Development of an Improved Bonobo Optimizer and Its Application for Solar Cell Parameter Estimation

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Abstract: Recently, photovoltaic (PV) energy has been considered one of the most exciting new technologies in the energy sector. PV power plants receive considerable attention because of their wide applications. Consequently, it is important to study the parameters of the solar cell model to control and determine the characteristics of the PV systems. In this study, an improved bonobo optimizer (IBO) was proposed to improve the performance of the conventional bonobo optimizer (BO). Both the IBO and the BO were utilized to obtain the accurate values of the unknown parameters of different mathematical models of solar cells. The proposed IBO improved the performance of the conventional BO by enhancing the exploitation (local search) and exploration (global search) phases to find the best optimal solution, where the search space was reduced using Levy flights and the sine–cosine function. Levy flights enhance the explorative phase, whereas the sine–cosine function improves the exploitation phase. Both the proposed IBO and the conventional BO were applied on single, double, and triple diode models of solar cells. To check the effectiveness of the proposed algorithm, statistical analysis based on the results of 20 runs of the optimization program was performed. The results obtained by the proposed IBO were compared with other algorithms, and all results of the proposed algorithm showed their durability and exceeded other algorithms.

Keywords: single, double and triple diode photovoltaic models; parameter estimation; optimization; improved bonobo optimizer

1. Introduction

In recent years, many countries have moved to use renewable energy sources (RES) to deal with energy shortages and environmental pollution. There are several energy sources such as wind, waves, biomass, etc. [1]. One of the most important sources that has received significant attention within all RES is solar energy [2]. Solar energy is transformed into electrical energy by photovoltaic (PV) modules. PV is one of the most modern technologies [3]. Much research has been done because of the prevalence of solar energy applications. One of the main topics of research is obtaining an accurate model for solar cells [4]. In general, the power system operation and its performance are affected by increasing the penetration of photovoltaic systems. Consequently, studying power systems that include photovoltaic resources needs suitable modelling and effective techniques to extract the parameters of these resources. The PV models based on accurate estimated parameters could be used in several studies in power systems such as power flow analysis, power system security, reliability, etc. [4]. Mathematical models of solar cells are divided into three types based on the number of diodes included in the circuit: single diode (SD), double diode (DD), and triple diode (TD). Thus, an effective technology design can be achieved by defining...
the typical parameters of solar cells based on the current–voltage measured [5]. The SD model contains only five parameters, which have to be optimally determined, and they are: the photon current, the diode current, the series and parallel resistances, and the diffusion diode ideality factor. Despite the simplicity of the SD model, many researchers tend to use the DD model [6–8], to overcome recombination losses [9], by adding the second diode current and recombination factor to the parameters of the SD model. Hence, the DD model is more accurate and effective. With the continuous development, the DD model has been modified by adding a third diode, which expresses the leakage current so that the TD model becomes more complicated. Many optimization techniques have been used to extract the parameters of PV system models [10]. They are the genetic algorithm (GA) [11], the particle swarm optimization (PSO) [12], the JAYA algorithm [13], the improved JAYA optimization algorithm (IJAYA) [13], the bee colony (BC) [14], the flower pollination algorithm (FPA) [15], the moth–flame optimization algorithm (MFO) [16], the biogeography-based heterogeneous cuckoo search (BHCS) algorithm [17], the cat swarm optimization algorithm (CSO) [18], the teaching–learning-based algorithm (TLBO) [19], and other algorithms [20–23]. Although good results have been obtained through the previous methods, it still needs further development to obtain optimal values of the model parameters. Bonobo optimizer (BO) is an algorithm inspired by the reproductive strategies and social behavior of bonobos. Several improvements have been made to solve BO control problems and standards to be consistent with nature [24]. In the literature, BO has been used in several recent applications such as finding the best preventive maintenance interval with the lowest overall maintenance cost [25], and the best prediction accuracy was seen with the adaptive neuro-fuzzy inference method (ANFIS) tuned by BO [26]. In [27], BO was applied for extracting the parameters of proton exchange membrane fuel cell (PEMFC) models. In [28], BO was utilized to optimally design a hybrid microgrid system including different renewable energy resources.

In this study, an improved bonobo optimizer (IBO) algorithm was proposed to improve the performance of the original BO. Both the BO and the IBO were applied to extract parameters of different solar cell models, SD, DD, and TD. The effectiveness of the proposed IBO was proved by testing it on various photovoltaic models. In addition, all results of the proposed IBO were compared with those obtained by the traditional BO and recent optimization algorithms. The main contributions are summarized as follows:

- The proposed IBO algorithm was able to improve the performance of the traditional BO by adjusting the exploitation and exploration phases to reach an appropriate balance.
- The proposed IBO was used to estimate the parameters of the solar cells.
- The proposed IBO was validated using single diode, double diode, and triple diode models.

