Review Article

Parameter Estimation of the Photovoltaic System Using Bald Eagle Search (BES) Algorithm

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The global demand for renewable energy is growing, and one of the proposed solutions to this energy crisis is the use of photovoltaic systems. So far, they are a reliable solution, as they are nonpolluting and can be used almost anywhere on the planet. However, the design and development of more efficient photovoltaic cells and modules require an accurate extraction of their intrinsic parameters. Up to date, metaheuristic algorithms have proven to be the best methods to obtain accurate values of these intrinsic parameters. Hence, to extract these parameters reliably and accurately, this paper presents an optimization method based on the principle of bald eagle search (BES) during fish hunting. This search is divided into three steps: in the first stage (space selection), the eagle selects the space with the largest number of prey; in the second stage (space search), the eagle moves into the selected space to search for prey; in the third stage (dive), the eagle swings from the best position identified in the second stage and determines the best point to hunt. Thus, we used the proposed BES algorithm to determine the parameters of the single-diode model (SDM), the double-diode model (DDM), and the PV modules. This algorithm converges very quickly and gives a root mean square error (RMSE) of 9.8602e−04 for the single-diode model and 9.8248e−04 for the dual-diode model. The results obtained show that the proposed algorithm is more efficient than the other methods available in the literature, in terms of the better accuracy of the results obtained. The good harmony of the I-V and P-V characteristic curve of the calculated parameters with that of the measured data from a PV module/cell data sheet proves that the proposed BES should be used among the methods provided in the literature for the identification of PV solar cell parameters.

1. Introduction

The energy demand of almost every country in the world is increasing due to its large-scale industrial expansion, population growth, and the continuous growth of per capita energy consumption. It is worth noting that most of the energy needs are in the form of electricity. In contrast, the use of fossil fuel-based electricity generation has reached saturation levels due to increased environmental concerns and limited resources. Thus, the gaps between demand and production in the future must be filled by renewable energy sources [1]. However, as the solar energy obtained from a solar PV module is not constant, a major challenge is therefore to maximise the use of solar energy due to the unpredictability of the power output of PV modules caused by the resulting variations in irradiance levels and cell temperature [2]. Thus, the competition to optimize and increase the efficiency of photovoltaic cells has led researchers to find...
methods to determine the intrinsic parameters of these cells. In the literature review, several methods have been proposed for the extraction of the parameters; each of these methods has drawbacks, either in terms of complexity of use and accuracy or in terms of convergence and speed. These methods are classified into three categories: analytical, numerical, and metaheuristic methods [3].

In the analytical method, a set of transcendental equations is solved to estimate the parameters of the solar cell. The main advantage of the analytical method is the speed of calculation and relatively accurate results. Analytical methods are simple, with a short computation time. Sometimes, a single iteration is sufficient to obtain the result [4]. Although this approach is very popular, it is not always easy to apply. In addition, they need many data points of the I–V curve, which in turn complicates the computation [5]. Analytical methods include Lambert’s W function [6], Taylor series expansion [7], and Chebyshev polynomials [8, 9]. Some of these methods estimate 5 parameters, and others extract only the series and shunt resistance. The main weakness of analytical methods is that they are only suitable for standard conditions; consequently, they have poor results with variable ambient conditions [10]. Numerical methods with curve-fitting techniques are better than analytical methods. The algorithms of these methods provide accurate results by evaluating all points of the PV–IV curves using the algorithm [10].

Metaheuristic algorithms are global optimization techniques which do not impose any restrictions on the problem formulation and have the ability to solve various complex problems [11]. In the literature, many metaheuristic algorithms have been suggested for extracting the parameters of PV solar cell models, such as the Genetic Algorithm (GA) [12, 13], the Cuckoo Search (CS) Algorithm [11, 14], Particle Swarm Optimization (PSO) [15–17], Differential Evolution (DE) algorithm [18], Artificial Bee Colony (ABC) algorithm [19–21], Artificial Algorithm of Bee Swarm Optimization (ABSO) [22], Bacterial Foraging Optimization (BFO) algorithm [23, 24], Biogeography-Based Optimization (BBO) algorithm [25], Floral Pollination Algorithm (FPA) [26, 27], Jaya Optimization Algorithm (JAYA) [28, 29], Salp Swarm Algorithm (SSA) [30], Bird Mating Optimization (BMO) algorithm [31], Teaching-Learning-Based Algorithm (TLBO) [20, 32–34], Whale Optimization Algorithm (WOA) [35–37], Backtracking Search Algorithm (BSA) [38], Sine-Cosine Algorithm (SCA) [39], Imperialist Competitive Algorithm (ICA) [40, 41], Multiverse Optimizer (MVO) algorithm [42], Ant-Lion Optimizer (ALO) algorithm [43, 44], Eagle Strategy (ES) [45], Cat Swarm Optimization (CSO) [46], Harmony Search (HS) [47], Firefly Algorithm (FA) [48], Simplified Swarm Optimization (SSO) [49], Moth-Flame Optimization (MFO) algorithm [50], Water Cycle Algorithm (WCA) [51], Enhanced Vibration of Particles System (EVPS) [52], Harris Hawks Optimization (HHO) [53], Shuffled Frog Leaping (SFL) algorithm [54], Metaphor-Free Dynamic Spherical Evolution (DSCE) [55], enhanced metaphor-free gradient-based optimizer (EGBO) [56], delayed dynamic step shuffling frog-leaping algorithm (DDSFLA) [57], evolutionary shuffled frog leap-
with $I_d$ as the saturation current of the diode, $q$ the charge of one electron ($q = 1.60217646 \times 10^{-19}$ C), $n$ the ideality factor of the diode, $K$ Boltzmann’s constant ($K = 1.3806503 \times 10^{-23}$ J/K), and $T$ the temperature in Kelvin.

The equation model (3) is also called the implicit model with five unknown parameters: $I_{ph}$, $I_{sd1}$, $R_s$, $R_{sh}$, and $n$.

