Artificial Bee Colony Algorithm based on a New Local Search Approach for Parameter Estimation of Photovoltaic Systems

Mehmet fatih Fatih TEFEK (✉ mftefek@gmail.com)

Osmaniye Korkut Ata University: Osmaniye Korkut Ata Universitesi <https://orcid.org/0000-0003-3390-4201>

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Artificial bee colony algorithm based on a new local search approach for parameter estimation of photovoltaic systems

Mehmet Fatih Tefek¹

¹Department of Computer Engineering, Osmaniye Korkut Ata University, Osmaniye, Turkey
(mehmetfatihtefek@osmaniye.edu.tr)

¹ Corresponding Author

Abstract

In this study, an ABC-Local Search (ABC-Ls) method was proposed by including a new local search procedure into the standard artificial bee colony (ABC) algorithm to perform the parameter estimation of photovoltaic systems (PV). The aim of the proposed ABC-Ls method was to improve the exploration capability of the standard ABC with a new local search procedure in addition to the exploitation and exploration balance of the standard ABC algorithm. The proposed ABC-Ls method was first tested on 15 well-known benchmark functions in the literature. After obtaining successful results on the benchmark tests, the proposed ABC-Ls method was applied to the single diode, double diode and PV modules of PV systems for parameter estimations. The success of the ABC-Ls method was compared with the algorithms commonly used in the literature such as genetic algorithm (GA), particle swarm optimization (PSO) algorithm and standard ABC algorithm, and the comparison results were presented in tables and graphics in detail. It was found that the ABC-Ls method was more successful and achieved better results compared to GA, PSO and standard ABC. It was determined that the ABC-Ls method performed similar or better PV parameter estimation compared to other studies in the literature.

Keywords: Artificial Bee Colony Algorithm, Local Search, Photovoltaic Systems, Photovoltaic Module Parameter Estimation

1. Introduction

The demand for alternative, renewable and non-polluting energy sources has increased day by day due to the decreased fossil fuel sources and increased environmental concerns around the world [1, 2]. Similarly, renewable energy sources play an important role in electricity generation [3]. Among the renewable energy sources, solar energy is widely used to produce electrical energy as it can directly convert the potential energy obtained from the sun into electrical energy via photovoltaic (PV) cell modules [1-3]. Because PV systems are installed in sun-exposed environments, they are highly affected by environmental conditions. An accurate and proper solar PV cell modeling is critical in solar PV energy systems [4, 5]. Therefore, it is important to obtain the energy using the PV systems with maximum efficiency [6, 7]. Simulation and design calculations of PV systems require that the parameters defining the nonlinear electricity model of solar cells be accurately estimated [8]. In the literature, the parameters of PV systems are estimated using deterministic methods and the methods based on artificial intelligence optimization algorithms. In deterministic methods, the parameter estimation of PV systems has mostly been performed through classical mathematical modeling [8-13]. For the PV parameter estimation using deterministic methods, the study performed by Easwarakhanthan et al. (1986) can be considered as a reference. This study compared the results obtained in experimental studies with a nonlinear least-squares algorithm based on the Newton model modified with the Levenberg parameter. It also determined the current-voltage (I-V) parameters in experimental studies [8].

Because the parameter estimation of PV systems is a nonlinear and multivariate problem, there is a high probability of being stuck to local optimum during the use of deterministic techniques [1, 14]. Therefore, recently, researchers have started to use various solutions based on artificial intelligence optimization algorithms, as an alternative to deterministic solutions, for the parameter estimation of PV systems to obtain better solutions [1, 4, 14-18]. As seen in the examination of some of the studies based on artificial intelligence optimization algorithms, Jervase et al. (2001) proposed a technique based on genetic algorithms (GA) to increase the accuracy of solar cell parameters extracted using traditional methods. Their approach is based on formulating the parameter extraction as a search and optimization problem [19]. Ye et al. (2009) extracted the solar cell parameters of single and double diode models using the particle swarm optimization (PSO) algorithm [20]. AlHajri et al. (2012) applied the pattern search (PS) method for optimum extraction of solar cell parameters [14]. Askarzadeh et al. (2013) used artificial bee swarm optimization (ABSO) algorithm to define the parameters of solar cell models [15]. Yuan et al. (2014) designed the chaotic asexual reproduction optimization (CARO) algorithm by improving the global search capability of the asexual reproduction optimization algorithm with the chaos-based optimization and then used this algorithm for the parameter extraction of solar cell models [16]. Yu et al. (2017) applied a self-adaptive weight parameter and the Improved Jaya (IJaya) method to the population update procedure of the Jaya algorithm for the parameter estimation of single diode, double diode and PV models [1]. Jordehi (2017) proposed a gravity search algorithm with a linearly decreasing gravity constant (GSA with linear G) to analyse the PV cell parameter

extraction problem [21]. Xiong et al. (2018) stated that the whale optimization algorithm (WOA) stagnates and suffers from early convergence while dealing with multimodal problems. Therefore, they designed the improved whale optimization algorithm (IWOA) to effectively balance local exploitation and global exploration. They extracted the parameters of three different single diode, double diode and PV models using the IWOA [17]. Yu et al. (2019) proposed a performance-guided JAYA (PGJAYA) algorithm to extract the parameters of different PV models. Premkumar et al. (2020) achieved the parameter estimation of the PV models with Rao II and Rao III heuristic algorithms which do not have any algorithm-specific parameter value [4].

In the literature, the recent optimization algorithms obtained by developing standard optimization algorithms are applied for the parameter estimation or extraction of PV systems [1, 17, 18, 22]. In the present study, an ABC Local search (ABC-Ls) was designed by including a new local search procedure into the standard artificial bee colony (ABC) algorithm for the parameter estimation of single-diode module, double-diode module and PV modules. The ABC-Ls method, which was developed by including the standard ABC into the balance of exploitation in local search and exploration in global search, repositions some unnoticed solutions. Accordingly, with the ABC-Ls method, it was aimed to improve the exploitation capability of the standard ABC in local search and obtain the optimum solution or solutions close to the optimum solution. To determine the success of the proposed ABC-Ls method, it was first tested on 15 benchmark functions well known in the literature. The commonly used literature algorithms such as standard ABC, GA and PSO artificial intelligence optimization algorithms were used to compare test results. The parameter estimation performance of the PV systems with the proposed ABC-Ls method was evaluated using three standard data sets: single diode, double diode and PV modules. The benchmark test results of the ABC-Ls and the parameter estimation results of the PV systems were presented comparatively and statistically in tables and graphs. Moreover, the comparisons made with the other studies in the literature were also provided in tables. After determining the success of the proposed method based on the results of benchmark functions, parameter estimation of the PV systems was performed and the results were found to be better than those in the literature. In this regard, the proposed ABC-Ls method was seen to obtain accurate and reliable parameters in the parameter estimation of PV systems.

For the rest of the article, the problem definition of PV system is given in section 2, the standard ABC is explained in section 3, the proposed ABC-Ls method is detailed in section 4, experimental results are discussed in section 5, and the study is concluded in section 6.