This rest of the article is organized as follows. Solar cell modeling and the optimization problem are shown in Section 2. The original BO and proposed IBO are discussed in Section 3. In Section 4, results are given. Finally, the main outcomes and conclusion are provided in Section 5.

2. PV Modeling and the Optimization Problem

There are numerous models that describe the electrical circuit of the photovoltaic cell, and the authors note the great interest of many researchers in developing these models. In the literature, the characteristics of the solar cells have been described by several models; they are the single diode, double diode, and triple diode models [5]. In this section, the mathematical modelling of the single diode, double diode, and triple diode models is described.

2.1. The Single Diode Model

The equivalent circuit of the single diode model is displayed in Figure 1. It contains the current source, which generates a photon current \( I_{ph} \), and connects in parallel with the diode. \( R_s \) and \( R_{sh} \) are the cell series and parallel resistances, \( I_{sd} \) is the diode current,
and $I_{sh}$ is the shunt current. The output current ($I_t$) can be formulated by the following equations [28]:

\[
I_t = I_{ph} - I_d - I_{sh} \tag{1}
\]

\[
I_d = I_{sd} \left[ \exp \left( \frac{q(Vt + Rs \times I_t)}{n \times K \times T} \right) - 1 \right] \tag{2}
\]

\[
I_{sh} = \frac{(Vt + Rs \times I_t)}{R_{sh}} \tag{3}
\]

\[
I_t = I_{ph} - I_{sd} \left[ \exp \left( \frac{q(Vt + Rs \times I_t)}{n \times K \times T} \right) - 1 \right] - \frac{(Vt + Rs \times I_t)}{R_{sh}} \tag{4}
\]

\[
V_t = \frac{kT}{q} \tag{5}
\]

where, $R_s$ is the series resistance (Ω), $R_{sh}$ denotes the shunt resistance (Ω), $V_t$ is the thermal voltage, $k = 1.3806503 \times 10^{-23}$, $J/K$ is the Boltzmann constant, $T$ is the temperature in Kelvin, and $q = 1.60217646 \times 10^{-19}$ C is the electron charge.

Figure 1. Equivalent circuit of the single diode (SD) model solar cell [28].

2.2. The Double Diode Model

As shown in Figure 2, the equivalent double diode circuit consists of two diodes to make voltage–current characteristics more accurate [4].

Figure 2. The equivalent circuit of the double diode (DD) model solar cell.
The output current (It) of the DD model is formulated as [6]:

\[ It = I_{ph} - I_{d1} - I_{d2} - I_{sh} \]  
(6)

\[ It = I_{ph} - I_{d1} \left[ \exp \left( \frac{q(V_t + R_s \times I_t)}{n_1 \times K \times T} \right) - 1 \right] - I_{d2} \left[ \exp \left( \frac{q(V_t + R_s \times I_t)}{n_2 \times K \times T} \right) - 1 \right] - \frac{(V_t + R_s \times I_t)}{R_{sh}} \]  
(7)

where, \( I_{d1} \) and \( I_{d2} \) represent the first and second diodes currents, respectively, and \( n_1 \) and \( n_2 \) are the diffusion diode ideality factor and the recombination diode ideality factor, respectively.

2.3. The Triple Diode Model

The equivalent circuit of the triple diode model consists of the third diode, which is connected in parallel with the DD model and which can be expressed by a vector \( x = (x_1, x_2, x_3, x_4, x_5) \). However, the objective function can be formulated [8] as:

\[ f_{SD}(V_t, I_t, X) = It - X_3 + X_4 \left[ \exp \left( \frac{(V_t + X_1 \times I_t)}{X_5 \times K \times T} \right) - 1 \right] + \frac{(V_t + X_1 \times I_t)}{X_2} \]  
(10)

In addition, the DD model includes seven parameters. They are \( R_s, R_{sh}, I_{ph}, I_{sd}, n_1, n_2 \), which can be expressed by a vector \( x = (x_1, x_2, x_3, x_4, x_5, x_6, x_7) \) as follows:

\[ f_{DD}(V_t, I_t, X) = It - X_3 + X_4 \left[ \exp \left( \frac{(V_t + X_1 \times I_t)}{X_6 \times K \times T} \right) - 1 \right] + X_5 \left[ \exp \left( \frac{(V_t + X_1 \times I_t)}{X_7 \times K \times T} \right) - 1 \right] + \frac{(V_t + X_1 \times I_t)}{X_2} \]  
(11)

Figure 3. The equivalent circuit of the triple diode (TD) model solar cell.
The TD model includes nine parameters, and they are $R_s$, $R_{sh}$, $I_{ph}$, $I_{d1}$, $I_{d2}$, $I_{d3}$, $n_1$, $n_2$, and $n_3$, which can be expressed by a vector $x = (\cdot)$ as follows:

$$f_{DD}(V_t, I_t, X) = I_t - X_3 + X_4 \left[ \exp \left( q \left( \frac{(V_t+X_1\times I_t)}{X_7K} \right) - 1 \right) \right] + X_5 \left[ \exp \left( q \left( \frac{(V_t+X_1\times I_t)}{X_8K} \right) - 1 \right) \right] + X_6 \left[ \exp \left( q \left( \frac{(V_t+X_1\times I_t)}{X_9K} \right) - 1 \right) \right] + \left( \frac{V_t}{X_2} \right)$$

