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A Chaotic Improved Artificial Bee Colony for Parameter Estimation of Photovoltaic Cells

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Abstract: The search for new energy resources is a crucial task nowadays. Research on the use of solar energy is growing every year. The aim is the design of devices that can produce a considerable amount of energy using the Sun's radiation. The modeling of solar cells (SCs) is based on the estimation of the intrinsic parameters of electrical circuits that simulate their behavior based on the current vs. voltage characteristics. The problem of SC design is defined by highly nonlinear and multimodal objective functions. Most of the algorithms proposed to find the best solutions become trapped into local solutions. This paper introduces the Chaotic Improved Artificial Bee Colony (CIABC) algorithm for the estimation of SC parameters. It combines the use of chaotic maps instead random variables with the search capabilities of the Artificial Bee Colony approach. CIABC has also been modified to avoid the generation of new random solutions, preserving the information of previous iterations. In comparison with similar optimization methods, CIABC is able to find the global solution of complex and multimodal objective functions. Experimental results and comparisons prove that the proposed technique can design SCs, even with the presence of noise.

Keywords: solar cells; photovoltaic modules; artificial bee colony; chaotic maps; parameter estimation

1. Introduction

The world is constantly changing, and societies demand energy to continue growing and living. New resources are necessary in order to avoid an energetic crisis. This fact is particularly true since fossil fuels have been overexploited for decades. In this sense, it is a need to find and explore new energy sources that can maintain a balance between price and cleanness. Solar energy (also called photovoltaic (PV) energy (PVE)) has attracted the attention of the scientific community because it is present all over the world. PV modules are applied to transform solar radiation into electrical energy, and in the last decades, the use of such modules has increased based on the features of PVE. The main advantages of using PVE instead other sources are that it is emission-free, available all over the world and easy to install [1]. However, since PVE use is focused on domestic purposes, the installation cost is expensive and also the cost of maintenance is higher. These situations occur primarily because the technology is not completely developed. Another cause is the outdoors environment that directly affects the solar modules making necessary their frequent replacement [2]. In the same context, the efficiency of photovoltaic modules (or PV cells) depends on environmental factors such as temperature or radiation that cannot be controlled [3–5]. This situation can be solved by including energy storage systems that increase the cost of the PV system.

Based on the drawbacks described above it is necessary to generate new alternative methods that help to increase the use of PVE. For example, to improve the performance of SCs requires an accurate method for design and modeling them. This situation has attracted the attention of researchers that are looking for new approaches that contribute to the design of efficient PV modules. This task is not trivial, but it is helpful for modeling, testing, control and simulation of PV systems [6–9].

The design process of SCs requires the definition of a relationship between the current (I) and voltage (V) considering the internal parameters of the cells. A mathematical model is then used to generate a representation of the elements that conforms this device, in practical terms, here is simulated the desired output of current vs. voltage (I–V). In the related literature, two approaches are used for to generate this output, (1) the single diode (SD) model and (2) the double diode (DD) model. Such methods involve electrical circuits that define the PV modules. The SD has five parameters, and the DD has seven parameters [1], their values are unknown, and their proper calibration defines the performance of the SC. In this context, it is necessary to estimate the diode saturation current, the series resistance, and the diode ideality factor for both circuits. Considering this fact, the biggest problem could be summarized as developing a mechanism able to find the best configuration of the parameters that approximate the results to the experimental data from the real SC [1].

The identification of the best parameter of PV cells can be formulated as an optimization problem. Considering the Root Mean Squared Error (RMSE) as an objective function is possible to define an algorithm to search the optimal values for the SD or DD model. The aim of using RMSE is to reduce the difference between the output of the mathematical model and an experimental dataset. It is important to notice that the experimental data is commonly obtained from measurements that involve imprecision that is reflected as noise. As a result, the optimization problem is established in a multimodal search space that contains several suboptimal solutions increasing its complexity [10,11]. To affront the problems of solar cells design, the use of classical deterministic methodologies has been proposed. Some of the most important approaches are:

- The least squares (Newton-based approach) [12],
- The Lambert W-functions [13],
- The iterative curve fitting [14].

Moreover, other interesting approaches like the one proposed in [15] consider the diode models as dynamic systems to estimate the best values. The use of this kind of methods implies some drawbacks, for example, the application of differentiability and convexity [16]. Moreover, the initialization of the candidate solutions affects their convergence, and they can be trapped in suboptimal solutions [16].

On the other hand, stochastic techniques are a good alternative to overcome the disadvantages that the deterministic methods present. Heuristic and metaheuristic algorithms are part of stochastic approaches. They are robust techniques able to explore complex search spaces and accurately find the best solutions considering simple initial conditions [1,17,18]. Some examples of these algorithms applied to modelling SCs are the following:

- Particle Swarm Optimization (PSO) [19,20],
- Artificial Bee Colony (ABC) [21],
- Harmony Search (HS) [1],
- Bacterial Foraging Algorithm (BFA) [22],
- Simplified Teaching-Learning Based Optimization (STBLO) [23],
- Cat Swarm Optimization (CSO) [2].

These algorithms are a good alternative to finding the best parameter configuration of SC diode models. However, based on the No-Free-Lunch (NFL) theorem a single metaheuristic algorithm cannot be used to solve all the optimization problems [24]. In other words, depending on the complexity of the search space, the search techniques could fall into local optima. This fact affects the performance and convergence in the iterative process. However, even with these limits, metaheuristic approaches have higher probabilities of obtaining a global solution in the SC design in comparison to deterministic methods.

The Artificial Bee Colony (ABC) is a metaheuristic algorithm that mimics the behavior of honey bees [25]. Different studies about the performance of the ABC algorithm show that it is able to obtain optimal solutions to various real-life problems [26–30]. The main advantage of ABC is the absence of a local search strategy in the iterative process. Under the ABC perspective, there exist food source positions, nectar amount and different kinds of honeybees. The food sources are positions in the search space; each food source has a nectar amount value that determines its quality. The nectar amount is defined by the fitness function. ABC employs three different operators that are capable of avoiding local optimal values in complex problems. Each operator represents one of the various kinds of bees that are used on the ABC. They are the worker bees, the onlooker bees, and the scout bees. The bees represent the entire optimization process that involves the exploration and exploitation of the search space. However, like other similar approaches, ABC has some parameters that must be carefully defined to obtain a good performance [31]. The main three parameters of ABC are the number of food sources, the limit value to determine the abandoned solutions and the number of foraging cycles. Such parameters are not random values, and they are selected depending on the implementation and problem. Considering this fact, the correct setting of these parameters is a complex task that is performed by the designer. In addition, the ABC applies the exploitation process in its search space by using onlookers and worker bees. The onlooker bee phase starts after finishing the worker bee phase depending on a probability value. In this context, the exploitation process is performed depending on this value, and it changes in each foraging cycle. In our study, we found that the selection of the probability value is a challenge and should be done carefully. Therefore, this paper uses a chaotic map to control this value.

On the other hand, non-linear dynamic systems define chaos as the behavior of a complex system, where small changes in the starting conditions can lead to very significant changes over time. Such changes can be random and unpredictable. The properties of chaotic systems have been applied to several optimization techniques to improve the accuracy of the optimization algorithm or to escape from local minima. The use of chaos instead random signals in metaheuristics considerably improve their performance [32]. In most of the cases the chaotic versions of these optimization methods, increase the diversity of the solution and the capability to avoid local solutions in the search space.