2. Benchmark functions and problem definition of PV system

In this study, 15 commonly used benchmark functions are shown in Table 1. Although there are different definitions for PV systems in the literature, PV is a system that generally examines the (I-V) relationship between current and voltage. Although many equivalent circuit models have been developed and proposed to describe the (I-V) characteristics of PV systems, three models are widely used in practice: single diode module, double diode module and PV module [4, 15-18]. This study presents the mathematical models of three different PV systems: single diode module, double diode module and PV module models. The more accurate the parameters of PV systems are, the better the performance of the solar cell will be [8, 23].

Table 1. Benchmark Functions (*D: Dimension, C: Characteristic, U: Unimodal, M: Multimodal, S: Separable, N: Non-separable*)

Fn.	Name	C	Search Range	Function
F1	Sphere	US	$[-100, 100]^D$	$f_1(x) = \sum_{i=1}^N x_i^2$
F2	Elliptic	UN	$[-100, 100]^D$	$f_2(x) = \sum_{i=1}^n (10^6)^{(i-1)/(n-1)} x_i^2$
F3	SumSquares	US	$[-10, 10]^D$	$f_3(x) = \sum_{i=1}^n ix_i^2$
F4	SumPower	MS	$[-10, 10]^D$	$f_4(x) = \sum_{i=1}^n x_i ^{(i+1)}$
F5	Schwefel2.22	UN	$[-10, 10]^D$	$f_5(x) = \sum_{i=1}^n x_i + \prod_{i=1}^n x_i $
F6	Schwefel2.21	UN	$[-100, 100]^D$	$f_6(x) = \max_i \{ x_i , 1 \leq i \leq n\}$
F7	Step	US	$[-100, 100]^D$	$f_7(x) = \sum_{i=1}^n (x_i + 0.5)^2$
F8	Quartic	US	$[-1.28, 1.28]^D$	$f_8(x) = \sum_{i=1}^n ix_i^4$

F9	QuarticWN	US	$[-1.28, 1.28]^D$	$f_9(x) = \sum_{i=1}^n ix_i^4 + \text{random}[0, 1]$
F10	Rosenbrock	UN	$[-10, 10]^D$	$f_{10}(x) = \sum_{i=1}^{N-1} [100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2]$
F11	Rastrigin	MS	$[-5.12, 5.12]^D$	$f_{11}(x) = \sum_{i=1}^N x_i^2 - 10 \cos(2\pi x_i) + 10$
F12	Non-Continuous Rastrigin	MS	$[-5.12, 5.12]^D$	$f_{12}(x) = \sum_{i=1}^N [y_i^2 - 10 \cos(2\pi y_i) + 10] \quad y_i = \begin{cases} x_i, & x_i < \frac{1}{2} \\ \frac{\text{round}(2x_i)}{2}, & x_i \geq \frac{1}{2} \end{cases}$
F13	Griewank	MN	$[-600, 600]^D$	$f_{13}(x) = \sum_{i=1}^N \frac{x_i^2}{4000} - \prod_{i=1}^N \cos\left(\frac{x_i}{\sqrt{i}}\right) + 1$
F14	Schwefel2.26	MS	$[-500, 500]^D$	$f_{14}(x) = 418.98 * n - \sum_{i=1}^n x_i \sin(\sqrt{ x_i })$
F15	Ackley	MN	$[-32, 32]^D$	$f_{15}(x) = 20 + e \pm 20 \exp\left(-0.2 \sqrt{\frac{1}{N} \sum_{i=1}^N x_i^2}\right) - \exp\left(\frac{1}{N} \sum_{i=1}^N \cos(2\pi x_i)\right)$

2.1. Single diode module

This module has one diode and one parallel-connected current source. It includes a shunt resistor for residual current and a series resistor showing the load current loss. Due to its simplicity, this model is often used to determine the static property of the solar cell. The equivalent circuit of this model is shown in Figure 1. The output current of the circuit is given in Eqs. (1)– (3).

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

$$I_d = I_{sd} \cdot \left[\exp\left(\frac{q \cdot (V_L + R_S \cdot I_L)}{n \cdot k \cdot T}\right) - 1 \right] \quad (2)$$

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

where I_L is the output current of the solar cell, I_{ph} is the total current generated by the solar cell, I_d is the diode current calculated by Shockley in Eq. (2), and I_{sh} is the shunt current calculated in Eq. (3). R_S is the series resistance while R_{sh} is the shunt resistance. V_L is the output cell voltage and I_{sd} is the reverse saturation current of the diode. n is the ideal factor of the diode. k is the Boltzmann constant and its value is $1.3806503 \times 10^{-23}$ J/K, while q is the electron constant and its value is $1.60217646 \times 10^{-19}$ C. Finally, T is the absolute temperature of the cell and indicated in Kelvin. Eq. (4) is obtained by combining the Eqs. (1), (2) and (3).

$$I_L = I_{ph} - I_{sd} \cdot \left[\exp\left(\frac{q \cdot (V_L + R_S \cdot I_L)}{n \cdot k \cdot T}\right) - 1 \right] - \frac{V_L + R_S \cdot I_L}{R_{sh}} \quad (4)$$

Eq. 4 shows that there are five different parameters for the single diode model. When these parameters are predicted correctly, the actual behavior of the solar cell is seen.

Figure 1. Electrical equivalent circuit of single diode module model

2.2. Double diode module

This module has two diodes and one parallel-connected current source. It includes a shunt resistor for residual current and a series resistor showing the load current loss. This circuit was created considering the recombination current loss effect. The equivalent circuit of this module is shown in Figure 2. The output current of the circuit is shown in Eq. (5) and Eq. (6), the last indicates the open form of Eq. (5).

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

$$I_L = I_{ph} - I_{sd1} \cdot \left[\exp \left(\frac{q \cdot (V_L + R_S \cdot I_L)}{n_1 \cdot k \cdot T} \right) - 1 \right] - I_{sd2} \cdot \left[\exp \left(\frac{q \cdot (V_L + R_S \cdot I_L)}{n_2 \cdot k \cdot T} \right) - 1 \right] - \frac{V_L + R_S \cdot I_L}{R_{sh}} \quad (6)$$

where I_{sd1} is the diffusion current, I_{sd2} is the saturation current, n_1 is the diffusion diode ideal factor, and n_2 is the recombination diode ideal factor.

Eq. (6) shows that there are seven different parameters for the double diode model. When these parameters are predicted correctly, the actual behavior of the solar cell is seen.

Figure 2. Electrical equivalent circuit of double diode module model

2.3. PV module model

This module has many series and parallel diodes and one parallel-connected current source. It includes a shunt resistor for residual current and a series resistor showing the load current loss. The equivalent circuit of this module is shown in Figure 3. The output current of the circuit is presented in Eq. (7).

$$I_L = I_{ph} N_p - I_{sd} N_p \left[\exp \left(\frac{q \cdot (V_L / N_s + R_s \cdot I_L / N_p)}{n_1 \cdot k \cdot T} \right) - 1 \right] - \frac{V_L / N_s + R_s \cdot I_L / N_p}{R_{sh}} \quad (7)$$

where N_p indicates the number of parallel solar cells and N_s is the number of series solar cells. As in the single diode module, this module has five different parameters shown in Eq. (7). When these parameters are predicted correctly, the actual behavior of the PV module is seen [23].