(12)

3. Optimization Algorithms

3.1. The Bonobo Optimizer

Recently, a new metaheuristic technique called BO has been developed. It arises from both the social behavior and the reproductive strategies of bonobos [25]. The main idea in the bonobo community is the fission strategy, which is based on dividing the community into several subgroups through different sizes and compositions, and then, afterward, reuniting them again to the community. In addition, there are four basic classes of bonobo strategies: promiscuous, restrictive, consortship, and extra-group mating. Each solution for all bonobos is known as the bonobo fitness value within the community. The better alternative the bonobo group has offered is known as the alpha bonobo ($\alpha_{bonobo}$).

(1) Initialization of the Undefined BO Parameters

In the BO, two-phase conditions were initialized as the positive phase count ($ppc$), the negative phase count ($npc$), the extra-group mating probability ($pxgm$), the phase shift ($cp$), the temporary sub-group sizing factor ($tsgs\text{factor}$), the phase probability ($pp$), and the probability of directional ($pd$). The configuration started as follows:

$$ppc = 0,\ \npc = 0,\ \ cp = 0,\ \ tsgs\text{factor} = tsgs\text{factor} - \ initial,\ \ pxgm = pxgm - \ initial,\ \ pp = 0.5,\ \ pd = 0.5.$$  

where, $tsgs\text{factor} - \ initial$ and $pxgm - \ initial$ were the initial values of $tsgs\text{factor}$ and $pxgm$, respectively.

(2) The Positive and Negative Phases

There was a two-phase state. It was estimated on the basis of phase-probability, either by option pressure or population diversity [25].

(3) The Bonobo Selection Using the Strategy of Fission–Fusion

It is known that the BO is a large group of a society temporarily divided into small groups according to size. After some time, they are reunited to the community. At the start, the maximum size of a temporary sub-group is calculated (say, $tsgsmax$, based on the total number of population size ($N$), and it is selected as the maximum value between the values of 2 and ($tsgs\text{factor} \times \ N$)) as follows:

$$tsgsmax = \ \maximum \ (2, \ (tsgs\text{factor} \times \ N))$$  

(13)

where, $tsgsmax$ is the size factor of the temporary sub-group and the $ith$–bonobo can build a new bonobo through exchanging properties with another bonobo (i.e., the $pth$–bonobo) or not. The values are either equal to 1, the $pth$–bonobo is randomly picked from the whole population, except the $ith$—bonobo, or greater than 1.

(4) New Bonobo Creation Using Various Mating Strategies

The bonobo community contains four various mating strategies: restrictive mating, promiscuous, extra-group mating, and consortship [30]. Bonobos use the fission–fusion social strategy, which entails dividing into a few smaller groups (fission) and engaging in a variety of activities to reunite (fusion) once more to serve certain unique activities, such as sleeping together, as shown in Figure 4 [31]. If the other random number (i.e., $r2$) that is generated in the range between 0 and 1 is found to be less than or equal to the probability of extra-group mating ($pxgm$), the solution is updated using the extra-group mating strategy as follows:
There was a two-phase state. It was estimated on the basis of phase probability ($pp$), and expressed through the probability of extra-group mating ($pxgm$):

\[
\text{new} - \text{bonobo} = \text{bonoboij} + r1 \times \text{scab} \times (\text{alpha bonobo} - \text{bonoboij}) + (1 - r1) \times \text{scsb} \times \text{flag} \times (\text{bonoboij} - \text{bonoboij})
\]

where, ($\text{new} - \text{bonobo}$) and ($\text{alpha bonobo}$) are the variables of the new offspring and the alpha bonobo, respectively. However, $J$ varies between 1 to the total number of variables, $r1$ is a random value between (0, 1), and $\text{scab}$ and $\text{scsb}$ are the participation coefficients for the alpha bonobo and the chosen $p$th-bonobo, respectively. $\text{flag}$ is expressed in two values, either 1 or $-1$, and represents two cases: promiscuous mating or restrictive mating.