### 2.2. Two-Diode Model

Due to its simplicity and accuracy, the above-mentioned single-diode model has been widely used to describe the static characteristics of the photovoltaic cell. However, the single-diode model has inherent drawbacks as it assumes that the ideality factor of the diode remains constant throughout the range of output voltage variation [29]. Currently, the closest electrical model to a photovoltaic cell is the two-diode (double exponential) model, where the cell is of course presented as an electrical current generator whose behaviour is equivalent to a current source with two diodes in parallel. The two-diode model is shown in Figure 2 [18, 52].

$$I = I_{ph} - I_{d1} - I_{d2} - I_{sh},$$

$$I_{sh} = \frac{V + R_s \times I}{R_{sh}},$$

$$I = I_{ph} - I_{sd1} \left( exp \left( \frac{q(V + R_s \times I)}{n_1 \times K \times T} \right) - 1 \right)$$

$$- I_{sd2} \left( exp \left( \frac{q(V + R_s \times I)}{n_2 \times K \times T} \right) - 1 \right)$$

$$- \frac{V + R_s \times I}{R_{sh}}. \quad (4)$$

The parameters of this double-diode model to be estimated are $I_{ph}$, $I_{sd1}$, $I_{sd2}$, $R_s$, $R_{sh}$, $n_1$, and $n_2$.
Table 1: Parameter range of different PV models.

| Parameters | Single and double diode | Photowatt-PWP201 | STM6-40/36 | STP6-120/36 |
|------------|-------------------------|-----------------|------------|------------|
|            | Lower bound             | Upper bound     | Lower bound| Upper bound|
| $I_{ph}$  (A) | 0                       | 1               | 0           | 2          | 0           | 2          | 0           | 8          |
| $I_{d1}, I_{d2}$ (μA) | 0                       | 1               | 0           | 50         | 0           | 50         | 0           | 50         |
| $R_s$ (Ω)  | 0                       | 0.5             | 0           | 2          | 0           | 0.36       | 0           | 0.36       |
| $R_{sh}$ (Ω) | 0                       | 2000            | 0           | 1000       | 0           | 1500       |
| $n, n_1, n_2$ | 1                       | 2               | 1           | 50         | 1           | 60         | 1           | 50         |

Table 2: Comparison of the results obtained from single diode model R.T.C. France solar cell with other methods in the literature.

| Algorithm   | $I_{ph}$ (A) | $I_{sd}$ (μA) | $R_s$ (Ω) | $R_{sh}$ (Ω) | $n$ | RMSE          |
|-------------|--------------|----------------|-----------|--------------|-----|---------------|
| BES         | 0.7607       | 0.3230         | 0.0364    | 53.7185      | 1.4812 | 9.8602e – 04 |
| ILSA [68]   | 0.7607       | 0.3229         | 0.0364    | 53.7204      | 1.4811 | 9.8602e – 04 |
| GAMS [3]    | 0.7607       | 0.3230         | 0.0364    | 53.7185      | 1.4812 | 9.8602e – 04 |
| ITLBO [69]  | 0.7607       | 0.3230         | 0.0364    | 53.7184      | 1.4812 | 9.8602e – 04 |
| IMFO [67]   | 0.7607       | 0.3234         | 0.0363    | 53.7608      | 1.4813 | 9.8602e – 04 |
| IIAYA [63]  | 0.7608       | 0.3228         | 0.0364    | 53.7595      | 1.4811 | 9.8603e – 04 |
| MADE [18]   | 0.7607       | 0.3230         | 0.0363    | 53.7185      | 1.4811 | 9.8602e – 04 |
| EVPS [52]   | 0.7607       | 0.3250         | 0.0363    | 53.8960      | 1.4821 | 9.8609e – 04 |
| GOTLBO [64] | 0.7608       | 0.3297         | 0.0363    | 53.3664      | 1.4833 | 9.8856e – 04 |
| TLABC [20]  | 0.7608       | 0.3230         | 0.0364    | 53.7164      | 1.4812 | 9.8602e – 04 |
| CLPSO [70]  | 0.7608       | 0.3430         | 0.0361    | 54.1965      | 1.4873 | 9.9633e – 04 |
| TLBO [71]   | 0.7607       | 0.3294         | 0.0363    | 54.3015      | 1.4831 | 9.8733e – 03 |
| TPTLBO [72] | 0.7608       | 0.3230         | 0.0364    | 53.7185      | 1.4812 | 9.8602e – 04 |
| DSCE [55]   | 0.7607       | 0.3230         | 0.0363    | 53.7185      | 1.4811 | 9.8602e – 04 |
| EGBO [56]   | 0.7608       | 0.3230         | 0.0364    | 53.7185      | 1.4811 | 9.8602e – 04 |
| DDSFLA [57] | 0.7608       | 0.3191         | 0.036     | 53.3770      | 1.4800 | 9.8630e – 04 |
| SFLBS [58]  | 0.7607       | 0.3230         | 0.0363    | 53.7185      | 1.4811 | 9.8602e – 04 |
| LCNMSE [59] | 0.7607       | 0.3230         | 0.0363    | 53.71     | 1.4811 | 9.8602e – 04 |
| PSOCS [60]  | 0.7607       | 0.3230         | 0.0363    | 53.719      | 1.4812 | 9.8602e – 04 |
| CNMSMA [61] | 0.7607       | 0.3230         | 0.0363    | 53.7182      | 1.4811 | 9.8602e – 04 |
2.3. The PV Model. The PV module model is shown in Figure 3 [52, 63, 64].

\[ I = I_{ph} \times N_p - I_{sd} \times N_p - I_{sh} \times N_p \times \exp \left( \frac{q(V/N_s) + (R_s/N_p) \times I}{n \times K \times T} \right) - 1 \]

\[ - \frac{V(N_p/N_s) + R_s \times I}{R_{sh}}, \]

where \( N_p \) and \( N_s \) represent the number of solar cells in parallel and in series, respectively. Thus, for this PV model, five unknown parameters \( (I_{ph}, I_{sd}, R_s, R_{sh}, \text{and} n) \) have to be identified.