This paper introduces the Chaotic Improved Artificial Bee Colony (CIABC) for the problem of solar cell design. In this context this article has two main goals, (1) generate an enhanced version of the ABC (CIABC); (2) apply CIABC for the parameter estimation of solar cells and photovoltaic modules. The standard ABC has been previously used for parameter estimation of SC [21]. However, considering that SC modeling is a complex optimization problem and according to the NFL. The use of ABC does not represent the most accurate solution. CIABC employs chaotic maps instead of the random values on the onlooker bee step of the optimization process. Moreover, another improvement is introduced in the scout bee phase. It permits the use of the best solution so far to generate new elements of the population, instead of the use of random values. Based on such modifications the CIABC perseveres the information of the best option at each iteration and also enhance its performance converge using chaos. In this sense, the aim of this paper is to present an alternative improved method that accurately estimates the parameters that define the output of SC and photovoltaic (PV) panels. In this implementation, a selected dataset of measurements and the CIABC is applied over the diode models to minimize the Root Mean Squared Error (RMSE) [33,34]. The RMSE is the fitness function, and for this problem, it determines if the values of the SC or the PV panels designed by CIABC is close to the values from the dataset.

For experimental purposes two datasets are used in this paper. The first one is for single SC, and it was extracted for the datasheet provided by the manufacturer. The second dataset corresponds to experimental information extracted from real PV modules [35]. The aim of using two information sources is to provide evidence of the capabilities of the CIABC for benchmark and real data. In addition, the use of the second dataset provides evidence that the proposed algorithm can work with models that include a different amount of diodes. The property of the standard ABC to work with multi-dimensional search spaces is also contained in the CIABC. An increment on the number of diodes in the model is reflected in the number of dimensions of the optimization problem. On the other hand, to show the proficiency of the CIABC, several experiments are performed and comparisons with similar algorithms selected from the state-of-the-art. Some statistical comparisons have also been conducted in order to verify the efficacy of the improvements included in the ABC. In addition, the computational effort of the CIABC is compared with the standard version of ABC. Experimental evidence indicates that CIABC is practically immune to the sensitivity generated by noisy conditions and it has a high performance regarding accuracy, robustness and preserving low computational requirements.

The remainder of the paper is organized as follows: Section 2 describes the Preliminaries, and the problem of solar cell modeling, the standard ABC, and the chaotic map concept are introduced. In Section 3 the proposed chaotic improved ABC is introduced. Section 4 discusses the results of the proposed algorithm. The conclusions and the future works are examined in Section 5.

2. Preliminaries

2.1. Photovoltaic Models

In the process of solar cell design, it is crucial to define a mathematical model that is used to estimate the internal parameters of the SC. Commonly electronic circuits help to set this model; in this sense, the single diode (SD) and double diode (DD) method are widely employed for describe SCs [36]. This section introduces both SD and DD that are also adapted to be considered as an optimization problem.

2.1.1. Single Diode Model

The single diode model is presented in Figure 1. The equivalent circuit contains one diode that shunts the photo-generated current source I_{ph}. This diode is configured as a rectifier and to model its non-physical ideality; the SD model considers an extra parameter [1,17,37]. The SD is commonly used in the related literature for PV modeling. This circuit is very easy to implement and has only five parameters to estimate.

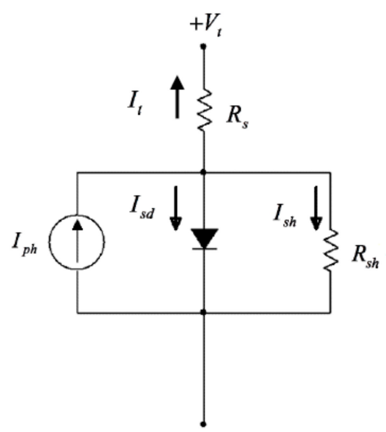


Figure 1. Single diode model of a solar cell.

From Figure 1, the current of the solar cell is obtained using Equation (1):

$$I_t = I_{ph} - I_{sd} - I_{sh}, \tag{1}$$

In Equation (1), I_t is the terminal current, I_{ph} the photo-generated current, I_{sd} is the diode current. Meanwhile I_{sh} is the shunt resistor current. To obtain a more accurate model of the PV cells, it is used the Shockley diode equation. Therefore Equation (1) is rewritten as shown in Equation (2):

$$I_t = I_{ph} - I_{sd}\left[\exp\left(\frac{q(V_t + R_s \cdot I_t)}{n \cdot k \cdot T}\right) - 1\right] - \frac{V_t + R_s \cdot I_t}{R_{sh}} \tag{2}$$

The internal parameters of the diode are included in Equation (2), where I_{sd} is the diode saturation current. V_t is the terminal voltage whereas the series and shunt resistances are represented by R_s and R_{sh} respectively. n is a non-physical ideality factor. Some parameters are also considered for the Shockley diode equation, some of them are constants extensively used in semiconductors physics. The magnitude of charge on an electron $q = 1.602 \times 10^{-19}$ C (coulombs), the Boltzmann constant $k = 1.380 \times 10^{-23}$ (J/°K) and T that is the cell temperature (°K). In Equation (2), the parameters to be estimated are R_s, R_{sh}, I_{ph}, I_{sd}, and n. The estimation or identification of such values is reflected in the performance of SC, for that reason, this task is critical in PV systems.

2.1.2. Double Diode Model

Considering the double diode (DD) model equivalent circuit presented in Figure 2, the two diodes are used to shunt the photo-generated current source I_{ph}. The first diode is configured as a rectifier. Meanwhile, the second diode represents the recombination current and other non-idealities of PV cells [1].

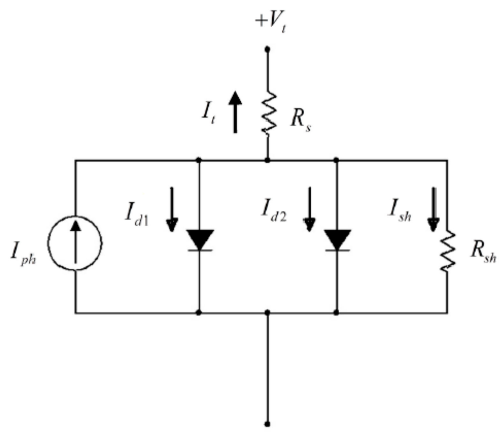


Figure 2. Double diode model of a solar cell.

From Figure 2, the current of the solar cell is obtained using a modified version of Equation (1), defined as follows:

$$I_t = I_{ph} - I_{d1} - I_{d2} - I_{sh}, \tag{3}$$

The parameters of Equation (3) are similar to Equation (1), the main difference is that I_{d1} and I_{d2} correspond to the first and second diode currents, respectively. In Equation (4) an accurate approximation of the DD obtained using the Shockley diode equation to include the internal parameter of the diode is presented:

$$I_t = I_{ph} - I_{sd1}\left[\exp\left(\frac{q(V_t + R_s \cdot I_t)}{n_1 \cdot k \cdot T}\right) - 1\right] - I_{sd2}\left[\exp\left(\frac{q(V_t + R_s \cdot I_t)}{n_2 \cdot k \cdot T}\right) - 1\right] - \frac{V_t + R_s \cdot I_t}{R_{sh}}, \tag{4}$$

where I_{sd1} and I_{sd2} are the diffusion and saturation current, respectively. Meanwhile, the diffusion and recombination diode ideality factors are represented using n_1 and n_2. The rest of the parameters have the same definition as in Equation (2). In this context, in the DD model, seven unknown parameters should be properly estimated, such elements are R_s, R_{sh}, I_{ph}, I_{sd1}, I_{sd2}, n_1 and n_2.