b. The Strategies of Consortship and Extra-Group Mating

The strategies of consortship and extra-group mating are randomly generated, dependent on phase probability ($pp$), and expressed through the probability of extra-group mating ($pxgm$):

\[
\beta1 = e \times (r42 + r4 + 2/r4)
\]
\[
\beta2 = e \times (-r42 + 2r4 + 2/r4)
\]
\[
\text{new} - \text{bonobo} = \text{bonoboij} + \beta1 \times (\text{Var}_{\text{maxj}} - \text{bonoboij})
\]
\[
\text{new} - \text{bonobo} = \text{bonoboij} + \beta2 \times (\text{bonoboij} - \text{Var}_{\text{minj}})
\]
\[
\text{new} - \text{bonobo} = \text{bonoboij} + \beta1 \times (\text{bonoboij} - \text{Var}_{\text{minj}})
\]
\[
\text{new} - \text{bonobo} = \text{bonoboij} + \beta2 \times (\text{Var}_{\text{maxj}} - \text{bonoboij})
\]
\[
\text{new} - \text{bonobo} = \{ \text{bonoboij} + \text{flag} \times e(-r5) \}
\]

where, $\beta1$ and $\beta2$ are the two intermediate parameters, $\text{Var}_{\text{maxj}}$ and $\text{Var}_{\text{minj}}$ are the maximum and minimum boundary values, respectively, and $r4$ is a random value and does not equal zero. Using the consortship mating strategy, a new offspring is produced in case $r2$ is greater than $pxgm$, and it is described in (22):

\[
\text{new\_bonobo} = f(x) = \begin{cases} 
\text{bonoboij} + A, & \text{if} (\text{flag} = 1) \\ 
\text{bonoboij}, & \text{otherwise} 
\end{cases} \text{maxj} \leq p_d
\]

where, $A = \text{flag} \times e(-r5) \times (\text{bonoboij} - \text{bonoboij})$ and $r5$ and $r6$ are random numbers.

5. Variable Boundary Limiting Conditions

Sometimes the new offspring value exceeds the limit, so minimum and maximum values must be set to control it.

6. Offspring Acceptance Criteria
Determining the value of the new bonobo depends on whether the fitness value is better than the bonobo replaced by the new - bonobo in the population, and similarly for the alpha bonobo.

(7) Parameters' Updating

There are two cases. In the first one, a new alpha bonobo in the existing iteration is a better solution, and, compared to the preceding iteration, the parameters are updated as follows:

\[ npc = 0, ppc = ppc + 1, cp = \text{minimum}(0.5, ppc \times rcpp), pxgm = pxgm_{\text{initial}}, pp = 0.5 + cp, pd = pp, ts\text{gsfactor} = \text{minimum}(\text{ts\text{gsfactor}}_{\text{max}}, (\text{ts\text{gsfactor}}_{\text{initial}} + ppc \times rcpp2)) \].

In the second case, there is no enhancement in the value of the alpha bonobo compared with the preceding iteration, and the parameters are updated as follows:

\[ ppc = 0, npc = npc + 1, cp = -(\text{minimum}(0.5, npc \times rcpp)), pp = 0.5 + cp, pd = pp, pxgm = \text{minimum}(0.5, (pxgm_{\text{initial}} + npc \times rcpp2)), ts\text{gsfactor} = \text{maximum}(0, (ts\text{gsfactor}_{\text{initial}} - npc \times rcpp2)) \].

Implementation of the BO is summarized through the following steps:

Step 1. Initialization of the parameters of the BO.
Step 2. Evaluate the fitness values of all bonobos.
Step 3. Identify the alpha bonobo.
Step 4. Choose the bonobo using the fission–fusion society strategy.
Step 5. Is a random number \((0, 1) \leq pp\)?
Step 6. In case true, create a new bonobo by the promiscuous/restrictive mating strategy.
Step 7. In case false, create a new bonobo by the consortship/extra group mating strategy.
Step 8. Determine the fitness values of new bonobos and determine the alpha bonobo.
Step 9. Update the used parameters.
Step 10. Calculate the objective function.

The flowchart displaying the solution process of the BO and the IBO is shown in Figure 5.

3.2. The Improved Bonobo Optimizer

The metaheuristic optimization technique performance can be enhanced using the right balancing between the local search (exploitation phase) and the global search (exploration phase) [27]. The exploration phase aims to search into the solutions space, and the exploitation phase has the ability to search locally around the optimal solutions [27]. Global minima could be guaranteed, and the search space can be reduced via these phases, which lead to the avoidance of local minima. The BO was modified to improve its performance. The modified contributions can be summarized as follows:

- Improving the exploration phase of the BO by applying a random walk strategy known as Levy flights.
- Improving the exploitation phase of the BO by applying a sine–cosine function.
The flowchart displaying the solution process of the BO and the IBO is shown in Figure 5.