2.4. Objective Function. For a single-diode model, the objective function is expressed as

\[ f(V, I, X) = I_{ph} - I_{sd} \left( \exp \left( \frac{q(V + R_s \times I)}{n_1 \times K \times T} \right) - 1 \right) - \frac{V + R_s \times I}{R_{sh}}, \]

\[ X = \{ I_{ph}, I_{sd}, R_s, R_{sh}, n \}. \]

For the double-diode model, the objective function is

\[ f(V, I, X) = I_{ph} - I_{sd1} \left( \exp \left( \frac{q(V + R_s \times I)}{n_1 \times K \times T} \right) - 1 \right) - I_{sd2} \left( \exp \left( \frac{q(V + R_s \times I)}{n_2 \times K \times T} \right) - 1 \right) - \frac{V + R_s \times I}{R_{sh}}, \]

\[ X = \{ I_{ph}, I_{sd1}, I_{sd2}, R_s, R_{sh}, n_1, n_2 \}. \]
The parameters can be estimated by minimizing the objective function $\text{RMSE}(x)$, i.e., by searching for the solution vector $x$ [11, 16, 29, 65, 66].

$$\text{RMSE}(X) = \sqrt{\frac{1}{N} \sum_{k=1}^{N} f(V, I, X)^2}, \quad (8)$$

where $X$ represents the parameters composed of the solution vector. $V$ and $I$ are the measured voltage and current, respectively. $N$ represents the number of experiments. Hence, to estimate the parameters is equivalent to search the $X$ in the range which minimizes the objective function.

### 3. Problem Formulation

The problem can be set as an optimization problem with the objective to minimize the difference between the measured and estimated current. The objective function (OF) is defined as the root mean square error (RMSE), where the error function is defined as the difference between the estimated and experimental currents. It is expressed as follows [11, 16, 29, 65, 66]:

$$\text{Min} \left( \text{RMSE}(X) \right) = \sqrt{\frac{1}{N} \sum_{k=1}^{N} (I_{k,\text{mes}} - I_{k,\text{ext}}(X))^2}, \quad (9)$$

where $\text{RMSE}(X)$ is the objective function to minimize, $N$ is the number of points measured, $I_{k,\text{mes}}$ is the measured current, and $I_{k,\text{ext}}(X)$ is the estimated current.

For a single-diode model, the fitness function is expressed as

$$\text{Min} \left( \text{RMSE}(X) \right) = \sqrt{\frac{1}{N} \sum_{k=1}^{N} \left( I_{k,\text{mes}} - I_{p} + I_{sd1} \left( \exp \left( \frac{q(V_{k,\text{mes}} + R_s \times I_{k,\text{mes}})}{n_i \times K \times T} \right) - 1 \right) + \frac{V_{k,\text{mes}} + R_s \times I_{k,\text{mes}}}{R_{sh}} \right)^2}, \quad (10)$$

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Table 3: The individual absolute error and relative error of a single-diode model obtained by BES.

| Item | Test data | Simulated current | Power | True | False |
|------|-----------|-------------------|-------|------|-------|
| | $V$ (V) | $I$ (A) | $I_{\text{ph}}$ (A) | $I_{\text{sd}}$ (A) | $I_{\text{sd}}$ (A) | $I_{\text{sd}}$ (A) | $I_{\text{sd}}$ (A) | $I_{\text{sd}}$ (A) | $I_{\text{sd}}$ (A) | $I_{\text{sd}}$ (A) | $I_{\text{sd}}$ (A) |
| 1   | -0.2057  | 0.7640            | 0.764112 | 0.000112 | -0.157178 | -0.000146 |
| 2   | -0.1291  | 0.7620            | 0.762687 | 0.000867 | -0.098463 | -0.000902 |
| 3   | -0.0588  | 0.7605            | 0.761379 | 0.000879 | -0.044769 | -0.001156 |
| 4   | 0.0057   | 0.7605            | 0.760178 | 0.000322 | 0.004333 | 0.000423 |
| 5   | 0.0646   | 0.7600            | 0.759079 | 0.000921 | 0.049037 | 0.001211 |
| 6   | 0.1185   | 0.7590            | 0.758066 | 0.000934 | 0.089831 | 0.001230 |
| 7   | 0.1678   | 0.7570            | 0.757116 | 0.001116 | 0.127044 | -0.000153 |
| 8   | 0.2132   | 0.7570            | 0.756166 | 0.000834 | 0.161214 | 0.001102 |
| 9   | 0.2545   | 0.7555            | 0.755111 | 0.000389 | 0.192176 | 0.000515 |
| 10  | 0.2924   | 0.7540            | 0.753689 | 0.000311 | 0.220379 | 0.000413 |
| 11  | 0.3269   | 0.7505            | 0.751417 | 0.000917 | 0.245638 | 0.000122 |
| 12  | 0.3585   | 0.7465            | 0.747383 | 0.000883 | 0.267937 | 0.000118 |
| 13  | 0.3873   | 0.7385            | 0.740152 | 0.001652 | 0.286661 | -0.002238 |
| 14  | 0.4137   | 0.7280            | 0.727430 | 0.000570 | 0.300938 | 0.000783 |
| 15  | 0.4373   | 0.7065            | 0.707043 | 0.000543 | 0.309190 | -0.000769 |
| 16  | 0.4590   | 0.6755            | 0.675389 | 0.000111 | 0.310003 | 0.000165 |
| 17  | 0.4784   | 0.6320            | 0.630925 | 0.001075 | 0.301835 | 0.001700 |
| 18  | 0.4960   | 0.5730            | 0.572180 | 0.000820 | 0.283801 | 0.001432 |
| 19  | 0.5119   | 0.4990            | 0.499971 | 0.000971 | 0.255935 | -0.001945 |
| 20  | 0.5265   | 0.4130            | 0.414157 | 0.001157 | 0.218054 | -0.002802 |
| 21  | 0.5398   | 0.3165            | 0.318194 | 0.001694 | 0.171761 | -0.005352 |
| 22  | 0.5521   | 0.2120            | 0.213046 | 0.001046 | 0.117623 | -0.004934 |
| 23  | 0.5633   | 0.1035            | 0.103375 | 0.000125 | 0.058231 | -0.002238 |
| 24  | 0.5736   | -0.0100           | -0.007341 | -0.004211 | 0.265897 | 0.001209 |
| 25  | 0.5833   | -0.1230           | -0.123850 | -0.072242 | 0.265897 | 0.001209 |
| 26  | 0.5900   | -0.2100           | -0.206601 | -0.121895 | 0.265897 | 0.001209 |
| Total IAE | 0.023977 |
Table 4: Statistical results for R.T.C. France PV cell single diode.