On the other hand, Table 1 shows the ranges of SD and DD parameters. The values of I_{sd1} and I_{sd2} in the DD are the same that I_{sd} in the SD model. This situation also occurs for the intrinsic diode parameters. In this paper, the values of Table 1 are selected due that they are extensively used in the related literature [13,38–40]. However, a good definition of the limits of each variable is desired in order to obtain a solution with real physical meaning [41]. Laudani et al. proposed an interesting analysis of the maximum and minimum values that have a physical meaning [41]. However, since the aim of this paper is to address the parameter estimation as an optimization problem, the values of Table 1 possess some tolerances that permit us to create a feasible search space.

Table 1. The range of the solar cell parameters.

Parameter	Lower Value	Upper Value
$R_s(\Omega)$	0	0.5
$R_{sh}(\Omega)$	0	100
$I_{ph}(\text{A})$	0	1
$I_{sd}(\mu\text{A})$	0	1
n	1	2

2.2. Solar Cells Design as an Optimization Problem

In the mathematical definition of both the SD and DD circuits described previously, there exist a different number of parameters that should be estimated. Using Equations (2) and (4) is possible to define an objective function that measures the quality of the estimated set of parameters (candidate solution). This equation defines if a set of parameters produce an accurate approximation between the output of the model and the measurements from the real SC. The error function for SD has then defined as:

$$f_{\text{SD}}(V_t, I_t, \mathbf{x}) = I_t - x_3 + x_4\left[\exp\left(\frac{q(V_t + x_1 \cdot I_t)}{x_5 \cdot k \cdot T}\right) - 1\right] + \frac{V_t + x_1 \cdot I_t}{x_2} \tag{5}$$

and for the DD model we have:

$$f_{\text{DD}}(V_t, I_t, \mathbf{x}) = I_t - x_3 + x_4\left[\exp\left(\tfrac{q(V_t + x_1 \cdot I_t)}{x_6 \cdot k \cdot T}\right) - 1\right] + x_5\left[\exp\left(\tfrac{q(V_t + x_1 \cdot I_t)}{x_7 \cdot k \cdot T}\right) - 1\right] + \tfrac{V_t + x_1 \cdot I_t}{x_2}, \tag{6}$$

From Equations (5) and (6) the values of V_t and I_t are measurements from the real CS, meanwhile, $\mathbf{x}$ is a vector with the parameters of the model, and it is defined as: $\mathbf{x} = \left[R_s,\ R_{sh},\ I_{ph},\ I_{sd}, n\right]$ for the single diode circuit and $\mathbf{x} = \left[R_s,\ R_{sh},\ I_{ph},\ I_{sd1},\ I_{sd2},\ n_1,\ n_2\right]$ for the double diode circuit. The terms f_{SD} and f_{DD} are used to evaluate the grade of similarity of the current values computed using the estimated parameters ($\mathbf{x}$) and a model with the real values defined by I_t. The optimization process defined for this problem requires the minimization of the difference between the output that is modified at each iteration the values estimated by $\mathbf{x}$. In this context using a dataset of N_E elements, the selected objective function is the Root Mean Square Error (RMSE), and it is defined in Equation (7):

$$RMSE(\mathbf{x}) = \sqrt{\frac{1}{N}\sum_{c=1}^{N_E}\left(f_M^c(V_t^c, I_t^c, \mathbf{x})\right)^2}, \tag{7}$$

From Equation (7), M is used to select the model DD o SD. The dataset used in the estimation could be extracted from a commercial PV cell provided by the manufactured in a datasheet or generated by experimental measurements. Here is important to mention that in most of the cases, the data is not accurate and contains a certain degree of noise. Such imprecisions are reflected in the search space where the parameters and the objective function are defined. The affectations are multi-modality and noisy features that also implies bad performance for the used search strategies [10,11,42].

2.3. Standard Artificial Bee Colony

The Artificial Bee Colony (ABC) is a swarm intelligence metaheuristic algorithm inspired by foraging behavior of real honey bees' colony in nature; it was firstly proposed by Karaboga in 2005 [25]. This algorithm contains three groups of bees; the first one is the worker bees. This kind of bees searches for new sources of food around other food locations in their memory. The information about this process is passed to a second group that includes the onlooker bees. The bees of this group are used to select a food source depending on the information provided by the first group. The third consists of scout bees which randomly search for a food source. The entire process of the standard ABC is described step by step in Algorithm 1, and an explanation of its operators is also provided in this subsection.

Algorithm 1: Standard ABC

1. Define the max iteration, bounds, number of bees, dimension, and trial limit values.
2. Generate the population randomly and evaluate it.
3. C = 0.
4. **While c < max iteration do**
5. Generate new solutions for the worker bees by using Equation (8).
6. Evaluate worker bees, then perform the greedy selection.
7. Compute the probability values by Equation (9).
8. t = 0, and compute the probability
9. **While t<number of onlooker bees**
10. **If probability of food source > rand value**
11. Generate new solutions for the onlooker bees and evaluate them.
12. Perform the greedy selection process for the onlookers.
13. t = t + 1;
14. **End IF**
15. **End While**
16. In the scout bee phase, determine the abandoned solution, and generate a new one randomly.
17. Update the best solution obtained.
18. c = c + 1
19. **End while**
20. **Return** the best solution.

Firstly, the ABC algorithm creates a random population of N solutions that represents the first group (employed bees) $\left(x_i \in \Re^d,\ i = 1, 2, \ldots, N\right)$. Each new solution v_i can be created based on x_i as follows [30]:

$$v_{ij} = x_{ij} + \varphi_{ij}\left(x_{ij} - x_{kj}\right),\ k = \mathrm{int}(rand \times N),\ j = 1, \ldots, d \tag{8}$$

where x_k is a neighbor employed bee of x_i, $\varphi_{ij} \in [-1, 1]$ and it is generated randomly.

The fitness function value for $f(x_i)$ and $f(v_i)$ is calculated for x_i and v_i respectively; then if $f(x_i) > f(v_i)$ the solution x_i is cleared from the memory of the first group and v_i is added. The fitness function value $f(x_i)$ which is obtained from the worker bee group is passed to the second group (onlooker bees). Then the roulette wheel selection method is applied to choose the x_i that has a higher probability of fitness function P_i that is determined as:

$$P_i = \frac{fit_i}{\sum_{i=1}^{N} fit_i},\ fit_i = \begin{cases} \frac{1}{1+f(x_i)} & \text{if} \quad f(x_i) > 0 \\ 1 + abs(f(x_i)) & \text{otherwhise} \end{cases} \tag{9}$$

Each one of the onlooker bees is updating its solution by the same method used by the worker bees. The onlooker bees also check the new solution and old one to determine whether the old solution will be cleared from the memory or not. If there is no improvement in the solutions after a specific number of repetitions, these solutions are rejected; then the scout bee group searching for a new solution to update x_j as:

$$x_{ij} = x_j^{\min} + \left(x_j^{\max} - x_j^{\min}\right) \times \delta \tag{10}$$

where x_{ij} is a parameter to be optimized for the *i-th* worker bee, $x_j^{\max}$ and $x_j^{\min}$ are the upper and lower bounds for x_{ij} respectively, and δ is a random number. After a new solution x_{ij} is created, then it becomes a worker bee. where x_{ij} is a parameter to be optimized for the *i-th* worker bee, $x_j^{\max}$ and $x_j^{\min}$ are the upper and lower bounds for x_{ij} respectively, and δ is a random number. After a new solution x_{ij} is created, then it becomes a worker bee.