Figure 3. Electrical equivalent circuit of PV module model

2.4. Objective function of the problem

The optimization techniques frequently used in parameter estimations are also used in the parameter estimation of the PV module problem. The aim is to minimize the difference between experimental and simulation data. The error calculation functions between each experimental and simulation points are given in Eqs. (8), (9) and (10) for single diode, double diode and PV modules, respectively.

$$\begin{cases} f_k(V_L, I_L, \mathbf{x}) = I_{ph} - I_{sd} \cdot \left[\exp\left(\frac{q \cdot (V_L + R_S \cdot I_L)}{n \cdot k \cdot T}\right) - 1 \right] - \frac{V_L + R_S \cdot I_L}{R_{sh}} - I_L \\ \mathbf{x} = \{I_{ph}, I_{sd}, R_S, R_{sh}, n\} \end{cases} \quad (8)$$

$$\begin{cases} f_k(V_L, I_L, \mathbf{x}) = I_{ph} - I_{sd1} \cdot \left[\exp\left(\frac{q \cdot (V_L + R_S \cdot I_L)}{n \cdot k \cdot T}\right) - 1 \right] - I_{sd2} \cdot \left[\exp\left(\frac{q \cdot (V_L + R_S \cdot I_L)}{n \cdot k \cdot T}\right) - 1 \right] - \frac{V_L + R_S \cdot I_L}{R_{sh}} - I_L \\ \mathbf{x} = \{I_{ph}, I_{sd1}, I_{sd2}, R_S, R_{sh}, n_1, n_2\} \end{cases} \quad (9)$$

$$\begin{cases} f_k(V_L, I_L, \mathbf{x}) = I_{ph} N_p - I_{sd} N_p \left[\exp\left(\frac{q \cdot (V_L + R_S \cdot I_L \cdot N_s / N_p)}{n \cdot k \cdot T \cdot N_s}\right) - 1 \right] - \frac{V_L + R_S \cdot I_L \cdot N_s / N_p}{R_{sh} \cdot N_s / N_p} - I_L \\ \mathbf{x} = \{I_{ph}, I_{sd}, R_S, R_{sh}, n\} \end{cases} \quad (10)$$

The objective function, which is used to measure the difference between experimental and simulated current data, is given in Eq. (11). In optimization problems, the objective function minimizes the RMSE obtained by the vector $\mathbf{x}$, which depends on the standard data V_L and I_L in the search space.

$$\text{RMSE}(\mathbf{x}) = \sqrt{\frac{1}{N} \sum_{k=1}^N f_k(V_L, I_L, \mathbf{x})^2} \quad (11)$$

where $\mathbf{x}$ indicates that the solution vector consists of unknown parameters. N is the number of experimental data.

3. Standard Artificial Bee Colony (ABC)

Artificial Bee Colony (ABC) is an optimization algorithm inspired by the unique methods used by swarms when searching for food [24, 25]. The ABC algorithm is used to solve the optimization problems based on the behavior of swarms while they are trying to find food. In the ABC, there are three bee groups in a colony: employed bees, onlooker bees, and scout bees. The ABC consists of three phases: employed and onlooker bees are sent to sources, the nectar amount of the sources are calculated, and the scout bee is identified and randomly located to a new source [26]. Food sources correspond to the possible solutions of the optimized problem. The nectar amount of a source is the quality value of the solution expressed with that source [27]. The ABC algorithm finds the point (solution) providing the minimum or maximum of the problem among the solutions in the search space by trying

to find the location of the source with the highest nectar amount [24-28]. The ABC algorithm can be divided into four phases: initialization, employed bee, onlooker bee and scout bee [24-28]. The general flow chart of ABC is shown in Figure 4.

Figure 4. General flow chart of ABC [28]

In the initialization phase, the algorithm should be started with various basic parameters such as the number of food sources (SN), the end condition (i.e., the maximum number of iterations (Maxiter)), the bound parameter value and the counter recording the number of consecutive failed updates for each. At this phase, an initial population can be generated as follows:

When $X_i = (X_{i,1}, X_{i,2}, \dots, X_{i,D})$ is the i^{th} food source location in the population, D is the dimension of the problem. Each solution is usually generated with Eq. (12).

$$X_{i,j} = X_j^{\min} + \text{rand}_{i,j} \cdot (X_j^{\max} - X_j^{\min}) \quad (12)$$

where $i \in \{1, 2, \dots, SN\}$, $j \in \{1, 2, \dots, D\}$; $X_j^{\min}$ and $X_j^{\max}$ are the lower and upper bounds of the j^{th} variable, respectively; $\text{rand}_{i,j}$ is a random number in $[0, 1]$ interval. Then, the fitness of the food source is calculated with Eq. (13).

$$\text{fit}_i = \begin{cases} \frac{1}{1+f(X_i)} & \text{if } (f(X_i) \geq 0) \\ 1 + \text{abs}(f(X_i)) & \text{otherwise} \end{cases} \quad (13)$$

where fit_i is the fitness value of the i^{th} food source, X_i , and $f(X_i)$ is the target function value of X_i for the optimization problem.

In the employed bee phase, each employed bee is associated with a food source (solution). Each employed bee tries to find a better food source, i.e., a better solution, by searching near its own food source. The employed bees' search is given in Eq. (14).

$$V_{i,j} = X_{i,j} + \phi_{i,j} \cdot (X_{i,j} - X_{k,j}) \quad (14)$$

where $V_{i,j}$ is the new solution of the i^{th} candidate food source at the j^{th} dimension; $X_{i,j}$ and $X_{k,j}$ are the j^{th} dimension of the i^{th} and k^{th} food source, respectively; k is a random number selected from $(1, 2, \dots, SN)$ and $k \neq i$; j is randomly selected from $(1, 2, \dots, D)$; and $\phi_{i,j}$ is a random real number in the $[-1, 1]$ interval. According to the fitness values, if the candidate solution is better than the previous one, the previous solution is replaced with the new solution. If the new fitness value is worse than the previous one, the previous solution is used.

In the onlooker bee phase, each onlooker bee selects a food source for further searches with the probability P_i calculated by Eq. (15). The more the nectar amount of the source is, the higher the probability of being selected by an onlooker bee will be for this source.

$$P_i = \text{fit}_i / \sum_{i=1}^{SN} \text{fit}_i \quad (15)$$

In the scout bee phase, the food source with the highest bound value in the population is selected. If the bound value is greater than the predefined threshold bound, this food source is abandoned by the bee and the process goes back to a scout bee to randomly create a new food source according to Eq. (12).