| Algorithm   | Min           | Mean          | Max           | Std.          |
|-------------|---------------|---------------|---------------|---------------|
| BES         | 9.8602e-04    | 9.8602e-04    | 9.8602e-04    | 2.6314e-13    |
| ITLBO       | 9.8602e-04    | 9.8602e-04    | 9.8602e-04    | 2.19e-17      |
| IMFO        | 9.8602e-04    | 9.8767e-04    | 9.9641e-04    | 2.1810e-06    |
| IJAYA       | 9.8606e-04    | 1.0261e-03    | 1.1223e-03    | 4.160e-05     |
| GOTLBO      | 9.8602e-04    | 1.4388e-03    | 1.0289e-03    | 1.01e-04      |
| CLPSO       | 9.9455e-04    | 1.0507e-03    | 1.1865e-04    | 4.6730e-05    |
| TPTLBO      | 9.8602e-04    | 9.8602e-04    | 9.8602e-04    | 2.28e-17      |
| MADE        | 9.8602e-04    | 9.8602e-04    | 9.8602e-04    | 2.47e-15      |
| TLABC       | 9.8602e-04    | 9.9852e-04    | 1.2358e-03    | 1.86e-05      |
| TLBO        | 9.8722e-04    | 1.0476e-04    | 1.0397e-03    | 6.59e-05      |
| DSCE        | 9.8602e-04    | 9.8602e-04    | 9.8602e-04    | 1.1320e-09    |
| EGBO        | 9.8602e-04    | 9.9500e-04    | 1.1161e-04    | 2.62e-05      |
| DDSFLA      | 9.8630e-04    | 1.0819e-03    | 1.3056e-03    | 8.6464e-05    |
| SFLSB       | 9.8602e-04    | 9.8602e-04    | 9.8602e-04    | 1.4301e-14    |
| PSOCS       | 9.8602e-04    | 9.8602e-04    | 9.8603e-04    | 1.7459e-09    |

![Figure 6: Convergence curve during the parameter extraction for one diode.](image)

with $X = [I_{ph}, I_{sd}, R_s, R_{sh}, n]$ the parameters to be estimated.

For the double-diode model, the fitness function is estimated.

$$\text{Min } \text{RMSE}(X) = \sqrt{\frac{1}{N} \sum_{k=1}^{N} \left( I_{k,\text{max}} - I_{ph} + I_{sd1} \left( \exp \left( \frac{q(V_{k,\text{max}} + R_s \times I_{k,\text{max}})}{n_1 \times k \times T} \right) - 1 \right) + I_{sd2} \left( \exp \left( \frac{q(V_{k,\text{max}} + R_s \times I_{k,\text{max}})}{n_2 \times k \times T} \right) - 1 \right) \right) + \frac{V_{k,\text{max}} + R_s \times I_{k,\text{max}}}{R_{sh}}}^2,$$

(11)

with $X = [I_{ph}, I_{sd1}, I_{sd2}, R_s, R_{sh}, n_1, n_2]$ the parameters to be estimated.

In this paper, the approach of bald eagle search (BES) is used for the optimization of results of equations (10) and (11).

4. Bald Eagle Search (BES) Algorithm [62]

Bald eagles are occasional predators and are at the top of the food chain only because of their size. Furthermore, bald eagles are considered scavengers that feast on any available, easy, and protein-rich food. Bald eagles are an opportunistic forager that mainly select fish (alive or dead), especially salmon, as the primary food. Bald eagles frequently hunt from perch but may also hunt while in flight. They are capable of spotting fish at enormous distances because obtaining fish from water is difficult. When they start to search for food over a water spot, these eagles set off in a specific direction and select a certain area to
Table 5: Comparison of the results obtained from the double-diode model R.T.C. France solar cell with other methods in the literature.

| Algorithm | $I_{ph}$ (A) | $I_{sd1}$ ($\mu$A) | $I_{sd2}$ ($\mu$A) | $R_s$ (Ω) | $R_{sh}$ (Ω) | $n_1$ | $n_2$ | Best RMSE  |
|-----------|-------------|-------------------|-------------------|-----------|-------------|-------|-------|------------|
| BES       | 0.7608      | 0.2259            | 0.7493            | 0.0367    | 55.4854     | 1.4510 | 2.000 | 9.8248e−4 |
| GAMS [3]  | 0.7606      | 0.2260            | 0.7594            | 0.0367    | 55.4854     | 1.2186 | 1.6247| 9.8293e−4 |
| ITLBO [69]| 0.7608      | 0.2260            | 0.7493            | 0.0367    | 55.4854     | 1.4510 | 2.0000| 9.8248e−4 |
| IMFO [67] | 0.7607      | 0.2350            | 0.6837            | 0.0367    | 55.2997     | 1.4537 | 2.0000| 9.8252e−4 |
| JJAYA [63]| 0.7601      | 0.0050            | 0.7509            | 0.0376    | 77.8519     | 1.2186 | 1.6247| 9.8293e−4 |
| MADE [18] | 0.7608      | 0.2246            | 0.7394            | 0.0368    | 55.4329     | 1.4505 | 1.9963| 9.8261e−4 |
| EVP [52]  | 0.7607      | 0.2975            | 0.2504            | 0.0363    | 55.8827     | 1.4749 | 1.9726| 9.8510e−4 |
| GOTLBO [64]| 0.7608     | 0.2717            | 0.2595            | 0.0366    | 53.6187     | 1.4668 | 1.9161| 9.9544e−4 |
| CLPSO [70]| 0.7606      | 0.2875            | 0.2686            | 0.0366    | 55.2895     | 1.9586 | 1.4652| 9.9224e−4 |
| TLABC [20]| 0.7608      | 0.4239            | 0.2401            | 0.0367    | 54.6680     | 1.9075 | 1.4567| 9.8415e−4 |
| TLBO [71] | 0.7610      | 0.2947            | 0.1373            | 0.0366    | 53.1210     | 1.4730 | 1.9938| 1.0069e−3 |
| TPTLBO [72]| 0.7608     | 0.7434            | 0.2266            | 0.0367    | 55.4831     | 2.0000 | 1.4513| 9.8248e−4 |
| DSCE [55] | 0.7608      | 0.6980            | 0.2318            | 0.0367    | 55.3750     | 1.9999 | 1.4553| 9.8250e−4 |
| EGBO [56] | 0.7608      | 0.225             | 0.749             | 0.0367    | 55.4855     | 1.4510 | 2.0000| 9.8248e−4 |
| DDSFLA [57]| 0.7608     | 0.2931            | 0.2271            | 0.0365    | 54.3710     | 1.4730 | 2.0000| 9.8434e−4 |
| SFLBS [58]| 0.7607      | 0.7759            | 0.2285            | 0.0367    | 55.5496     | 2.0000 | 1.4498| 9.8249e−4 |
| LCNMSE [59]| 0.7607     | 0.7493            | 0.2259            | 0.0367    | 55.4854     | 2.0000 | 1.4510| 9.8248e−4 |
| PSOCS [60]| 0.7607      | 1.0000            | 0.1981            | 0.0368    | 56.172      | 2.0000 | 1.4401| 9.8297e−4 |
| CNMSMA [61]| 0.7607     | 0.2259            | 0.7506            | 0.0367    | 55.4854     | 1.4510 | 1.9999| 9.8249e−4 |