2.4. Chaotic Maps

A chaotic map is defined as a method that generates non-repetitive numbers which have some properties such as stochastically intrinsic and showing irregular conduct that is also sensitive to the initial values [43]. The behavior of a non-linear system is changed widely whenever the initial values present a small difference. According to these properties, the population variety can be maintained, improve the performance of determining the global optimum and escape from local optima [44,45]. The chaos can be determined as a discrete-time dynamical system defined as:

$$cp_{k+1}^i = f\left(cp_k^i\right),\ i = 1, 2, 3, \ldots, \mathrm{t}_{\max} \tag{11}$$

where $\mathrm{t}_{\max}$ is the dimension of the map (the number of iterations in this study). Meanwhile, $f\left(cp_k^i\right)$ is the function that generates the chaotic model and it is described using one of the maps presented in Equation (12). Such maps are widely used in the related literature [44,45]. They are many types of chaotic maps such as Sinusoidal, Logistic, Singer or Tent. In this paper, the Tent map is selected, since its performance is better than other maps according to our study and this will be illustrated in Section 4.3. The Tent map is then defined as:

$$p_{k+1} = G(p_k), G(p) = \begin{cases} \frac{p}{0.7}, & p < 0.7 \\ \frac{1}{0.3} p(1-p) & \text{otherwise} \end{cases} \tag{12}$$

3. Chaotic Improved Artificial Bee Colony

The proposed algorithm Chaotic Improved Artificial Bee Colony (CIABC) is introduced in this section. The improvement of the standard ABC can be explained in two steps defined as follows:

(1) *The use of a chaotic map*. The Tent chaotic map is combined with ABC to improve the "onlooker bee" phase, which works to select a food source depending on the information provided by the first group as shown in Equation (9). The Tent map is used instead of the random number which is applied to start this phase. This modification makes ABC inherit the strengths of chaos such as the ergodic and non-repetition properties. This will help in improving the exploitation process as well as reduce the computational time that may occur if the random value is less than the probability for a long time.

(2) *Updating the solution if there is no improvement occurs with the onlooker bee*. When the trial counter exceeds the limit of improving the solution in the "onlooker bee" phase, the standard ABC applies Equation (10) to generate a new solution randomly by the "scout bee" group. Whereas, the CIABC uses the best solution obtained so far to update the "scout bee" group's solution instead of Equation (10), that makes the CIABC searches around the best solution rather than random solutions.

Figure 3 illustrates the entire CIABC sequence. It starts by defining the standard ABC parameters and initializing the population. Also, it generates the matrix of a chaotic map. Then the main cycle of the algorithm starts by dealing with each of worker bees, after that, the probabilities of food sources are calculated. The onlooker bees cycle is started by checking the probability with the chaotic map (CM) value and if it greater than CM the position and fitness values will be updated. Then, if there is no improvement in the solutions after a specific number of repetitions, these solutions are rejected, and scout bee group generates a new solution using the best solution obtained. Finally, this cycle is repeated until the satisfied condition is met.

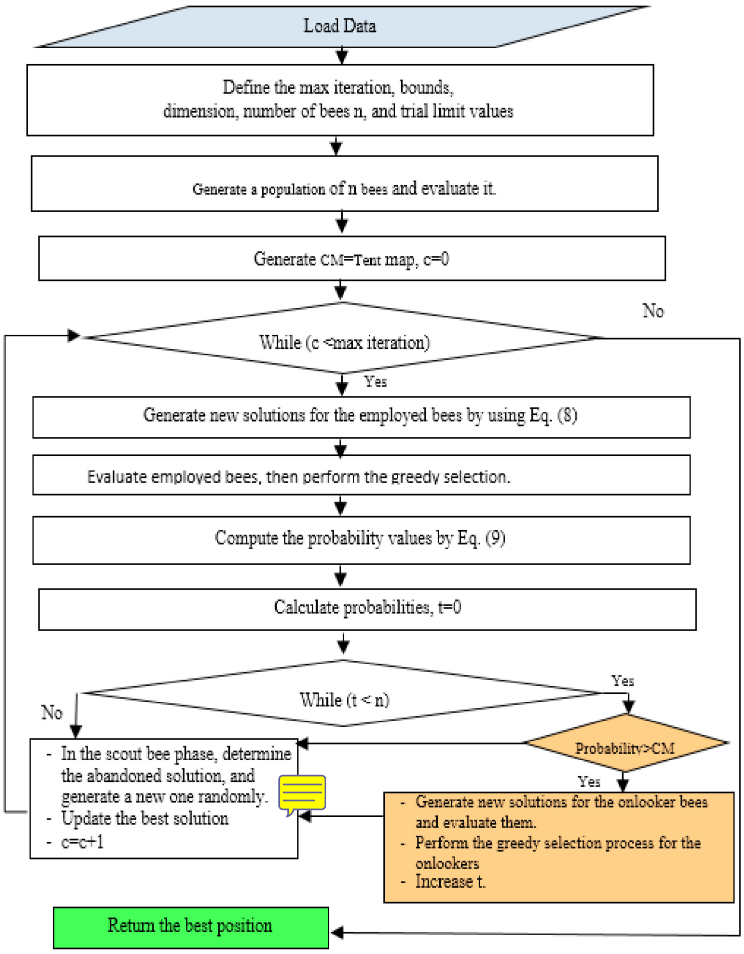


Figure 3. The CIABC algorithm.

4. Results and Discussion

This section presents the result obtained after applying the CIABC to the problem of SC design. The experiments performed are divided in two: (1) parameter estimation of a single solar cell using and (2) parameter estimation of PV modules. In order to test the performance of the proposed method, for a single SC, a set of experimental I–V data has been used [21]. Such data is applied to determine the parameter of the photovoltaic model. For experimental purposes is considered a commercial silicon solar cell (from the R.T.C. Company, Paris, France) with a diameter of 57 mm under standard test conditions (STC). For the STC the solar cell (SC) works at 1 Sun (1000 W/m^2) with a temperature T = 33 °C.

Under the optimization context, the search domain for the SC parameters according to the related literature [21] is presented in Table 1. On the other hand, Table 3 shows the values of the dataset; it consists of 23 samples that are widely used in several approaches for the design of photovoltaic models [19,21]. The CIABC method is configured using a number of food sources N = 200. Meanwhile, the maximum number of iterations is set to 10,000. The experiments were performed using "Matlab 2014b" under Windows 10, 64 bit on an Intel Core2 Duo CPU with 4 GB RAM.

The results of the CIABC are compared with similar optimization algorithms. These techniques are chaos particle swarm optimization (CPSO) [19], simulated annealing (SA) [37], cat swarm optimization (CSO) [2], simplified teaching-learning based optimization (STLBO) [23], generalize depositional teaching learning-based optimization (GOTLBO) [46], artificial bee swarm optimization [6], harmony search (IGHS) [1], artificial bee colony (ABC) [21] and modified artificial bee colony (MABC) [47].

