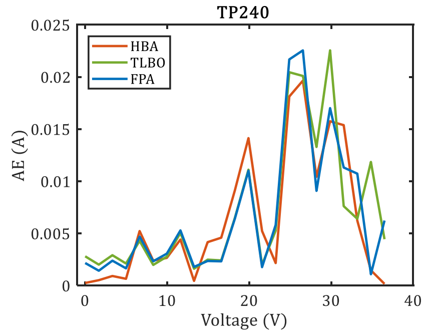

Fig. 7. The curves of the absolute error for TP240 module.

4. Conclusion

This study evaluated the efficacy of three widely used metaheuristic algorithms in ascertaining parameters for both the single-diode model (SDM) and the PV module model (MM). The study's results indicate that all three algorithms demonstrate effective and accurate estimation of PV parameters, with nearly identical performance, as reflected in the low values of RMSE and AE. Nonetheless, the Honey Badger Algorithm (HBA) exhibits superiority, yielding the best RMSE at 9.860218e-04 A for the RTC. France solar cell, while the Flower Pollination Algorithm (FPA) produces the highest RMSE at 9.458277e-03 A for the TP240 module. Concerning time complexity, both HBA and FPA demonstrate similar computational times, each requiring approximately 8 minutes. In contrast, Teaching-Learning-Based Optimization (TLBO) takes around 13 minutes to ascertain the PV parameters. Future research directions will focus on enhancing the algorithms' performance in solving PV model parameters, with the goal of reducing complexity time and minimizing errors.

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Оцінка фотоелектричних параметрів за допомогою трьох метаевристичних алгоритмів: порівняльне дослідження

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Сонячне світло служило основним джерелом енергії з моменту зародження життя на Землі. Незважаючи на появу альтернативних джерел енергії, таких як викопна та ядерна енергія, сонячна енергія залишається найбільш екологічно чистим і економічно ефективним варіантом. Використання цієї енергії передбачає використання фотоелектричних (PV) модулів для виробництва електроенергії. Грунтовні дослідження присвячені фотоелектричним модулям з основним акцентом на електричному моделюванні, яке відіграє вирішальну роль в ефективному керуванні фотоелектричною системою та визначенні її вольт-амперних характеристик. Фотоелектричні модулі охоплюють різні електричні моделі, включаючи однодіодну модель (SDM), подвійну діодну модель (DDM) і потрійну діодну модель (TDM). Складність полягає в точному визначенні невідомих параметрів, які пов'язані з кожною моделлю. Це дослідження має чітку мету: вирішити проблему визначення невловимих параметрів у межах SDM. Основною метою є порівняння ефективності трьох метаевристичних алгоритмів, а саме: алгоритму запилення квітів (FPA), оптимізації на основі викладання й навчання (TLBO) та алгоритму медоноса (HBA) у визначенні цих невідомих параметрів. На практиці це дослідження поширюється на оцінку цих алгоритмів на конкретних фотоелектричних модулях, таких як модуль Photowatt-PWP201, модуль Tata Solar Power TP240 і сонячна батарея RTC France. Оцінка результатів базується на значеннях середньоквадратичної помилки (RMSE). Примітно, що HBA виділяється тим, що демонструє чудову продуктивність, досягаючи найнижчого RMSE 9.860218e-04 A для сонячної батареї RTC France. І навпаки, FPA фіксує найвищий RMSE, досягаючи 9.458277e-03 A для модуля TP240.

Ключові слова: *сонячна енергія; моделювання фотоелектричних систем; оцінка параметрів; метаевристичні алгоритми.*