4. The proposed ABC-Ls method

In this study, an ABC local search (ABC-Ls) was proposed by adding a new local search phase after the employed bee, onlooker bee and scout bee phases of the standard ABC algorithm. With the proposed ABC-Ls method, it was aimed to improve the exploitation capability of the standard ABC in local search and reach the optimum solution (or a solution as close to the optimum solution as possible) more efficiently.

In the proposed ABC-Ls method, the local search procedure was created being inspired by the local search function of the multiple trajectory search (MTS) algorithm developed by Tseng and Chen (2008) [29]. The proposed ABC-Ls method runs every ten iterations ($\text{mod}(\text{iter}, 10) = 0$) of the standard ABC algorithm. The pseudo-codes of the proposed ABC-Ls and the local search (Ls) method are shown in Algorithm 1 and Algorithm 2, respectively. In the ABC-Ls method, the search range coefficient (SRC) is determined between 0 and 1 ($\text{SRC} \in (0, 1]$). The SRC value is entered at the initialization of Algorithm 1. In Algorithm 2, the SRC value decreases by half until achieving success in the local search and is redetermined within the maximum and minimum bounds of the function when it reaches $1E - 15$. According to the value calculated after the employed bee, onlooker bee and scout bee phases of Algorithm 1, the local search procedure in Algorithm 2 is run. Individuals as many as the number of food are repositioned under the maximum and minimum bounds based on the SRC value in Algorithm 2 and then applied to the objective function. If the obtained solution is good, it is used and the position of the individuals achieving that solution is stored. The SRC value is repeatedly calculated and the good new solutions are given to the output of Algorithm 2. The new solutions obtained in Algorithm 2 are reevaluated in the employed bee, onlooker bee and scout bee phases in Algorithm 1 and the bees are repositioned. Thus, in Algorithm 1, a balance is achieved between exploration in global search and exploitation in local search in the employed bee, onlooker bee and scout bee phases. The ABC-Ls repeats the local searches until the maximum number of iterations is reached. By doing so, the proposed ABC-Ls method tries to obtain the best solution by recreating different combinations with the local search procedure for the unnoticed values in the calculation. Thus, the exploitation capability of the standard ABC in local search was improved with the ABC-Ls method, which performs a new local search without distorting the balance of exploration and exploitation of the standard ABC. Figure 5 shows the flow chart of the ABC-Ls method.

Algorithm 1. Pseudo code of proposed ABC-Ls

Input:

Set the control parameters of the ABC algorithm

SN : Number of foods (population size)

Search Range Coefficient (SRC) value (SRC is a number determined between 0 and 1 in the initialization phase. $SRC \in (0,1]$)

$iter$: Number of iteration; $limit$: maximum number of trials to abandon a food source

$Maxiter$: Maximum number of iterations (The stop criterion)

Output:

The best value of the function (X_{best}) and the (X_i) value making the function the best

while $iter < Maxiter$

for $i = 1$ to SN // employed bee phase

 Calculate the new candidate solution (V_i) for the food source (X_i) as shown in Eq. 14

if $f(V_i) < f(X_i)$

swap (X_i, V_i)

$trial(i) = 0$

else

$trial(i) = trial(i) + 1$

end if

end for // end employed bee phase

 Calculate the probability value p_i in Eq. 15

$t = 1, i = 1$

while $t \leq SN$ // onlooker bee phase

if $rand < p_i$

 Calculate the new candidate solution (V_i) for the food source (X_i) as shown in Eq. 14

 Evaluate the new solution (V_i)

$t = t + 1$

if $f(V_i) < f(X_i)$

swap (X_i, V_i)

$trial(i) = 0$

else

$trial(i) = trial(i) + 1$

end if

end if

$i = i + 1$

if $i == SN$

$i = 1$

end if

end while // end onlooker bee phase

 Take the value with maximum number of trials ($trial(max)$)

if $trial(max) > limit$ // scout bee phase

 Calculate new X_i values randomly generated in Eq. 12

$f(max) = f(X_i)$

$f(X_{best}) = f(max)$

$trial(max) = 0$

end if // end scout bee phase

 Memorize the best solution (X_{best}) achieved

 Take X_i values calculated to obtain the best solution (X_{best})

if ($mod(iter, 10) == 0$) // **Algorithm 2 phase**

 Take the best solution (X_{best}) and X_i values determined for the best solution as inputs in **Algorithm 2**

 Apply **Algorithm 2**

end if // end **Algorithm 2 phase**

$iter = iter + 1$

if $iter == Maxiter$

 Memorize the best solution achieved so far and exit main loop

end if

end while

Algorithm 2. Pseudo-code of Local search (LS) procedure [29]

Input:

The best solution of the function (X_{best}) obtained by the ABC algorithm and X_i values required for this solution

SN : Number of foods (population size)

SRC : Enter the value decreased by half in Algorithm 2 after the value determined between 0 and 1 in Algorithm 1

Output:

Last value calculated for SRC

The best new value of the function ($X_{best,new}$)

New X_i value required to find the best new solution ($X_{best,new}$)

```
For  $i = 1$  to  $SN$ 
     $D[i] = X_i^{max} - X_i^{min}$     // ( $X_i^{max}$ : Upper Bound,  $X_i^{min}$ : Lower Bound)
     $SRC = SRC/2$ 
    If  $SRC < 1e-15$ 
         $SRC = D[i] * 0.4$ 
    End If
    For  $i = 1$  to  $SN$ 
         $X_i[i] = X_i[i] - SRC * D[i]$ 
    End For
     $F(X_{best,new}) = F(X_i)$ 
    If  $X_i$  is better than current best solution ( $X_{best}$ )
        Update current best solution ( $X_{best,new}$ )
    End If
    If function value of  $X_i$  is the same
        Restore  $X_i$  to its original value ( $X_{best}$ )
    Else
        If function value of  $X_i$  degenerates
            Restore  $X_i$  to its original value ( $X_{best}$ )
            For  $i = 1$  to  $SN$ 
                 $X_i[i] = X_i[i] + 0.5 * SRC * D[i]$ 
            End For
             $F(X_{best,new}) = F(X_i)$ 
            If  $X_i$  is better than current best solution ( $X_{best}$ )
                Update current best solution ( $X_{best,new}$ )
            End If
            If function value of  $X_i$  has not been improved
                Restore  $X_i$  to its original value ( $X_{best}$ )
            End If
        End If
    End If
End For
```

Figure 5. Flow chart of ABC-Ls

5. Experimental results

In this section, the parameter values of single diode module, double diode module and PV module problems were estimated and benchmark functions were solved to determine the effectiveness of ABC-Ls compared to ABC, GA and PSO algorithms. The processes are performed using solar cells and solar module current voltage data. The data used for solar cells were measured at 33 °C from a PV cell with a diameter of 57 mm under 1000 W/m² irradiance. The data used for the solar module were measured at 45 °C from 36 series polycrystalline silicon PV cells under 1000 W/m² irradiance [8]. The parameter values required to solve the single diode, double diode and PV modules are taken based on the literature and shown in Table 2.