![Flowchart of the bonobo optimizer (BO) (a) and the improved bonobo optimizer (IBO) algorithms (b).](image)

**Figure 5.** Flowchart of the bonobo optimizer (BO) (a) and the improved bonobo optimizer (IBO) algorithms (b).

Levy flights were proposed to improve the randomness of the BO. Levy flights consist of a series of consecutive random steps, which have a significant role in the exploration phase. Levy flights improve the algorithm’s global capability of searching in the exploration phase, which can be expressed as [29]:

\[
Levy(M_{va}) = 0.01 \times \frac{rr_1 \times \delta}{|rr_2|^{\beta}}
\]

(23)

where, \(r1\) and \(r2\) represent random numbers \((0,1)\), \(\beta\) represents a constant, \(M_{va}\) represents the dimension of the position vectors, and \(\delta\) is determined as [29]:

\[
\delta = \left( \frac{\Gamma(1 + \beta) \times \sin(\frac{\pi \beta}{2})}{\Gamma(\frac{1 + \beta}{2}) \times \beta \times 2^{(\frac{1 + \beta}{2})}} \right)
\]

(24)

where:

\[
\Gamma(x) = (x - 1)!
\]

(25)
The sine–cosine function was suggested to improve the performance of the BO in the exploitation phase. The sine–cosine function was used to create different solutions, and it fluctuates towards the best possible solution as follows [30]:

\[
\text{new} - \text{bonobo} = \begin{cases} A & r_3 < 0.5 \\ B & r_3 > 0.5 \end{cases}
\]

(26)

where,

\[
A = \text{bonobo}_i^j + \sin(r_2) \times \text{Levy}(M_{va}) \times r_1 \times \text{scab} \times (\alpha_{bonobo}^j - \text{bonobo}_i^j) + (1 - r_1) \times \text{scab} \times \text{flag} \times (\text{bonobo}_i^j - \text{bonobo}_p^j)
\]

\[
B = \text{bonobo}_i^j + \cos(r_2) \times \text{Levy}(M_{va}) \times r_1 \times \text{scab} \times (\alpha_{bonobo}^j - \text{bonobo}_i^j) + (1 - r_1) \times \text{scab} \times \text{flag} \times (\text{bonobo}_i^j - \text{bonobo}_p^j)
\]

(27)

\[
r_1 = 2 - \text{Iter} \times \left(\frac{2}{\text{Maxiter}}\right)
\]

(28)

where, \(r_3\) is a random number between (0, 1). These modifications enhance the balancing between the exploration and exploitation phases to search for the global optimal solutions.

4. Results

The performance of the proposed IBO was comprehensively checked. The proposed algorithm was used to determine the optimal values of the parameters of different PV models. The results are divided into three subsections as follows:

A. The single-diode model
B. The double-diode model
C. The triple-diode model

The actual solar cell data of the current versus voltage was taken from the literature [28]. The solar cell operates at a solar radiation of 1000 W/m\(^2\) and a temperature \(T = 33^\circ C\). To accomplish the effectiveness of the algorithm, all results were compared with those obtained by the original BO and other optimization algorithms. In the IBO, the population size was 200, the maximum iterations number was 1500, and the number of runs was 20. The constraints of the unknown parameters are given in Table 1.

| Parameter | Lower Value | Upper Value |
|-----------|-------------|-------------|
| \(R_s\)  | 0           | 0.5         |
| \(R_{sh}\) | 0           | 100         |
| \(I_{ph}\) | 0           | 1           |
| \(I_{d1}\) | 0           | 1           |
| \(I_{d2}\) | 0           | 1           |
| \(I_{d3}\) | 0           | 1           |
| \(n_1\)  | 1           | 2           |
| \(n_2\)  | 1           | 2           |
| \(n_3\)  | 1           | 2           |

4.1. The Single Diode Model

To overcome the randomness of the proposed PV parameter estimation algorithms, both the IBO and the BO were operated 20 individual times, and a statistical study was performed based on the final values of the objective function obtained each run. Figure 6 shows the convergence curves over the 20 individual runs for the SD model using the BO and the IBO. Figure 7 shows the objective function values over the 20 runs for the SD model.
Table 1. The upper and lower constraints of the parameters.

| Parameter | Lower Value | Upper Value |
|-----------|-------------|-------------|
| $R_s$     | 0           | 0.5         |
| $R_{sh}$  | 0           | 100         |
| $I_{ph}$  | 0           | 1           |
| $I_{d1}$  | 0           | 1           |
| $I_{d2}$  | 0           | 1           |
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![Convergence curves over the 20 individual runs for the SD model: (a) BO, (b) IBO.](image)

Figure 6. Convergence curves over the 20 individual runs for the SD model: (a) BO, (b) IBO.

![The objective function (best value) over the 20 runs for the SD model.](image)

Figure 7. The objective function (best value) over the 20 runs for the SD model.

Table 2 presents the statistical results for the SD model based on the BO and the IBO. The statistical analysis was done to ensure the performance of the proposed algorithm and evaluate its robustness and efficiency. The proposed IBO calculated 20 implements for each run to obtain the best value for the objective function. Statistical analysis included the mean, the relative error, the standard deviation, and the maximum and minimum of the objective function over the 20 runs. Table 3 presents the estimated parameters in the case of the SD obtained based on different optimization techniques. Figure 8 shows the real, estimated PV current values for the SD using the IBO and the BO. The absolute error between the real output current and the output current was calculated from the parameter estimated using the IBO and the BO. Figure 9 shows the convergence curves obtained by the IBO and the BO for the SD. Based on the obtained results of the optimized parameters of the single diode model using the IBO, Figure 10 shows the I–V and P–V characteristics of the solar cell. It can be observed that the results of the algorithm for the SD model are better than those obtained by other algorithms.