4.1. Performance Measures

The performance of the proposed modified version of ABC is evaluated using different metrics; they are listed in Table 2 [21].

Table 2. The measures used to calculate the performance.

Metric	Formula
Relative Error R_{err}	$\frac{I_{tm}-I_{te}}{I_{te}} \times 100$
Normalized R_{err}	$\frac{R_{error}}{\max(I_{te})-\min(I_t)}$
Mean Absolute Error (MAE)	$\sum_{i=1}^{N_E} \frac{\lvert I_{tm}-I_t \rvert}{N_E}$
Normalized MAE(NMAE)	$\sum_{i=1}^{N_E} \frac{\lvert I_{tm}-I_{te} \rvert / I_{te}}{N_E}$
Normalized RMSE	$\frac{RMSE}{\max(I_{te})-\min(I_{te})}$
Mean Bias Error (MBE)	$\sum_{i=1}^{N_E} \frac{I_{tm}-I_{te}}{N_E}$
Normalize MBE (NMBE)	$\frac{MBE}{\max(I_{te})-\min(I_{te})}$

From Table 2, I_{tm} is the measured value, I_{te} the estimated value, $N_E = 37$ (the number of all experiments). The $\min(I_{te})$ and $\max(I_{te})$ are the minimum and maximum values (respectively) of I_{te} over N_E.

4.2. Experimental Results of CIABC

Tables 3 and 4, as well as Figures 4 and 5 illustrate the results of the CIABC method in determining the unknown parameters of SC using the single diode (SD) and the double diode (DD) models. Table 3 displays the I_{te} and R_{err} for SD and DD models after estimating the parameters of them, in addition to the original data. Table 4 shows the estimated values of the SD parameters which have been predicted by the CIABC model. These values are also compared with those obtained by the other selected algorithms. Comparisons illustrate that the RMSE value of the CIABC (9.8602×10^{-4}) is better than the original ABC and the MABC (9.862×10^{-4} and 9.861×10^{-4} respectively), that indicates the CIABC increased the performance of another version of ABC. Also, the RMSE of CIABC equals the values obtained by STLBO and CSO. In addition, CIABC outperformed all other algorithms; however, the worst value is 0.00139 for CPSO. Moreover, several methods are used to determine the parameters of SD model and it uses does not depend on the swarm. For example, in [48] the authors proposed a method which used the reduced forms. From reference [48], the results of the second case study (since it used the same dataset) that is listed in Table 10 are 1.1388×10^{-2}, 8.8437×10^{-4}, 8.9605×10^{-3} and 7.7301×10^{-4} for 2.A, 2.B, 2.C and 2.D respectively. By comparing these results with the obtained using CIABC from in Table 4, it can be seen that the CIABC is better than 2.A and 2.C while it is less accurate than two other cases.

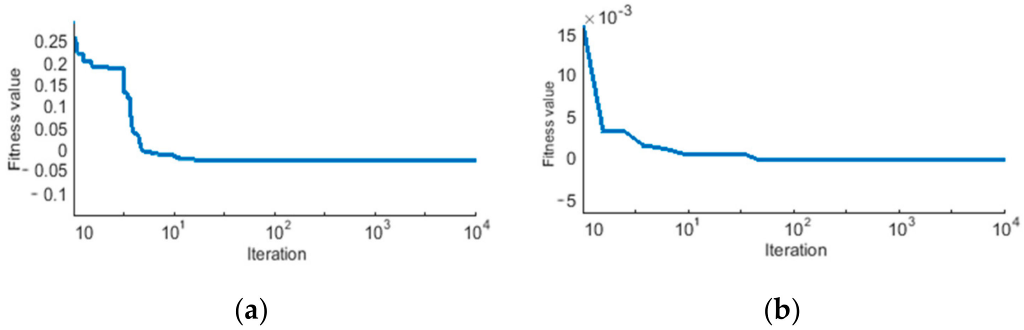


Figure 4. Convergence curve of CIABC for unknown parameter identification of (**a**) SD and (**b**) DD models.

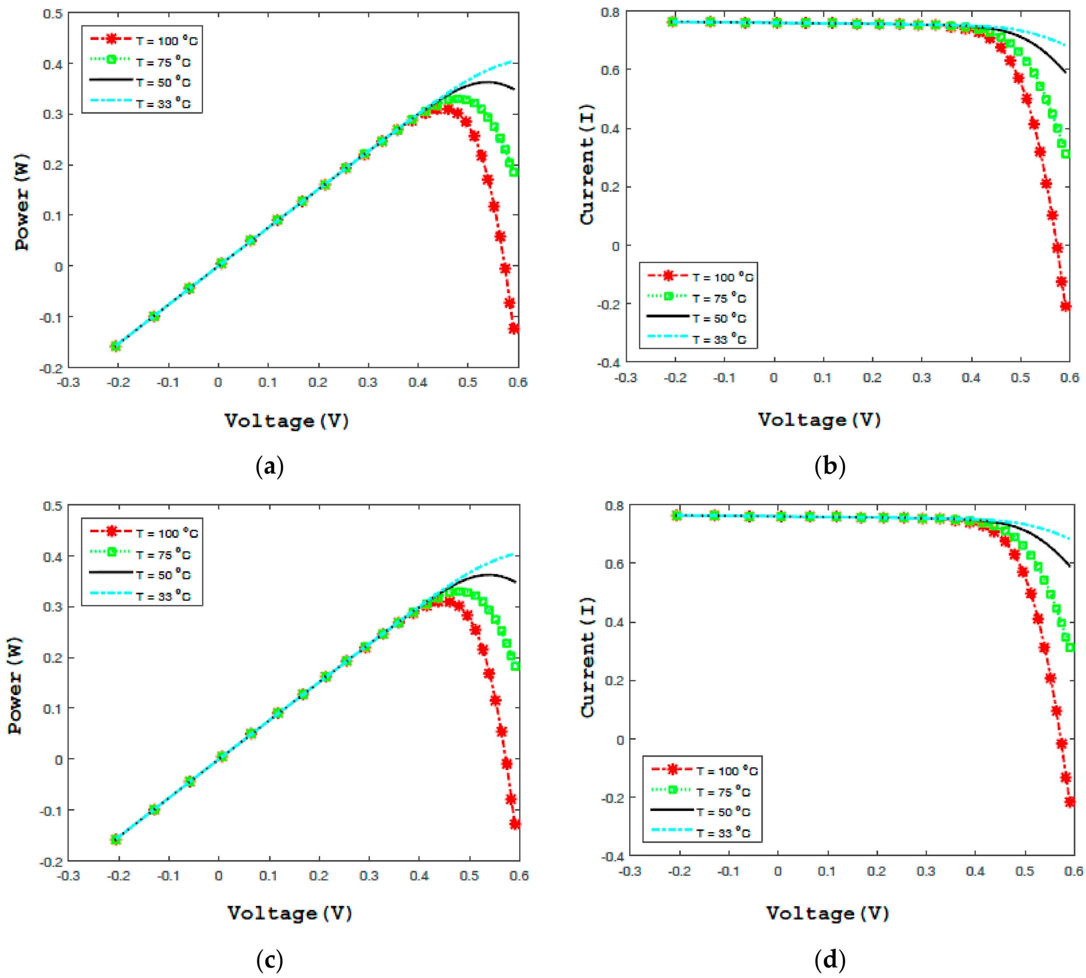


Figure 5. For the SD model: (**a**) Measured voltage vs. CABC-power at different temperatures; (**b**) Measured voltage vs. CABC computed current for different temperatures; DD model: (**c**) Measured voltage vs. CABC-power at different temperatures; (**d**) Measured voltage vs. CABC computed current for different temperatures.