Figure 7: Characteristics of the measured and estimated curve with two diodes: (a) $P$-$V$ and (b) $I$-$V$. 
| Item | Test data | Simulated current | Power | RE |
|------|-----------|------------------|-------|----|
|      | $V$ (V)   | $I$ (A)          | $I_{sim}$ (A) | IAE (A) | $P_{sim}$ (W) |       |
| 1    | -0.2057  | 0.7640           | 0.764003   | 0.000003 | -0.157155      | -0.000004 |
| 2    | -0.1291  | 0.7620           | 0.762624   | 0.000624 | -0.098455      | -0.000818 |
| 3    | -0.0588  | 0.7605           | 0.761357   | 0.000857 | -0.044768      | -0.001127 |
| 4    | 0.0057   | 0.7605           | 0.760193   | 0.000307 | 0.004333       | 0.000403  |
| 5    | 0.0646   | 0.7600           | 0.759127   | 0.000873 | 0.049040       | 0.001148  |
| 6    | 0.1185   | 0.7590           | 0.758141   | 0.000859 | 0.089840       | 0.001132  |
| 7    | 0.1678   | 0.7570           | 0.757208   | 0.000208 | 0.127060       | -0.000275 |
| 8    | 0.2132   | 0.7570           | 0.756263   | 0.000737 | 0.161235       | 0.000973  |
| 9    | 0.2545   | 0.7555           | 0.755197   | 0.000303 | 0.192198       | 0.000400  |
| 10   | 0.2924   | 0.7540           | 0.753744   | 0.000256 | 0.220395       | 0.000340  |
| 11   | 0.3269   | 0.7505           | 0.751423   | 0.000923 | 0.245640       | -0.001230 |
| 12   | 0.3585   | 0.7465           | 0.747332   | 0.000832 | 0.267919       | -0.001114 |
| 13   | 0.3873   | 0.7385           | 0.740054   | 0.001554 | 0.286623       | -0.002104 |
| 14   | 0.4137   | 0.7280           | 0.727313   | 0.000687 | 0.300889       | 0.000943  |
| 15   | 0.4373   | 0.7065           | 0.706955   | 0.000455 | 0.309151       | -0.000644 |
| 16   | 0.4590   | 0.6755           | 0.675376   | 0.000124 | 0.309997       | 0.000184  |
| 17   | 0.4784   | 0.6320           | 0.631010   | 0.000990 | 0.301875       | 0.001567  |
| 18   | 0.4960   | 0.5730           | 0.572351   | 0.000649 | 0.283886       | 0.001132  |
| 19   | 0.5119   | 0.4990           | 0.500188   | 0.001188 | 0.256046       | -0.002381 |
| 20   | 0.5265   | 0.4130           | 0.414353   | 0.001353 | 0.218157       | -0.003277 |
| 21   | 0.5398   | 0.3165           | 0.318305   | 0.001805 | 0.171821       | -0.005702 |
| 22   | 0.5521   | 0.2120           | 0.213015   | 0.001015 | 0.117605       | -0.004787 |
| 23   | 0.5633   | 0.1035           | 0.103172   | 0.000328 | 0.058117       | 0.003166  |
| 24   | 0.5736   | -0.0100          | -0.007691  | 0.002309 | -0.004412      | 0.230909  |
| 25   | 0.5833   | -0.1230          | -0.124367  | 0.001367 | -0.072543      | -0.011111 |
| 26   | 0.5900   | -0.2100          | -0.207164  | 0.002836 | -0.122226      | 0.013507  |
| Total IAE |          |                  |          | 0.023441 |               |          |
begin the search. Accordingly, finding the search space is achieved by self-searching and tracking other birds with the concentration of fish (dead or alive).

The proposed BES algorithm mimics the behaviour of bald eagles during hunting to justify the consequences of each hunting step. This algorithm is divided into three parts, namely, search space selection, search in the selected search space, and swooping.

4.1. Selection Stage. In the selection stage, bald eagles identify and select the best area (in terms of amount of food) within the selected search space where they can hunt for prey. Equation (12) presents this behaviour mathematically.

\[ P_{\text{new}} = P_{\text{best}} + \alpha \cdot (P_{\text{mean}} - P_{\text{i}}) \cdot r, \]  

where \( \alpha \) is the position change control parameter that takes a value between 1.5 and 2 and \( r \) is a random number that takes a value between 0 and 1; \( P_{\text{new}} \) and \( P_{\text{i}} \) are updated position and old position, respectively, at time \( t \). In the selection step, the bald eagles select an area based on the information available from the previous step. The eagles randomly select another search area that differs from the previous search area but is located nearby. \( P_{\text{best}} \) denotes the search area that is currently selected by the bald eagles based on the best position identified in their previous search. The eagles randomly search all points near the previously selected search space. Meanwhile, \( P_{\text{mean}} \) indicates that these eagles have used all the information from the previous points.