Table 2. Parameter value bounds for the single and double diode models and PV module model [8]

Parameter	Single diode/Double diode		PV module	
	Lower bound	Upper bound	Lower bound	Upper bound
I_{ph} (A)	0	1	0	2
I_{sd}, I_{sd1}, I_{sd2} (μA)	0	1	0	50
R_s (Ω)	0	0.5	0	2
R_{sh} (Ω)	0	100	0	2000
n, n_1, n_2	1	2	1	50

To compare the performance of the proposed ABC-Ls algorithm, well known literature algorithms such as GA, PSO and standard ABC algorithms were used. All algorithms were run 30 times under the same conditions and the maximum number of function evaluations (MaxFEs) was taken as 50000. Parameter adjustments of the algorithms were designed according to the literature and presented in Table 3.

Table 3. Algorithm parameters

GA [30]		PSO [31]		ABC [32]		ABC-Ls	
Population Size	20	Population Size	20	Colony Size	100	Colony Size	100
Crossover rate	0.85	C_1	2	n_o	50	n_o	50
Mutation rate	0.1	C_2	2	n_e	50	n_e	50
		w_{min}	0.4	n_s	1	n_s	1
		w_{max}	0.9	Limit	$n_e \times D$	Limit	$n_e \times D$

n_o : Onlooker number, n_e : Employed bee number, n_s : Scout number, D : Dimension of the problem

5.1. Benchmark results

Table 4 shows the results obtained by applying the ABC-Ls, ABC, GA and PSO algorithms to 15 different benchmark functions.

Table 4. Benchmark function results of algorithms

Functions		GA	PSO	ABC	ABC-Ls
F1	Best	2.60E-13	2.80E-18	4.49E-13	9.32E-26
	Mean	2.14E-08	1.83E-11	5.13E-12	1.31E-25
	Std.	1.04E-07	4.89E-11	5.33E-12	1.95E-26
F2	Best	2.29E-08	8.21E+05	2.16E-09	3.27E-21
	Mean	8.62E-05	6.94E+07	8.39E-08	1.23E-20
	Std.	3.31E-04	6.08E+07	1.15E-07	8.25E-21
F3	Best	4.03E-14	8.02E-20	6.67E-14	1.29E-26
	Mean	9.56E-09	2.83E+02	7.61E-13	1.96E-26
	Std.	3.73E-08	3.09E+02	9.11E-13	5.99E-27
F4	Best	8.67E-17	1.91E-21	6.31E-09	2.85E-23
	Mean	8.67E-17	3.74E+13	3.34E-06	2.63E-16
	Std.	1.38E-27	1.80E+14	5.53E-06	4.27E-16
F5	Best	2.79E-07	5.03E-08	2.03E-07	1.18E-13
	Mean	8.21E-07	2.70E+01	5.89E-07	1.63E-13
	Std.	1.74E-06	1.51E+01	2.07E-07	2.25E-14
F6	Best	1.55E+01	2.65E+00	4.65E+01	5.40E-13
	Mean	2.67E+01	7.53E+00	5.72E+01	1.42E-11
	Std.	5.31E+00	3.35E+00	4.49E+00	4.91E-11
F7	Best	0.00E+00	0.00E+00	0.00E+00	0.00E+00
	Mean	2.03E+00	3.33E+02	3.03E+00	0.00E+00
	Std.	1.30E+00	1.80E+03	1.33E+00	0.00E+00
F8	Best	9.39E-34	1.40E-35	3.06E-32	1.73E-58
	Mean	6.67E-16	7.16E-01	4.89E-30	5.21E-58
	Std.	3.42E-15	2.39E+00	1.63E-29	2.09E-58
F9	Best	1.71E-02	1.34E-02	3.25E-01	1.41E-02
	Mean	6.28E-02	4.75E-01	4.81E-01	4.63E-02
	Std.	2.94E-02	1.22E+00	8.00E-02	1.78E-02
F10	Best	1.06E+02	1.21E+01	5.86E-01	4.67E-04
	Mean	4.07E+02	1.89E+03	4.29E+00	1.13E+00
	Std.	2.53E+02	3.65E+03	2.33E+00	1.68E+00
F11	Best	3.86E+01	4.08E+01	2.03E-01	0.00E+00
	Mean	6.02E+01	1.09E+02	3.20E+00	2.35E-01
	Std.	1.13E+01	3.57E+01	1.29E+00	4.37E-01
F12	Best	2.90E+01	3.00E+01	1.25E+01	0.00E+00
	Mean	4.76E+01	1.16E+02	1.76E+01	1.68E+00
	Std.	1.09E+01	3.31E+01	2.53E+00	1.20E+00
F13	Best	1.13E-12	0.00E+00	5.54E-12	0.00E+00
	Mean	3.24E-01	3.04E+00	2.55E-08	5.75E-03
	Std.	2.74E-01	1.63E+01	6.06E-08	5.56E-03
F14	Best	1.48E+03	2.10E+03	3.63E+02	2.37E+02
	Mean	1.96E+03	3.34E+03	7.23E+02	6.66E+02
	Std.	3.70E+02	5.53E+02	2.22E+02	3.23E+02
F15	Best	1.78E+00	1.84E-09	2.53E-06	5.33E-14
	Mean	2.28E+00	4.54E+00	7.29E-06	8.31E-14
	Std.	2.76E-01	7.22E+00	3.34E-06	1.06E-14

In this section, the proposed ABC-Ls algorithm was compared with well-known literature algorithms. Table 4 shows that the proposed method yielded a superior success compared to basic ABC and other algorithms. Only in the F9 function, the PSO algorithm was more successful compared to the other algorithms, but it did not achieve any success in other functions. The GA and ABC were not successful in any of the functions. The success of the basic ABC algorithm was lower than that of the PSO algorithm; on the other hand, it can be said that the ABC-Ls algorithm achieved a better success compared to the PSO algorithm as it was improved with local search capability.

In addition, Figure 6 shows that the convergence performance of the proposed ABC-Ls algorithm was surprisingly better than other algorithms in the graphs of all functions except F9 and F14. The box-plot graphs indicate that the ABC-Ls algorithm achieved a more stable result and the proposed local search strategy was a significant improvement for ABC.

Figure 6. Convergence graphs and box-plots of algorithms for all functions

Figure 7 numerically compares the rank performances of all algorithms according to their results. It can be said based on the results that the performance of the proposed method was very good, indicating the success of the ABC-Ls algorithm in 14 out of 15 functions.

Figure 7. Rank performances of algorithms

5.2. Single diode module results

Table 5 shows the parameter estimation and RMSE values of GA, PSO, ABC and ABC-Ls algorithms for the single diode model. Figure 8 shows the convergence graphs and box-plots of the minimum RMSE values according to the parameter values estimated by algorithms. Table 6 shows the standard and estimated current and voltage values used for the single diode as well as the absolute error (AE). The graphical representations of the standard and simulation data in Table 6 are shown in Figure 9, and Table 7 compares the ABC-Ls algorithm with the results of some studies in the literature.