The performance of the algorithm was determined by the root-mean-square error (RMSE) values calculated by the difference between the simulated results and the real measured data. The RMSE was determined as:

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{f=1}^{N} (V_{sh}, I_{d, f, X})}$$

where, $N$ is the real data number.

Table 2. Statistical results for the SD model based on the BO and the IBO.

| Measures | BO | IBO |
|----------|----|-----|
| Min.     | 0.000986021877891511 | 0.000986021877891504 |
| Worst    | 0.000986021877892065 | 0.000986021877895150 |
| Mean     | 0.000986021877891611 | 0.000986021877891938 |
| Median   | 0.000986021877891600 | 0.000986021877891635 |
| STD      | $8.57137311152287 \times 10^{-14}$ | $8.57137311152287 \times 10^{-14}$ |
| RE       | $8.79745666513143 \times 10^{-12}$ | $8.79745666513143 \times 10^{-12}$ |
| MAE      | $8.67448474162202 \times 10^{-17}$ | $8.67448474162202 \times 10^{-17}$ |
| RMSE     | $4.20967187227626 \times 10^{-16}$ | $4.20967187227626 \times 10^{-16}$ |
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| Mean     | 0.000986021877891611 | 0.000986021877891938 |
| Median   | 0.000986021877891600 | 0.000986021877891635 |
| STD      | 1.17635780565586 e^{-14} | 8.57137311152287 e^{-14} |
| RE       | 2.02453219826016 e^{-12} | 8.7974566513143 e^{-12} |
| MAE      | 1.9962303998031 e^{-17} | 8.6748474162202 e^{-17} |
| RMSE     | 6.79832768683650 e^{-17} | 4.20967187227626 e^{-16} |
| Efficiency | 99.9999999999899 | 99.9999999999560 |

Table 3. Estimated parameter values of the single diode obtained by optimization algorithms.

| Method       | Rs (Ω) | Rsh (Ω) | Iph (A) | Id (A) | n     | RMSE  |
|--------------|--------|---------|---------|-------|-------|-------|
| ETLBO        | 0.0364 | 53.7191 | 0.7608  | 0     | 1.4769 | 9.86022 e^{-4} |
| TLBO         | 0.0364 | 53.7197 | 0.7608  | 0.0000 | 1.4769 | 9.86022 e^{-4} |
| ABC [10]     | 0.0364 | 53.6433 | 0.7608  | 0.3251 | 1.4817 | 9.8602 e^{-4} |
| CSO [13]     | 0.0364 | 53.7185 | 0.76078 | 0.3230 | 1.4812 | 9.8602 e^{-4} |
| IJAYA [16]   | 0.0364 | 53.7595 | 0.7608  | 0.3228 | 1.4811 | 9.8603 e^{-4} |
| PGJAYA [20]  | 0.0364 | 53.71850| 0.7608  | 1.48120| 1.48120| 9.8602 e^{-4} |
| TLABC [21]   | 0.0364 | 53.71636| 0.76078 | 0.32302| 1.4812 | 9.86022 e^{-4} |
| SATLBO [21]  | 0.0364 | 53.72560| 0.7608  | 0.32315| 1.4812 | 9.86022 e^{-4} |
| BHCS [21]    | 0.0364 | 53.71852| 0.76078 | 0.32302| 1.4812 | 9.86022 e^{-4} |
| GOTLBO [29]  | 0.0364 | 54.11543| 0.760780| 0.33155| 1.4838 | 9.87442 e^{-4} |
| CIABC [31]   | 0.0364 | 53.71867| 0.760776| 0.32302| 1.4810 | 9.8602 e^{-4} |
| GSA [31]     | 0.0347 | 67.70030| 0.76037 | 4.75 x 10^{-7} | 1.5191 | 2.6140 e^{-3} |
| BO           | 0.0354756 | 57.6104 | 0.760366 | 3.8086 x 10^{-7} | 1.2295 | 9.8602 e^{-4} |
| IBO          | 0.0363771 | 53.7185 | 0.760776 | 3.2302 x 10^{-7} | 1.21567 | 9.8602 e^{-4} |
Figure 8. Error between the real current and the estimated current using the IBO and the BO for the SD model.

Figure 9. Convergence curves obtained by the IBO and the BO for the SD model.
The performance of the algorithm was determined by the root-mean-square error (RMSE) values calculated by the difference between the simulated results and the real measured data. The RMSE was determined as:

\[
RMSE = \sqrt{\frac{1}{N} \sum_{k=1}^{N} f(V_{tm}, I_{tm}, X)}
\]  

where, \( N \) is the real data number.