Table 3. Terminal ($V_{tm} - I_{tm}$) measurements and relative error values for double and single diode models.

Experimental Data			Single Diode Model CIABC		Double Diode Model CIABC	
Data	$V_{tm}(V)$	$I_{tm}(A)$	$I_{te}(A)$	R_{err}	$I_{te}(A)$	R_{err}
1	−0.2057	0.7640	0.7641	−0.0001	0.7640	0.0000
2	−0.1291	0.7620	0.7627	−0.0007	0.7626	−0.0006
3	−0.0588	0.7605	0.7614	−0.0009	0.7613	−0.0008
4	0.0057	0.7605	0.7602	0.0003	0.7602	0.0003
5	0.0646	0.7600	0.7591	0.0009	0.7591	0.0009
6	0.1185	0.7590	0.7580	0.0010	0.7581	0.0009
7	0.1678	0.7570	0.7571	−0.0001	0.7572	−0.0002
8	0.2132	0.7570	0.7561	0.0009	0.7564	0.0006
9	0.2545	0.7555	0.7551	0.0004	0.7555	−0.0000
10	0.2924	0.7540	0.7537	0.0003	0.7547	−0.0007
11	0.3269	0.7505	0.7514	−0.0009	0.7537	−0.0032
12	0.3585	0.7465	0.7474	−0.0009	0.7526	−0.0061
13	0.3873	0.7385	0.7401	−0.0016	0.7512	−0.0127
14	0.4137	0.7280	0.7274	0.0006	0.7493	−0.0213
15	0.4373	0.7065	0.7070	−0.0005	0.7467	−0.0402
16	0.4590	0.6755	0.6753	0.0002	0.7434	−0.0679
17	0.4784	0.6320	0.6308	0.0012	0.7393	−0.1073
18	0.4960	0.5730	0.5719	0.0011	0.7343	−0.1613
19	0.5119	0.4990	0.4996	−0.0006	0.7287	−0.2297
20	0.5265	0.4130	0.4137	−0.0007	0.7225	−0.3095
21	0.5398	0.3165	0.3175	−0.0010	0.7159	−0.3994
22	0.5521	0.2120	0.2122	−0.0002	0.7090	−0.4970
23	0.5633	0.1035	0.1023	0.0012	0.7022	−0.5987
24	0.5736	−0.0100	−0.0087	−0.0013	0.6955	−0.7055
25	0.5833	−0.1230	−0.1254	0.0024	0.6886	−0.8116
26	0.5900	−0.2100	−0.2084	−0.0016	0.6839	−0.8939

Table 4. Estimated values of SD model and the corresponding RMSEusing different algorithms.

Parameter	CIABC	STLBO	GOTLBO	ABC	IGHS	ABSO	CPSO	CSO	MABC
$I_{ph}(\mathrm{A})$	0.760776	0.76078	0.76078	0.7608	0.7608	0.7608	0.7607	0.7608	0.760779
$I_{sd}(\mu\mathrm{A})$	0.32302	0.32302	0.33155	0.3251	0.3435	0.3062	0.4000	0.3230	0.321323
n	1.48102	1.48114	1.48382	1.4817	1.4874	1.4758	1.5033	1.4812	1.481385
$R_s(\Omega)$	0.036377	0.03638	0.03627	0.0364	0.0361	0.0366	0.0354	0.0364	0.036389
$R_{sh}(\Omega)$	53.71867	53.7187	54.11543	53.6433	53.2845	52.2903	59.012	53.7185	53.39999
RMSE	9.8602×10^{-4}	9.8602×10^{-4}	9.87442×10^{-4}	9.862×10^{-4}	9.9306×10^{-4}	9.9124×10^{-4}	0.0013	9.8602×10^{-4}	9.861×10^{-4}

Table 5 illustrates the values and the corresponding RMSE obtained for the DD model parameters by the CIABC and eight different algorithms. In this table, the RMSE value of the CIABC (9.8262×10^{-4}) is smaller than those obtained by standard ABC and MABC which proves that the CIABC is indeed still better than other ABC versions in both of SD and DD models. In addition, the CIABC obtains the best performance compared with all algorithms except STLBO and CSO which yielded 9.8248×10^{-4} and 9.8252×10^{-4} respectively. Furthermore, in Table 6 the results of several performance metrics are provided to analyze the accuracy of CIABC algorithm for both SD and DD models. These metrics are the mean and the standard deviation (STD) of RMSE values over 40 runs; as well as, the NRMSEMAE, NMAE, MBE and NMBE. These results prove that the CIABC algorithm is consistency and has a high efficiency to determine unknown parameters of SD and DD models.

Furthermore, the convergence performance of CIABC for SD and DD models are illustrated in Figure 4. From this figure can be observed that the CIABC, in both models, has fast convergence; whereby it achieved an optimal value before 2000 iterations. In the same context, the proposed CIABC requires less amount of time to achieve the optimal solutions, for a single run in SD it takes 1300 s and for DD 1500 s. Figure 5 shows the current vs. voltage and power vs. voltage at different five temperatures (33 °C, 50 °C, 75 °C and 100 °C) for the DD and SD models. It demonstrates that when the solutions yielded by CIABC are adopted, both solar cell models can accurately represent the characteristics of the solar cell. It also indicates that CIABC obtained an accurate approximation for I_{tm}. However, the temperatures affect the current values in the CIABC and also in the power values.

Table 5. Estimated values of DD model and the corresponding RMSE using different algorithms.

Parameter	CIABC	STLBO	GOTLBO	ABC	IGHS	ABSO	SA	CSO	MABC
$I_{sd}(\mu A)$	0.760781	0.760780	0.760752	0.7608	0.76079	0.76078	0.7623	0.76078	0.76078
$I_{sd1}(\mu A)$	0.227828	0.225660	0.800195	0.0407	0.9731	0.26713	0.4767	0.22732	0.63069
$I_{sd2}(\mu A)$	0.647650	0.036740	0.036783	0.2874	0.16791	0.38191	0.01	0.72785	0.241029
n_1	1.451623	1.450850	1.448974	1.4495	1.92126	1.46512	1.5172	1.45151	2.000005
n_2	1.988343	2	1.999973	1.4885	1.42814	1.98152	2	1.99769	1.45685
$R_s(\Omega)$	0.036728	0.752170	0.220462	0.0364	0.0369	0.03657	0.0345	0.036737	0.036712
$R_{sh}(\Omega)$	55.378261	55.49200	56.075304	53.7804	56.8368	54.6219	43.1034	55.3z813	54.75500
RMSE	9.8262×10^{-4}	9.8248×10^{-4}	9.83177×10^{-4}	9.861×10^{-4}	9.8635×10^{-4}	9.8344×10^{-4}	0.01664	9.8252 × 10−4	9.8276×10^{-4}

Table 6. The performance metrics for SD and DD models over 40 runs.