4.2. Search Stage. In the search stage, bald eagles search for prey within the selected search space and move in different directions within a spiral space to accelerate their search.

\[ P_{\text{new}} = P_{\text{i}} + y(i) \cdot (P_{\text{i}} - P_{\text{i+1}}) + x(i) \cdot (P_{\text{i}} - P_{\text{mean}}), \]  

\[ x(i) = \frac{\sqrt{r(i)}}{\max(\|x\|)}, \]  

\[ y(i) = \frac{\sqrt{r(i)}}{\max(\|y\|)}, \]  

\[ x(i) = r(i) \cdot \sin(\theta(i)), \]  

\[ y(i) = r(i) \cdot \cos(\theta(i)), \]  

\[ \theta(i) = a \cdot \pi \cdot \text{rand}, \]  

\[ r(i) = \theta(i) + R \cdot \text{rand}, \]  

where \( a \) is a parameter that takes a value between 5 and 10 for determining the corner point search in the central point and \( R \) takes a value between 0.5 and 2 for determining the number of search cycles.

### Table 7: Statistical results for R.T.C. France PV cell two diodes.

| Algorithm | Min     | Mean    | Max     | Std.     |
|-----------|---------|---------|---------|----------|
| BES       | 9.8248e – 04 | 9.9518e – 04 | 1.1881e – 03 | 4.6013e – 05 |
| TLBO      | 9.8248e – 04 | 9.8812e – 04 | 9.8497e – 04 | 1.54e – 06  |
| IMFO      | 9.8252e – 04 | 9.9737e – 04 | 1.1409e – 03 | 3.2939e – 05 |
| JJAYA     | 9.8380e – 04 | 1.0240e – 03 | 1.3507e – 03 | 8.5647e – 05 |
| GOTLBO    | 9.8407e – 04 | 1.4380e – 03 | 1.0453e – 03 | 1.01e – 04  |
| CLPSO     | 9.9224e – 04 | 1.0522e – 03 | 1.1462e – 03 | 4.3141e – 05 |
| TPTLBO    | 9.8248e – 04 | 9.8602e – 04 | 9.8363e – 04 | 9.31e – 07  |
| MADE      | 9.8261e – 04 | 9.8608e – 04 | 9.8786e – 04 | 8.02e – 05  |
| TLABC     | 9.8415e – 04 | 1.0555e – 03 | 1.5048e – 03 | 1.54e – 06  |
| TLBO      | 1.0069e – 03 | 1.1598e – 03 | 1.5206e – 03 | 1.56e – 04  |
| EGO       | 9.8248e – 04 | 9.8484e – 04 | 9.8681e – 04 | 1.66e – 04  |
| DDFSFLA   | 9.8434e – 04 | 1.1071e – 03 | 1.4225e – 03 | 1.3014e – 04 |
| SFLBS     | 9.8249e – 04 | 9.8541e – 04 | 9.8787e – 04 | 1.7882e – 06 |
| PSCOS     | 9.8297e – 04 | 1.0286e – 03 | 1.4133e – 03 | 9.9217e – 05 |

**Figure 8:** Convergence curve during the parameter extraction for the two-diode models.

The best position for the swoop is mathematically expressed in

\[ P_{\text{new}} = P_{\text{i}} + y(i) \cdot (P_{\text{i}} - P_{\text{i+1}}) + x(i) \cdot (P_{\text{i}} - P_{\text{mean}}), \]
Table 8: Comparison of the results obtained from Photowatt-PWP201 model with other methods in the literature.

| Algorithm   | $I_{ph}$ (A) | $I_{sd}$ ($\mu$A) | $R_s$ (Ω) | $R_{sh}$ (Ω) | $n$     | RMSE     |
|-------------|-------------|------------------|----------|-----------|--------|----------|
| BES         | 1.0305      | 3.4823           | 1.2013   | 981.9824  | 48.6428| 2.42507e-03 |
| GAMS [3]    | 1.0320      | 3.2681           | 1.2062   | 828.2928  | 1.3445 | 2.4426e-03  |
| ITLBO [69]  | 1.0305      | 3.4823           | 1.2013   | 981.9823  | 48.6428| 2.4251e-03  |
| IMFO [67]   | 1.0305      | 3.4783           | 1.2013   | 980.4672  | 48.6385| 2.4251e-03  |
| IJAYA [63]  | 1.0302      | 3.4703           | 1.2011   | 984.8760  | 48.6482| 2.4251e-03  |
| MADE [18]   | 1.0305      | 3.4823           | 1.2013   | 981.9823  | 48.6428| 2.4251e-03  |
| EVPS [52]   | 1.0318      | 3.2679           | 1.2066   | 845.759   | 1.3445 | 2.4267e-03  |
| GOTLBO [64] | 1.0305      | 3.4991           | 1.2008   | 989.6889  | 48.6611| 2.4251e-03  |
| TLABC [20]  | 1.0306      | 3.4715           | 1.2017   | 972.9357  | 48.6313| 2.4251e-03  |
| TLBO [71]   | 1.0305      | 3.4872           | 1.2011   | 984.8760  | 48.6482| 2.4251e-03  |
| CLPSO [70]  | 1.0304      | 3.6131           | 1.1978   | 1017.0    | 48.7847| 2.4280e-03  |
| TPTLBO [72] | 1.0305      | 3.4823           | 1.2013   | 981.9822  | 48.6428| 2.4251e-03  |
| EGBO [56]   | 1.0305      | 3.48            | 1.2013   | 981.9822  | 48.6428| 2.4151e-03  |
| DDSFLA [57] | 1.0306      | 3.4473           | 1.2023   | 971.2500  | 48.6040| 2.4252e-03  |
| SFLBS [58]  | 1.0305      | 3.4822           | 1.2012   | 981.9804  | 48.6428| 2.4251e-03  |
| LCNMSE [59] | 1.0315      | 3.4822           | 1.2013   | 981.9741  | 48.6428| 2.4251e-03  |
| PSOCS [60]  | 1.0305      | 3.4823           | 1.2013   | 981.98    | 48.643  | 2.4251e-03  |

Figure 9: Characteristics of the measured and estimated curve with one diode: (a) $I$-$V$ and (b) $P$-$V$. 
Table 9: The individual absolute error and relative error of Photowatt-PWP201 obtained by BES.