4.2. The Double Diode Model

The performance of the proposed IBO for the double diode model was studied. Figure 11 shows the fitness value convergence curves over the 20 individual runs for the DD model.
using the IBO and the BO. The best values of the objective function over the 20 runs for the DD model are shown in Figure 12. The statistical analysis of the IBO and the BO for the DD are listed in Table 4.

Figure 11. Convergence curves of IBO over the 20 individual runs for the DD model.

Figure 12. The objective function (the best value) over the 20 runs for the DD model.
Table 4. Statistical results for the DD model based on the BO and the IBO.

| Measures | BO | IBO |
|----------|----|-----|
| Min.     | 0.000977088321488726 | 0.000977088321514344 |
| Worst    | 0.000986021877893467 | 0.00098602177900693 |
| Mean     | 0.000980280577605764 | 0.000981064808651406 |
| Median   | 0.000978278332104993 | 0.000977089747736947 |
| STD      | 0.000423632509066615 | 0.000451183565687315 |
| RE       | 0.0770095401673857 | 0.0813946303421039 |
| MAE      | 7.5245123407695 e^{-7} | 7.95297427412468 e^{-7} |
| RMSE     | 2.49814726748887 e^{-6} | 2.65146291303962 e^{-6} |
| Efficiency | 99.6181922108548 | 99.5966757340291 |

Table 5 presents the estimated parameters in the case of the DD obtained by different optimization algorithms. Figure 13 shows the absolute error between the real output current and the estimated output current based on the parameters obtained by the IBO and the BO. Figure 14 shows the convergence obtained by the IBO and the BO. Figure 15 shows the I–V and P–V curves of the solar cell for the DD model, respectively.

Table 5. Estimated parameters in the case of the DD based on different optimization algorithms.

| Method   | Rs (Ω) | Rsh (Ω) | Iph (A) | Id1 (A) | Id2 (A) | n1 | n2 | RMSE          |
|----------|--------|---------|---------|---------|---------|----|----|----------------|
| ETLBO    | 0.0363 | 55.2169 | 0.7607  | 0.0000  | 0       | 1.4789 | 2  | 9.8241 e^{-4} |
| TLBO     | 0.0364 | 53.7184 | 0.7608  | 0.0000  | 0       | 1.4769 | 1.0000 | 9.8602 e^{-4} |
| ABC [10] | 0.0364 | 53.7804 | 0.7608  | 0.0407  | 0.2874  | 1.4495 | 1.4885 | 9.861 e^{-4} |
| CSO [13] | 0.0367 | 55.3813 | 0.7608  | 0.2273  | 0.72785 | 1.4515 | 1.9976 | 9.8251 e^{-4} |
| IJAYA [16]| 0.0376 | 77.8519 | 0.7601  | 0.0050  | 0.75094 | 1.2186 | 1.6247 | 9.823 e^{-4} |
| TLABC [21]| 0.0367 | 54.6680 | 0.7608  | 0.4239  | 0.24011 | 1.9075 | 1.45671 | 9.8414 e^{-4} |
| PGJAYA [20]| 0.0368 | 55.8135 | 0.7608  | 0.2103  | 0.88534 | 1.4450 | 2.00000 | 9.8263 e^{-4} |
| SATLBO [21]| 0.0366 | 55.0494 | 0.7608  | 0.2671  | 0.545148 | 2.0000 | 1.99941 | 9.8280 e^{-4} |
| BHCS [21]| 0.0367 | 55.4854 | 0.7608  | 0.7494  | 0.22597 | 2.0000 | 1.45102 | 9.8248 e^{-4} |
| GOTLBO [29]| 0.0368 | 56.0753 | 0.7608  | 0.8002  | 0.220462 | 1.99999 | 1.44897 | 9.83177 e^{-4} |
| CIABC [31]| 0.0367 | 55.3783 | 0.7608  | 0.2278  | 0.647650 | 1.4516 | 1.9883 | 9.8262 e^{-4} |
| GSA [31]| 0.0339 | 81.6876 | 0.7603  | 5.66 × 10^{-3} | 6.9 × 10^{-8} | 1.5386 | 1.93118 | 1.3089 e^{-3} |
| BO       | 0.0363426 | 54.2353 | 0.76077 | 3.23016 × 10^{-7} | 1.34222 × 10^{-7} | 1.21577 | 2  | 9.8565 e^{-4} |
| IBO      | 0.0368679 | 57.1026 | 0.760789 | 2.31715 × 10^{-7} | 3.05367 × 10^{-6} | 1.19108 | 2  | 9.7709 e^{-4} |
Figure 13. Error between the real current and the estimated current using the IBO and the BO for the DD model.

Figure 14. Convergence curves obtained by the IBO and the BO for the DD model.
Figure 15. The measured and evaluated data obtained via the IBO for the double diode model: (a) I–V curve, (b) P–V curve.