Model	Mean RMSE	STD	NRM	MAE	NMAE
Single	9.8603×10^{-4}	6.7206×10^{-9}	0.6282	8.3187×10^{-4}	−0.0056
Double	9.82811×10^{-4}	1.05485×10^{-7}	0.5214	0.0022	−0.0129

4.3. Sensitivity Analysis

In this section the performance of Tent map is explained against different seven chaotic maps such as Chebyshev, Circle, Gauss/mouse, Logistic, Piecewise, Sine and Sinusoidal [49]. Table 7 shows the mean and standard deviation (STD) of the RMSE values obtained using CIABC based on eight chaotic maps. From this table, is possible to conclude that Tent map has the lower mean RMSE (also the STD) compared with other maps. Also, the circle map and Piecewise map is in the second rank for dimension 5 and dimension 7, respectively.

Table 7. Comparison between Tent map and seven chaotic maps for both dimensions.

Chaotic Map	SD Model		DD Model	
	Average	**STD**	**Average**	**STD**
Chebyshev	0.000999928	1.86974×10^{-5}	0.000982856	1.70529×10^{-7}
Circle	0.000989398	4.86071×10^{-6}	0.000982848	1.68879×10^{-7}
Gauss/mouse	0.001347782	0.000543292	0.000982868	7.85493×10^{-8}
Logistic	0.000997560	2.20587×10^{-5}	0.000982892	1.41315×10^{-7}
Piecewise	0.000989960	2.37263×10^{-6}	0.000982820	8.03119×10^{-8}
Sine	0.000997022	9.61685×10^{-6}	0.000982772	5.71839×10^{-8}
Sinusoidal	0.000990722	5.04149×10^{-6}	0.000982920	6.63325×10^{-8}
Tent	0.000986036	2.30217×10^{-8}	0.000982702	5.31037×10^{-8}

4.4. CIABC on PV Panels

In this experimental section, another two real datasets are used to further investigate the performance of the proposed CIABC approach, where the CIABC is used to identify the parameters of PV panels that namely, a polycrystalline and monocrystalline one [35]. In this experiment, the parameters of SC are modified as $R_{sh} = R_p$ and $I_{sh} = I_p$ in order to differentiate them from the single cell experiments.

In general, the PV panel contains M solar cells which are interconnected in series, as well as the current of this panel (I) equals to I_M. Assuming that the same level of photon flux is received by the M cells, then the same current and voltage are generated from these cells [35]. The most of the related literature the SD model is used for each element of the PV panel. According to this fact, to calculate the I of the entire PV panel, the I-V relation introduced in Equation (2) can be written as:

$$I_{te} = I_{ph} - I_{sd}\left[\exp\left(\frac{(V_t + M \cdot R_s \cdot I_{te})}{n \cdot k \cdot T \cdot M/q}\right) - 1\right] - \frac{V_t + M \cdot R_s \cdot I_{te}}{M \cdot R_{sh}} \tag{13}$$

Based on the values of the current (I_{SC}) (when the cells are short-circuited) and the voltage (V_{oc}) (when the cells are open-circuited), the I-V data is computed from each panel. The results of the proposed CIABC method are compared against two other methods called ABC and the results given in [35].

4.4.1. The Polycrystalline PV Panel Description

For the experiments a commercial model STM6-120/36 solar panel manufactured by Schutten Solar (Nanjing, Jiangsu, China) is considered which consists of 36 polycrystalline cells (of size 156 mm × 156 mm) in series form. For this solar panel different measures are taken that represent the real data. This panel is formed by 22 points at a temperature of 55 °C; $I_{SC} = 7.48\ A$, $V_{OC} = 19.21\ V$, $V_M = 14.93\ V$ and $I_M = 6.83\ A$. The entire dataset is provided in the second and third columns of Table 8.

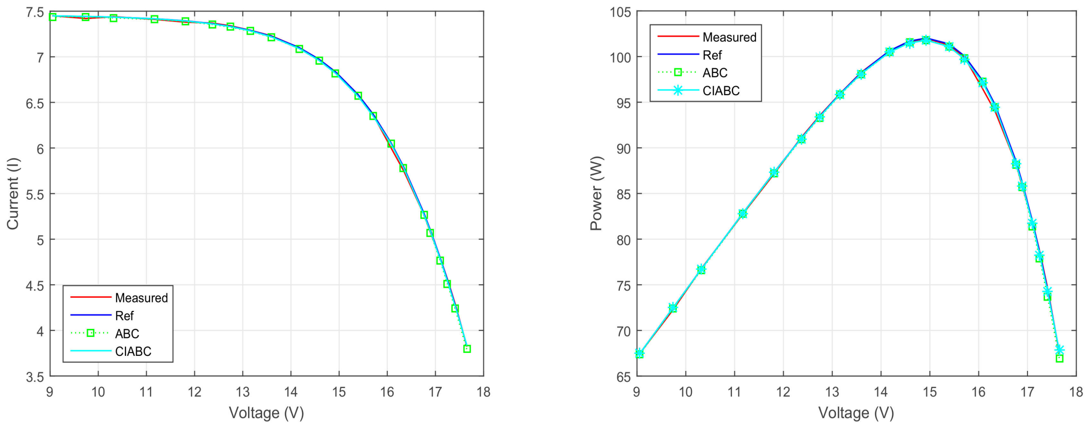
Table 8. The calculated current and its Absolute Error (**| Error |**) results.

Data	Measured		ABC		CIABC		Reference [35]	
	V (V)	I (A)	I (A)	| Error |	I(A)	| Error |	I (A)	| Error |
1	17.65	3.83	3.7947	0.0353	3.8415	0.0115	3.836	0.006
2	17.41	4.29	4.2348	0.0552	4.2663	0.0237	4.28	0.01
3	17.25	4.56	4.5136	0.0464	4.5371	0.0229	4.5541	0.0059
4	17.1	4.79	4.7618	0.0282	4.7791	0.0109	4.794	0.004
5	16.9	5.07	5.0692	0.0008	5.0800	0.0100	5.093	0.023
6	16.76	5.27	5.2618	0.0082	5.2689	0.0011	5.287	0.017
7	16.34	5.75	5.7793	0.0293	5.7794	0.0294	5.794	0.044
8	16.08	6	6.0452	0.0452	6.0432	0.0432	6.055	0.055
9	15.71	6.36	6.3511	0.0089	6.3474	0.0126	6.3691	0.0091
10	15.39	6.58	6.5721	0.0079	6.5686	0.0114	6.5881	0.0081
11	14.93	6.83	6.8192	0.0108	6.8170	0.0130	6.8334	0.0034
12	14.58	6.97	6.9622	0.0078	6.9613	0.0087	6.9748	0.0048
13	14.17	7.1	7.0900	0.0100	7.0906	0.0094	7.1014	0.0014
14	13.59	7.23	7.2163	0.0137	7.2190	0.0110	7.2265	0.0035
15	13.16	7.29	7.2803	0.0097	7.2843	0.0057	7.2898	0.0002
16	12.74	7.34	7.3255	0.0145	7.3304	0.0096	7.3345	0.0055
17	12.36	7.37	7.3556	0.0144	7.3613	0.0087	7.3643	0.0057
18	11.81	7.38	7.3865	0.0065	7.3930	0.0130	7.3947	0.0147
19	11.17	7.41	7.4094	0.0006	7.4165	0.0065	7.4174	0.0074
20	10.32	7.44	7.4273	0.0127	7.4349	0.0051	7.4352	0.0048
21	9.74	7.42	7.4349	0.0149	7.4427	0.0227	7.4426	0.0226
22	9.06	7.45	7.4410	0.0090	7.4489	0.0011	7.4487	0.0013

On the other hand, Tables 8 and 9 illustrates the calculated current and the identified parameters of the PV panel. From these tables, it can be observed that the results of [35] are better than the ABC method. However, the proposed CIABC gives the best results. Also, we can find that the proposed method is faster than the other algorithm which takes less time to reach the stable value. In other words, the modification performed over the CIABC does not affect the computational effort of its operators. Moreover, Figure 6 shows the estimated current and power of the three methods (ABC, CIABC, and [35]) and the measured data against the voltage. From this figure, it can be seen that the curve of the proposed CIABC method is the closest curve to the curve of the measurement data.