| Item | Test data V (V) | Test data I (A) | Simulated current I_{sim} (A) | IAE (A) | Power P_{sim} (W) | RE |
|------|----------------|----------------|-------------------------------|---------|-------------------|-----|
| 1    | 0.1248         | 1.0315         | 1.029105                      | 0.002395| 0.128432          | 0.002322 |
| 2    | 1.8093         | 1.0300         | 1.027367                      | 0.002633| 1.858815          | 0.002557 |
| 3    | 3.3511         | 1.0260         | 1.025728                      | 0.000272| 3.437315          | 0.000266 |
| 4    | 4.7622         | 1.0220         | 1.024093                      | 0.002093| 4.876936          | -0.002048|
| 5    | 6.0538         | 1.0180         | 1.022278                      | 0.004278| 6.188666          | -0.004202|
| 6    | 7.2364         | 1.0155         | 1.019918                      | 0.004418| 7.380532          | -0.004350|
| 7    | 8.3189         | 1.0140         | 1.016352                      | 0.002352| 8.454931          | -0.002320|
| 8    | 9.3097         | 1.0100         | 1.010490                      | 0.000490| 9.407354          | -0.000485|
| 9    | 10.2163        | 1.0035         | 1.000631                      | 0.002869| 10.222748         | 0.002859 |
| 10   | 11.0449        | 0.9880         | 0.984567                      | 0.003433| 10.874439         | 0.003475 |
| 11   | 11.8018        | 0.9630         | 0.959567                      | 0.003433| 11.324616         | 0.003565 |
| 12   | 12.4929        | 0.9255         | 0.922926                      | 0.002574| 11.530023         | 0.002781 |
| 13   | 13.1231        | 0.8725         | 0.872748                      | 0.000248| 11.453153         | -0.000284|
| 14   | 13.6983        | 0.8075         | 0.807504                      | 0.000004| 11.061434         | -0.000005|
| 15   | 14.2221        | 0.7265         | 0.728669                      | 0.002169| 10.363202         | -0.002985|
| 16   | 14.6995        | 0.6345         | 0.637592                      | 0.003092| 9.372288          | -0.004874|
| 17   | 15.1346        | 0.5345         | 0.536806                      | 0.002306| 8.124337          | -0.004313|
| 18   | 15.5311        | 0.4275         | 0.430253                      | 0.002753| 6.682303          | -0.006440|
| 19   | 15.8929        | 0.3185         | 0.319674                      | 0.001174| 5.080544          | -0.003686|
| 20   | 16.2229        | 0.2085         | 0.208450                      | 0.000050| 3.381663          | 0.000024 |
| 21   | 16.5241        | 0.1010         | 0.097391                      | 0.003609| 1.609294          | 0.035736 |
| 22   | 16.7987        | -0.0080        | -0.006947                     | 0.001053| -0.116694         | 0.131670 |
| 23   | 17.0499        | -0.1110        | -0.109404                     | 0.001596| -1.865323         | 0.014380 |
| 24   | 17.2793        | -0.2090        | -0.207566                     | 0.001434| -3.586589         | 0.006863 |
| 25   | 17.4885        | -0.3030        | -0.299042                     | 0.003958| -5.229796         | 0.013063 |
|      | Total IAE      |                |                               | 0.054687|                   |       |
This algorithm uses the polar graph property to mathematically represent this movement. This property also allows the BES algorithm to discover new spaces and increase diversification by multiplying the difference between the current point and the next point with the polar point in the y-axis and adding the difference between the current point and the center point with the polar point in the x-axis. We use the average solution in the search point because all search points move towards the centre point. All points in the polar plot take a value between -1 and 1, and we use a special equation for the shape of the spiral (20–22).

4.3. Swooping Stage. In the swooping stage, bald eagles swing from the best position in the search space to their target prey. All points also move towards the best point. Equation (14) mathematically illustrates this behaviour.

\[
P_{i,new} = \text{rand} \times P_{\text{best}} + x1(i) \times (P_i - c1 \times P_{\text{mean}}) + y1(i) \times (P_i - c2 \times P_{\text{best}}),
\]

\[
x1(i) = \frac{xr(i)}{\max(|xr|)},
\]

\[
y1(i) = \frac{yr(i)}{\max(|yr|)},
\]

\[
rx(i) = r(i) \times \sinh(\theta(i)),
\]

\[
ry(i) = r(i) \times \cosh(\theta(i)),
\]

\[
\theta(i) = a \times \pi \times \text{rand},
\]

\[
r(i) = \theta(i),
\]

where \(c1, c2 \in [1, 2]\).

4.4. Complete BES Algorithm. The previous steps have presented the main components of BES, which include the selection, search, and swooping steps. To describe the remaining operations and facilitate the implementation of BES, the flowchart algorithm is described in Figure 4:

5. Simulation Results and Analysis

The BES algorithm is applied to extract the SDM, DDM, and PV module parameters. To examine in more detail the accuracy of the data obtained by the BES method for the optimized parameters, the current was calculated from the values estimated on the basis of the different models and compared with that obtained from the experimental measurements. The error in the measured values for each of the models was evaluated by IAE (individual absolute error) and RE (relative error), calculated as shown in equations (21) and (22), respectively.

\[
\text{IAE} = \frac{|I_{\text{measured}} - I_{\text{estimated}}|}{I_{\text{measured}}},
\]

\[
\text{RE} = \frac{I_{\text{measured}} - I_{\text{estimated}}}{I_{\text{measured}}},
\]
The lower and upper bounds are expressed in Table 1 [18, 63, 67].

5.1. Case Study 1: Single-Diode Model. In this case study, the BES optimization algorithm is used to extract the parameters of the two proposed models of the R.T.C. France solar cell. The measured data of the characteristic curves (I-V) of the R.T.C. France solar cell are reported in [63, 67]. Table 2 includes the results of the parameters estimated based on BES and those estimated based on other optimization techniques such as ILSA [68], GAMS [3], ITLBO [69], IMFO [67], IJAYA [63], MADE [18], EVPS [52], GOTLBO [64], DDSFLA [57], EGBO [56], and CLPSO [70]. From Table 2, it can be seen that for the SDM, the application of the proposed BES algorithm results in the minimum RMSE value which is equal to \(9.8602e-04\).

From Figure 5, it can be clearly seen that the I-V and P-V curves of the simulated data found by BES are very compatible with the experimental data. From Table 3, it is evident that all IAE values are lower than 3.399e–03 and the RE values are between \(-6.91e-02\) and 2.65897e–01, demonstrating the high efficiency identified by BES for the single-diode model.

Table 4 and Figure 6 show the statistical results and the convergence curve, respectively. From Table 4, it can be seen that BES obtains the best minimum value of RMSE.