Table 5 indicates that the ABC-Ls was the algorithm obtaining the best value, indicated in bold. GA had the worst value, followed by the ABC algorithm. Although the PSO algorithm obtained a value close to the ABC-Ls algorithm, the success of the ABC-Ls algorithm can be seen in Table 5, which shows the values obtained from the parameter estimation according to the best results of GA, PSO, ABC and proposed ABC-Ls.

Table 5. Comparison of different algorithms on the single diode module

Algorithm	$I_{ph}(A)$	$I_{sd}(\mu A)$	$R_s(\Omega)$	$R_{sh}(\Omega)$	n	RMSE
ABC-Ls	0.7608	0.3222	0.0364	53.6462	1.4809	9.8602E-04
ABC	0.7609	0.3553	0.0359	54.1769	1.4909	1.0223E-03
PSO	0.7608	0.3250	0.0364	53.8709	1.4818	9.8609-04
GA	0.7595	0.5117	0.0342	75.0000	1.5293	1.6904E-03

The convergence graphs and box-plots in Figure 8 indicate that the ABC-Ls algorithm converged faster than the standard ABC while the ABC-Ls and ABC obtained more balanced and stable results in the box-plot. Table 6 shows the voltage, current and power values in the standard data. Simulation data, on the other hand, includes the current and power values obtained by the ABC-Ls. It also shows the AE values of the current and power values.

Figure 8. The algorithms' (a) convergence graphs and (b) box-plots for single diode module

Table 6. Absolute errors for the ABC-Ls

Item	Standard data			Simulation data			
	V (V)	I (A)	P (W)	I _{sim} (A)	P _{sim} (W)	I _{AE} (A)	P _{AE} (W)
1	-0.2057	0.764	-0.157154800	0.764093222	-0.157173976	0.000093222	0.000019176
2	-0.1291	0.762	-0.098374200	0.762666684	-0.098460269	0.000666684	0.000086069
3	-0.0588	0.7605	-0.044717400	0.761357143	-0.044767800	0.000857143	0.000050400
4	0.0057	0.7605	0.004334850	0.760154210	0.004332879	0.000345790	0.000001971
5	0.0646	0.76	0.049096000	0.759053956	0.049034886	0.000946044	0.000061114
6	0.1185	0.759	0.089941500	0.758039758	0.089827711	0.000960242	0.000113789
7	0.1678	0.757	0.127024600	0.757087882	0.127039347	0.000087882	0.000014747
8	0.2132	0.757	0.161392400	0.756136584	0.161208320	0.000863416	0.000184080
9	0.2545	0.7555	0.192274750	0.755081357	0.192168205	0.000418643	0.000106545
10	0.2924	0.754	0.220469600	0.753658036	0.220369610	0.000341964	0.000099990
11	0.3269	0.7505	0.245338450	0.751385412	0.245627891	0.000885412	0.000289441
12	0.3585	0.7465	0.267620250	0.747349426	0.267924769	0.000849426	0.000304519
13	0.3873	0.7385	0.286021050	0.740114914	0.286646506	0.001614914	0.000625456
14	0.4137	0.728	0.301173600	0.727382964	0.300918332	0.000617036	0.000255268
15	0.4373	0.7065	0.308952450	0.706976835	0.309160970	0.000476835	0.000208520
16	0.459	0.6755	0.310054500	0.675287421	0.309956926	0.000212579	0.000097574
17	0.4784	0.632	0.302348800	0.630767194	0.301759025	0.001232806	0.000589775
18	0.496	0.573	0.284208000	0.571936885	0.283680695	0.001063115	0.000527305
19	0.5119	0.499	0.255438100	0.499613131	0.255751962	0.000613131	0.000313862
20	0.5265	0.413	0.217444500	0.413650848	0.217787171	0.000650848	0.000342671
21	0.5398	0.3165	0.170846700	0.317507763	0.171390690	0.001007763	0.000543990
22	0.5521	0.212	0.117045200	0.212148945	0.117127433	0.000148945	0.000082233
23	0.5633	0.1035	0.058301550	0.102243795	0.057593930	0.001256205	0.000707620
24	0.5736	-0.01	-0.005736000	-0.008722682	-0.005003331	0.001277318	0.000732669
25	0.5833	-0.123	-0.071745900	-0.125507401	-0.073208467	0.002507401	0.001462567
26	0.59	-0.21	-0.123900000	-0.208464332	-0.122993956	0.001535668	0.000906044

Figure 9. Comparison graphs between the ACB-Ls' standard and simulation data for single diode module: (a) I-V characteristics, (b) P-V characteristics, (c) current, and (d) power

Table 7 compares the ABC-Ls algorithm with some previous studies that achieved values close to those of the ABC-Ls, the same values, or worse results. Generally, it is seen from the results that the ABC-Ls algorithm achieved a very high performance for the single diode model compared to many studies in the literature, and its success was the same only with PGJaya.

Table 7. Comparison of the algorithms in the literature on the single diode model

Algorithm	$I_{ph}(A)$	$I_{sd}(\mu A)$	$R_s(\Omega)$	$R_{sh}(\Omega)$	n	RMSE
ABC-Ls	0.7608	0.3222	0.0364	53.6462	1.4809	9.8602E-04
PGJaya [18]	0.7608	0.3230	0.0364	53.7185	1.4812	9.8602E-04
Jaya [18]	0.7068	0.3281	0.0364	54.9298	1.4828	9.8946E-04
Rao-II [4]	0.76077	0.32301	0.03639	53.71854	1.48118	9.86022E-04
Rao-III [4]	0.76079	0.32302	0.03637	53.71851	1.48118	9.86022E-04
ABC [4]	0.76082	0.33018	0.03624	53.59878	1.48334	9.86092E-04
PSO [4]	0.76076	0.33302	0.03538	56.03853	1.48458	9.86035E-04
ABSO [15]	0.76080	0.30623	0.03659	52.2903	1.47583	9.9124E-4
CARO [16]	0.7608	0.3172	0.0364	53.0893	1.4817	9.8665E-04
IJAYA [1]	0.7608	0.3228	0.0364	53.7595	1.4811	9.8603E-04
PS [14]	0.7617	0.9980	0.0313	64.1026	1.6000	2.8630E-01
WOA [17]	0.7606	0.3881	0.0357	60.5623	1.4999	1.0480E-03
CWOA [17]	0.7600	0.2831	0.0371	62.6183	1.4678	1.1812E-03
LWOA [17]	0.7602	0.4607	0.0350	75.4619	1.5177	1.2352E-03
PSO-WOA [17]	0.7597	0.3140	0.0366	58.8019	1.4783	1.1983E-03

5.3. Double diode module results

For the double diode module, the results obtained by the GA, PSO, standard ABC and proposed ABC-Ls indicate that the performance of the GA was not very good, the ABC and PSO algorithms achieved similar results, and the proposed ABC-Ls algorithm had a superior performance compared to others achieving the best result, as shown in Table 8. Figure 10 shows the convergence graphs and box-plots of the minimum RMSE values according to the parameter values estimated by the algorithms. According to the results of the algorithms in Figure 10, the

convergence graph of the ABC-Ls was the highest, and the box plots show that it performed well in terms of stability. Table 9 shows the standard and estimated current and voltage values used for the double diode module as well as the absolute error (AE). The graphical representations of the standard and simulation data in Table 9 are shown in Figure 11.