4.3. The Triple Diode Model

The performance of the proposed IBO in the case of the triple diode model was validated. The convergence curves over the 20 individual runs for the TD model using the BO and the IBO are shown in Figure 16. Figure 17 shows the best values of the objective function over the 20 runs for the TDM. The statistical analysis results of the TDM based on the BO and the IBO are presented in Table 6. All statistical results confirmed the effectiveness of the proposed algorithm in estimating the parameters of different PV models.
Figure 16. Convergence curves over the 20 individual runs for the TD model: (a) BO, (b) IBO.

Figure 17. The best value of the objective function over the 20 runs for the TD model.
Table 6. Statistical results for the TD model based on the BO and the IBO.

| Measures | BO | IBO |
|----------|----|-----|
| Min.     | 9.7709 e^{-4} | 9.7709 e^{-4} |
| Worst    | 9.8601 e^{-4} | 9.8602 e^{-4} |
| Mean     | 9.8194 e^{-4} | 9.7849 e^{-4} |
| Median   | 9.8411 e^{-4} | 9.7709 e^{-4} |
| STD      | 4.0862 e^{-4} | 3.1524 e^{-4} |
| RE       | 0.0994         | 0.0288         |
| MAE      | 9.7102 e^{-7} | 2.8110 e^{-7}  |
| RMSE     | 2.8084 e^{-6} | 1.5110 e^{-6}  |
| Efficiency | 99.5072     | 99.8573        |

The estimated parameters for the TD obtained by various optimization algorithms are listed in Table 7. Figure 18 shows the convergence curves obtained by the IBO and the BO for the TD model, and Figure 19 shows the characteristic curves of the real system and the TD model at different temperatures.

Table 7. The estimated parameters for the TD model obtained by different optimization algorithms.

| Method | Rs (Ω) | Rsh (Ω) | Iph(A) | Id1(A) | Id2(A) | Id3(A) | n1 | n2 | n3 | RMSE |
|--------|--------|---------|--------|--------|--------|--------|----|----|----|------|
| EHHA   | 0.0368247 | 130.9152 | 0.7609674 | 1.43 e^{-16} | 2.72 × 10^{-7} | 3.1156 e^{-3} | 5.452853 | 1.46025 | 15.18492 | 9.503 e^{-4} |
| HHA    | 0.017431 | 28.26    | 0.768106    | 2.38 e^{-10} | 8.89 × 10^{-7} | 6.12 e^{-6} | 12.41 | 6.76475 | 1.85013 | 9.610 e^{-3} |
| TLBO   | 0.0366   | 800      | 0.7608      | 0.0089 | 0       | 5.1 e^{-3} | 25.8033 | 1.4676 | 250 | 9.5 762 e^{-4} |
| FFA    | 0.013315 | 2.756    | 0.7504      | 0.04 | 1.03    | 0.89519 | 94.75 | 125.873 | 143.42 | 0.22813 |
| PSO    | 0.0363   | 7.9988   | 0.7608      | 2.0493 e^{-30} | 0.0215 | 3.2267 e^{-6} | 119.01 | 53.106 | 1.4769 | 0.0009 |
| BO     | 0.0363777 | 53.7639  | 0.760774    | 0 | 3.2302 e^{-7} | 1.58273 e^{-9} | 1.92132 | 1.21567 | 2 | 9.8602 e^{-4} |
| IBO    | 0.0368702 | 57.1258  | 0.760789    | 2.31318 e^{-7} | 3.0694 e^{-6} | 0 | 1.19095 | 2 | 1.50349 | 9.7709 e^{-4} |

Figure 18. Convergence curves obtained by the IBO and the BO for the TD model.
From the results obtained based on the SD, the DD, and the TD models, it was found that the algorithm gives the best value of the objective function (RMSE) compared with the conventional BO algorithm and other optimization algorithms.

5. Conclusions
An improved version of a recent optimization technique called bonobo optimizer was proposed with the aim of improving its performance. Then, two algorithms based on the proposed IBO and the original BO were developed for optimal estimation of several unknown parameters of different solar cell models. The proposed IBO has the ability to improve the performance of the original BO using Levy flights, which improve the algorithm searching capability globally and locally in the exploration and exploitation phases by using sine and cosine functions that fluctuate toward the best optimal solution. The developed algorithms based on the BO and the IBO were validated through the parameter estimation of SD, DD, and TD models of a commercial solar cell. By comparing the results of the IBO with those obtained by other algorithms, it became clear that the IBO has a distinct and better performance based on several criteria including the square root and absolute error. In all cases, the results obtained by the IBO were more accurate than those obtained by the original BO and other optimization algorithms. Therefore, it may be concluded that the proposed modified version of the BO algorithm is stable and reliable. In future work, the proposed IBO could be applied to other complicated engineering optimization problems such as economical dispatch problems, smart home applications, fuel cell parameter estimations, among others.

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