5.2. Case Study 2: Two-Diode Model. Table 5 lists the results obtained from the application of the BES technique to extract the DDM parameters of the R.T.C. France solar cell. To validate the applied technique, the table also presents the results from the application of other techniques of GAMS [3], ITLBO [69], IMFO [67], IJAYA [63], MADE [18], EVPS [52], GOTLBO [64], and CLPSO [70]. The table shows that the BES optimization technique applied gives the best results with the minimum objective function of RMSE being \(0.00098248451801148\).

From Figure 7, it can be clearly seen that the I-V and P-V curves of the simulated data found by BES are very compatible with the experimental data. From Table 6, it is evident that all IAE values are lower than 2.836e–03 and the RE values are between \(-1.111e-02\) and 2.3090e–01, demonstrating the high efficiency identified by BES for the two-diode model.

Table 7 and Figure 8 show the statistical results and the convergence curve, respectively. From Table 7, it can be seen that BES obtains the best minimum value of RMSE.
5.3. Case Study 3: Photowatt-PWP201 PV Module. To further validate the BES technique and show its effectiveness in estimating the optimal parameters of different models, we used this algorithm on the Photowatt-PWP201 PV module, which consists of 36 silicon cells connected in series under operating conditions of 1000 W/m² of solar irradiation and a cell temperature of 45°C. The results obtained were compared with those reported in the literature based on other techniques.

The results have been listed in Table 8. This table also presents a comparison with the results of other techniques from

![Figure 12: Convergence curve during the parameter extraction for Solar STM6-40/36 PV model.](image-url)
the literature ITLBO [69], IMFO [67], IJAYA [63], and MADE [18]. The comparison validated the effectiveness of BES compared to other techniques. The RMSE based on BES application to extract the parameters of PV model is equal to 0.00242507 which is better. From Figure 9, it can be clearly seen that the I-V and P-V curves of the simulated data found by BES are very compatible with the experimental data.

From Table 9, it is evident that all IAE values are lower than $4.418e^{-03}$ and the RE values are between $-6.44e^{-03}$ and $1.3167e^{-01}$, demonstrating the high efficiency identified by BES for the PV model.

Table 10 and Figure 10 show the statistical results and the convergence curve, respectively. From Table 10, it can be seen BES obtains the best minimum value of RMSE.

5.4. Case Study 4: Schutten Solar STM6-40/36 Monocrystalline PV Module. Here, we use the BES algorithm to extract the parameters of the Schutten Solar STM6-40/36 PV module. It contains 36 polycrystalline cells (size 156 mm $\times$ 156 mm) connected in series. The data set contains 20 data points measured at $T = 51°C$ [66]. For the STM6-40/36 PV module model, Table 11 shows the results of the parameters obtained from ITLBO, IJAYA, GOTLBO, TPTLBO …. From the results, it can be seen that the BES provides a better RMSE: $0.00172981370994066$.

In addition, to confirm the accuracy of the extracted parameters, Figure 11 shows the I-V and P-V curves. It is evident that the simulated data from the BES match well with the measured data in the voltage range for both I-V and P-V curves.

In addition, the IAE and RE (relative error) are given in Table 12. The IAE describes the error between the extracted parameter and the measured data. In other words, the extracted parameters are better when the IAE is small.

According to Table 12, the sum of the IAE is less than $2.50 \times 10^{-02}$, which indicates that the measured and extracted data coincide well.

To further prove the reliability of the BES, the statistical results containing the minimum (Min), maximum (Max), mean value (Mean), and standard deviation (Std.) are analyzed. Table 13 shows the statistical results, and Figure 12 shows the convergence curve of Photowatt STM6-40/36.
Table 16: The statistical results for Photowatt STP6-120/36 obtained by BES.

| Algorithm | Min | Mean | Max | Std. |
|-----------|-----|------|-----|------|
| BES       | 1.678e-02 | 1.69034e-02 | 1.7223e-02 | 1.1219e-04 |
| ITLBO     | 1.6601e-02 | 1.6601e-02 | 1.6601e-02 | 7.22e-17 |
| IJAYA     | 1.6731e-02 | 1.6891e-02 | 1.7304e-02 | 1.12e-04 |
| GOTLBO    | 1.6601e-02 | 2.9588e-02 | 1.8099e-01 | 3.05e-02 |
| MADE      | 1.6601e-02 | 1.6601e-02 | 1.6601e-02 | 1.69e-15 |
| TLABC     | 1.6601e-02 | 1.6963e-02 | 2.1497e-02 | 9.47e-04 |
| TLBO      | 1.6892e-02 | 3.6690e-02 | 2.1604e-02 | 3.51e-02 |
| EGBO      | 1.6601e-02 | 1.6601e-04 | 1.6601e-02 | 1.47e-16 |
5.5. Case Study 5: STP6-120/36 Module. The polycrystalline STP6-120/36 has 36 cells connected in series and is measured under 1000 W/m² at 55°C. The current-voltage data was obtained from [72]. The results have been listed in Table 14. This table also presents a comparison with the results of other techniques from the literature ITLBO [69], Table 15. The IAE describes the error between the extracted parameters and the measured data. In other words, the estimated parameters are better when the IAE is small.

Table 16 and Figure 14 show the statistical results and the convergence curve, respectively.

6. Conclusion

In this paper, we have presented a new and very recent algorithm based on the metaheuristic technique, called the bald eagle search (BES) algorithm to extract the best values of cell and panel parameters. To demonstrate the performance of the algorithm, many cases were implemented using the single-diode, double-diode, and PV panel models. The current-voltage and power-voltage characteristics of the measured and estimated data show the good accuracy of the proposed method. Simulation result after 20 tests and comparisons with other methods show the accuracy and validity of the method for extracting the parameters of a PV cell and module. It has the advantage of producing stable results of each test result and converging rapidly (in less than 50 iterations). The method is verified using practical data from various manufacturers. Its accuracy is confirmed by comparing its RMSE with many metaheuristic methods. In all considered scenarios, a high level of accuracy is obtained. Therefore, the excellent correspondence of the simulated I-V and P-V curves with the measured characteristics confirms the accuracy of the BES and its applicability to parameter estimation and for solving the optimization problems of other power systems.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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