Table 8. Comparison of different algorithms on the double diode model

Algorithm	$I_{ph}(A)$	$I_{sd1}(\mu A)$	$R_s(\Omega)$	$R_{sh}(\Omega)$	n_1	$I_{sd2}(\mu A)$	n_2	RMSE
ABC-Ls	0.7608	0.22788	0.0367	53.5381	1.4518	0.72734	1.9952	9.8257E-04
ABC	0.7608	0.31906	0.0361	55.6829	1.4818	0.18365	1.9376	1.0092E-03
PSO	0.7609	0.91545	0.0368	51.0151	1.4172	0.31897	1.6532	1.0087E-03
GA	0.7598	0.20128	0.0381	53.5156	1.4368	0.62500	1.7508	1.3887E-03

Figure 10. The algorithms' (a) convergence graphs and (b) box-plots for the double diode module

Table 9. Absolute error for ABC-Ls

Item	Standard data			Simulation data			
	V (V)	I (A)	P (W)	I_{SIM} (A)	P_{SIM} (W)	I_{AE} (A)	P_{AE} (W)
1	-0.2057	0.764	-0.157154800	0.763979932	-0.157150672	0.000020068	0.000004128
2	-0.1291	0.762	-0.098374200	0.762601926	-0.098451909	0.000601926	0.000077709
3	-0.0588	0.7605	-0.044717400	0.761336737	-0.044766600	0.000836737	0.000049200
4	0.0057	0.7605	0.004334850	0.760173953	0.004332992	0.000326047	0.000001858
5	0.0646	0.76	0.049096000	0.759108910	0.049038436	0.000891090	0.000057564
6	0.1185	0.759	0.089941500	0.758123694	0.089837658	0.000876306	0.000103842
7	0.1678	0.757	0.127024600	0.757191960	0.127056811	0.000191960	0.000032211
8	0.2132	0.757	0.161392400	0.756248100	0.161232095	0.000751900	0.000160305
9	0.2545	0.7555	0.192274750	0.755182977	0.192194068	0.000317023	0.000080682
10	0.2924	0.754	0.220469600	0.753729113	0.220390393	0.000270887	0.000079207
11	0.3269	0.7505	0.245338450	0.751406530	0.245634795	0.000906530	0.000296345
12	0.3585	0.7465	0.267620250	0.747308511	0.267910101	0.000808511	0.000289851
13	0.3873	0.7385	0.286021050	0.740015846	0.286608137	0.001515846	0.000587087
14	0.4137	0.728	0.301173600	0.727248372	0.300862652	0.000751628	0.000310948
15	0.4373	0.7065	0.308952450	0.706846488	0.309103969	0.000346488	0.000151519
16	0.459	0.6755	0.310054500	0.675201182	0.309917342	0.000298818	0.000137158
17	0.4784	0.632	0.302348800	0.630747529	0.301749618	0.001252471	0.000599182
18	0.496	0.573	0.284208000	0.571980807	0.283702480	0.001019193	0.000505520
19	0.5119	0.499	0.255438100	0.499695139	0.255793941	0.000695139	0.000355841
20	0.5265	0.413	0.217444500	0.413729009	0.217828323	0.000729009	0.000383823
21	0.5398	0.3165	0.170846700	0.317549123	0.171413017	0.001049123	0.000566317
22	0.5521	0.212	0.117045200	0.212132802	0.117118520	0.000132802	0.000073320
23	0.5633	0.1035	0.058301550	0.102176618	0.057556089	0.001323382	0.000745461
24	0.5736	-0.01	-0.005736000	-0.008781998	-0.005037354	0.001218002	0.000698646
25	0.5833	-0.123	-0.071745900	-0.125541881	-0.073228579	0.002541881	0.001482679
26	0.59	-0.21	-0.123900000	-0.208384389	-0.122946789	0.001615611	0.000953211

Figure 11. Comparison graphs between the ACB-Ls' standard and simulation data for the double diode module: (a) I-V characteristics, (b) P-V characteristics, (c) current, and (d) power

Table 10 shows that the proposed ABC-Ls method performed a better parameter estimation than the standard ABC in the double diode module [4]. The proposed ABC-Ls method achieved better results than all other studies except the Rao-II algorithm [4].

Table 10. Comparison of the algorithms in the literature on the double diode model

Algorithm	$I_{ph}(A)$	$I_{sd1}(\mu A)$	$R_s(\Omega)$	$R_{sh}(\Omega)$	n_1	$I_{sd2}(\mu A)$	n_2	RMSE
ABC-Ls	0.7608	0.2279	0.0367	53.5381	1.4518	0.7273	1.9952	9.8257E-04
PGJaya [18]	0.7608	0.21031	0.0368	55.8135	1.4450	0.88534	2.0000	9.8263E-04
Jaya [18]	0.7607	0.0061	0.0364	52.6575	1.8436	0.3151	1.4788	9.8934E-04
Rao-II [4]	0.76078	0.22641	0.03675	55.71854	1.45471	0.74911	2.00000	9.82485E-04
Rao-III [4]	0.76078	0.21911	0.03674	55.71851	1.45145	0.74814	2.00000	9.83508E-04
ABC [4]	0.76073	0.21456	0.03624	55.14781	1.46224	0.51241	1.68078	9.85941E-04
PSO [4]	0.76111	0.19781	0.03538	53.41254	1.48345	0.42589	1.68418	9.86020E-04
ABSO[15]	0.76078	0.26713	0.03657	54.6219	1.46512	0.38191	1.98152	9.8344 E-04
CARO [16]	0.7608	0.2932	0.0364	54.3967	1.4734	0.0910	1.7732	9.8260E-04
IJAYA [1]	0.7601	0.0050	0.0376	77.8519	1.2186	0.7509	1.6247	9.8293E-04
PS [14]	0.7602	0.9889	0.0320	81.3008	1.6000	0.0001	1.1920	1.5180E-02
WOA [17]	0.7611	0.3656	0.0354	55.5644	1.4970	0.1274	1.7961	1.1293E-03
CWOA [17]	0.7613	0.1905	0.0359	50.0905	1.4564	0.2459	1.6065	1.0968E-03
LWOA [17]	0.7608	0.1667	0.0361	55.2366	1.6086	0.2323	1.4658	1.0004E-03
PSO-WOA [17]	0.7604	0.1079	0.0367	74.3924	1.4072	0.6665	1.7141	1.1842E-03

5.4. PV module results

Table 11 shows that the GA algorithm achieved a result close to the ABC-Ls algorithm in PV module, unlike the single and double diode models, which indicates that its performance was better than the standard ABC and PSO algorithms. While the PSO algorithm achieved the third best result, the success of the ABC algorithm followed the success of the PSO. It was observed that the ABC-Ls algorithm performed a better result than all of the other methods. Although the GA algorithm achieved a success in the second rank, it did not show a well performance in terms of stability. and the box-plot in Figure 12 shows that ABC-Ls continued to indicate a better stability. Moreover, the graph shows that ABC-Ls and PSO converged closely to each other.

Table 11. Comparison of different algorithms on the PV module model

Algorithm	$I_{ph}(A)$	$I_{sa}(\mu A)$	$R_s(\Omega)$	$R_{sh}(\Omega)$	n	RMSE
ABC-Ls	1.0305	3.4742	1.2016	984.1798	48.6338	2.4251E-03
ABC	1.0302	3.8202	1.1892	1005.717	49.0048	2.4731E-03
PSO	1.0307	3.4054	1.2036	957.2148	48.5576	2.4587E-03
GA	1.0303	3.6295	1.1971	1033.105	48.8017	2.4278E-03

Figure 12. The algorithms' (a) convergence graphs and (b) box-plots for the PV module model

Table 12 shows the standard and estimated current and voltage values used for the double diode module as well as the absolute error. The graphical representations of the standard and simulation data in Table 12 are shown in Figure 13.

Table 12. Absolute error for ABC-Ls

Item	Standard data			Simulation data			
	V (V)	I (A)	P (W)	I_{SIM} (A)	P_{SIM} (W)	I_{AE} (A)	P_{AE} (W)
1	0.1248	1.031500	0.128731200	1.029096922	0.128431296	0.002403078	0.000299904
2	1.8093	1.030000	1.863579000	1.027362698	1.858807329	0.002637302	0.004771671
3	3.3511	1.026000	3.438228600	1.025727015	3.437313801	0.000272985	0.000914799
4	4.7622	1.022000	4.866968400	1.024095798	4.876949009	0.002095798	0.009980609
5	6.0538	1.018000	6.162768400	1.022283845	6.188701942	0.004283845	0.025933542
6	7.2364	1.015500	7.348564200	1.019926288	7.380594591	0.004426288	0.032030391
7	8.3189	1.014000	8.435364600	1.016362666	8.455019384	0.002362666	0.019654784
8	9.3097	1.010000	9.402797000	1.010500218	9.407453879	0.000500218	0.004656879
9	10.2163	1.003500	10.252057050	1.000638105	10.222819072	0.002861895	0.029237978
10	11.0449	0.988000	10.912361200	0.984562818	10.874397874	0.003437182	0.037963326
11	11.8018	0.963000	11.365133400	0.959540956	11.324310454	0.003459044	0.040822946
12	12.4929	0.925500	11.562178950	0.922861454	11.529215859	0.002638546	0.032963091
13	13.1231	0.872500	11.449904750	0.872623197	11.451521478	0.000123197	0.001616728
14	13.6983	0.807500	11.061377250	0.807295434	11.058575040	0.000204566	0.002802210
15	14.2221	0.726500	10.332355650	0.728352394	10.358700585	0.001852394	0.026344935
16	14.6995	0.634500	9.326832750	0.637146414	9.365733714	0.002646414	0.038900964
17	15.1346	0.534500	8.089443700	0.536212914	8.115367968	0.001712914	0.025924268
18	15.5311	0.427500	6.639545250	0.429503393	6.670660147	0.002003393	0.031114897
19	15.8929	0.318500	5.061888650	0.318760270	5.066025099	0.000260270	0.004136449
20	16.2229	0.208500	3.382474650	0.207371811	3.364172155	0.001128189	0.018302495
21	16.5241	0.101000	1.668934100	0.096148718	1.588771025	0.004851282	0.080163075
22	16.7987	-0.008000	-0.134389600	-0.008339301	-0.140089422	0.000339301	0.005699822
23	17.0499	-0.111000	-1.892538900	-0.110943452	-1.891574758	0.000056548	0.000964142
24	17.2793	-0.209000	-3.611373700	-0.209244435	-3.615597372	0.000244435	0.004223672
25	17.4885	-0.303000	-5.299015500	-0.300847688	-5.261374789	0.002152312	0.037640711

Figure 13. Comparison graphs between the ACB-Ls' standard and simulation data for the PV module: (a) I-V characteristics, (b) P-V characteristics, (c) current, and (d) power

For the PV module parameter estimation, the proposed ABC-Ls method achieved a better estimation result compared to other studies in the literature, as seen in Table 13. It is understood from Table 13 that the proposed ABC-Ls method in local search was more usable than other standard and developed methods in the PV module parameter estimation.

Table 13. Comparison of the algorithms in the literature on the PV module model

Algorithm	$I_{ph}(A)$	$I_{sd}(\mu A)$	$R_s(\Omega)$	$R_{sh}(\Omega)$	n	RMSE
ABC-Ls	1.0305	3.4742	1.2016	984.1798	48.6338	2.4250E-03
PGJaya [18]	1.0305	3.4818	1.2013	981.8545	48.6424	2.425075E-03
Jaya [18]	1.0302	3.4931	1.2014	1022.5000	48.6531	2.4278E-03
CARO [16]	1.0319	3.2840	1.2056	841.3213	48.4036	2.4270E-03
IJAYA [1]	1.0305	3.4703	1.2016	977.3752	48.6298	2.4251E-03
PS [14]	1.0313	3.1756	1.2053	714.2857	48.2889	1.1800E-02
WOA [17]	1.0309	3.4375	1.1994	921.7861	48.5958	2.4407E-03
CWOA [17]	1.0272	4.2334	1.1879	1923.9615	49.3908	2.5962E-03
LWOA [17]	1.0293	3.6916	1.1985	1198.7830	48.8626	2.4529E-03
PSO-WOA [17]	1.0301	3.6169	1.1900	965.9555	48.7927	2.5313E-03

6. Conclusion

In this study, an ABC-Local Search (ABC-Ls) method was proposed to estimate the parameters of the PV system. The proposed ABC-Ls method runs a new local search procedure for every 10 iterations in addition to the employed bee, onlooker bee and scout bee phases of the standard ABC algorithm. It was tested on 15 different benchmark functions to show the effectiveness of the ABC-Ls method. The experimental results indicated that the success of the proposed method was very high compared to its standard version. The proposed method was applied to three real-world problems of the PV systems: single diode, double diode and PV module. The convergence graph and box-plots of the RMSE values indicated that the ABC-Ls method provided better results in single diode module, double diode and PV module problems compared to the GA, PSO and standard ABC methods. According to the convergence graphs and box-plots, ABC-Ls had very good convergence rate and stability. Accordingly, it can be said that the ABC-Ls algorithm showed a good performance. As a result, it can be suggested that ABC-Ls

is a suitable method for different PV systems and it should be used in the studies to be conducted with other PV systems.

CRedit authorship contribution statement

Mehmet Fatih Tefek: Methodology. Writing - original draft. Data curation. Validation. Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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