Table 9. The results of the parameters estimation and their accuracy for a polycrystalline cell solar panel.

Parameter	ABC	CIABC	Reference [35]
$R_s(m)$	0.00491	0.0051	4.9
R_p	9.70	9.89	9.745
$I_{sd}(\mu)$	7.476291	7.484126	7.4838
I_p	1.2	1.29	1.2
n	1.206992	1.214854	1.2072
MAE	0.0177	0.0132	0.0117
RMSE	0.019174	0.016286553	0.017879
averageTime	1370 s	1200 s	-



(**a**) (**b**)

Figure 6. The estimated (**a**) current and (**b**) power by the proposed CIABC method based on polycrystalline cells.

4.4.2. The Monocrystalline PV Panel Description

In this experiment, another solar panel model which called STM6-40/36 manufactured by Schutten Solar is used [35]. This panel contains 36 monocrystalline cells (with size 38 mm × 128 mm) configured in series. Table 10 shows the data that measured at a temperature of 51 °C, with V_M = 16.98 V, I_{SC} = 1.663 A, V_{OC} = 21.02 V, I_M = 1.50 A.

Tables 10 and 11 give the comparison results of the CIABC with the ABC and reference [35] algorithms according to the estimated current with it absolute value for error (|Error|) and the estimated parameters, respectively. From these tables, it can be observed that the CIABC has better values in terms of |Error|, MAE and RMSE. Also, the ABC is better than the results of reference [35]. Also, regarding the time consumption, the CIABC need a smaller amount of time to estimate the parameters than the other algorithms.

The estimated current and the estimated power, at a temperature of 51 °C, are plotted against the voltage as in Figure 7. From this figure, it can be observed that the ABC and CIABC give better results than reference [35].

Table 10. The calculated current and the (**|Error|**) for monocrystalline PV panels.

Data	Measured		ABC		CIABC		Reference [35]	
	V (V)	I (A)	I (A)	|Error|	I (A)	|Error|	I (A)	|Error|
1	0.118	1.663	1.664	0.0007	1.664	0.0005	1.6627	0.0003
2	2.237	1.661	1.660	0.0011	1.660	0.0012	1.659	0.0020
3	5.434	1.653	1.654	0.0010	1.654	0.0010	1.6531	0.0001
4	7.26	1.65	1.650	0.0005	1.651	0.0006	1.6497	0.0003
5	9.68	1.645	1.645	0.0002	1.645	0.0004	1.6445	0.0005
6	11.59	1.64	1.639	0.0011	1.639	0.0008	1.6383	0.0017
7	12.6	1.636	1.633	0.0026	1.634	0.0024	1.633	0.0030
8	13.37	1.629	1.627	0.0019	1.627	0.0018	1.6267	0.0023
9	14.09	1.619	1.618	0.0008	1.618	0.0007	1.6171	0.0019
10	14.88	1.597	1.603	0.0061	1.603	0.0061	1.603	0.0060
11	15.59	1.581	1.582	0.0007	1.582	0.0006	1.582	0.0010
12	16.4	1.542	1.543	0.0005	1.542	0.0004	1.5432	0.0012
13	16.71	1.524	1.521	0.0026	1.521	0.0027	1.5225	0.0015
14	16.98	1.5	1.499	0.0006	1.499	0.0007	1.5006	0.0006
15	17.13	1.485	1.485	0.0005	1.485	0.0003	1.4867	0.0017
16	17.32	1.465	1.466	0.0008	1.466	0.0007	1.4674	0.0024
17	17.91	1.388	1.388	0.0004	1.388	0.0004	1.3897	0.0017
18	19.08	1.118	1.118	0.0001	1.118	0.0002	1.1208	0.0028

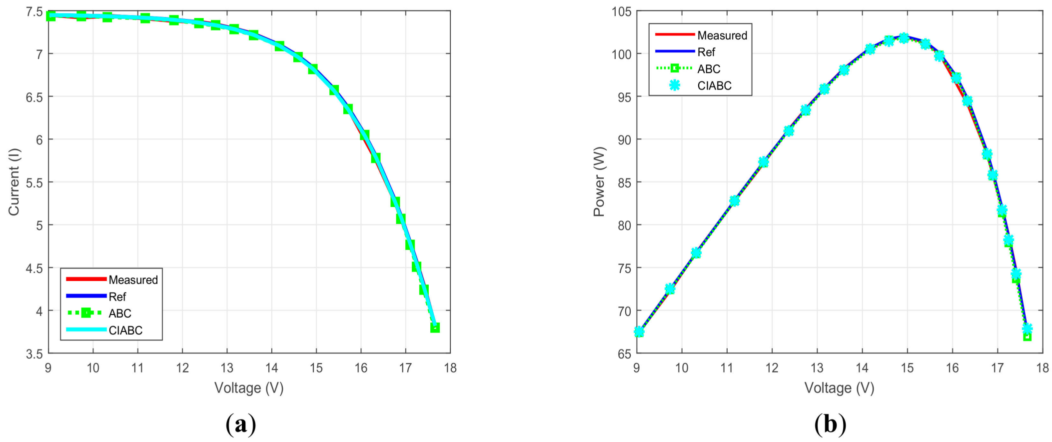


Figure 7. The Estimated (a) Current and (b) Power by the Proposed CIABC method based on polycrystalline.

Table 11. The results of the parameters estimation and their accuracy for a monocrystalline solar panel

Parameter	ABC	CIABC	Reference [35]
R_s(m)	4.99	4.40	4.879
R_p	15.206	15.617	15.419
I_{sd}(μA)	1.6644	1.6760	1.4142
I_p	1.50	1.6642	1.6635
n	1.4866	1.4976	1.4986
MAE	0.001229	0.001206	0.001722
RMSE	0.0018379	0.001819	0.002181
Average Time	1300s	1240s	-

5. Conclusions

This paper has proposed a new method to solve the photovoltaic cell design problem by estimating the parameters of solar cells. The proposed algorithm is based on improving the Artificial Bee Colony algorithm in two stages. Firstly, the chaotic Tent map is combined with the "onlooker bee" phase instead of the random number which is used to start this phase. This improvement makes ABC inherit the strength of chaos such as the ergodic and non-repetition properties and saves the computational time that may be needed if the random value is less than the probability for a long time. Secondly, instead of generating a random population using the scout bees if no improvement is made, the best solution obtained is used; that makes the ABC searche around the best value rather than random solutions.

The proposed algorithm is tested by using a dataset of experimental values. The CIABC results have been compared with eight different algorithms used in the state of the art; these algorithms are STLBO, GOTLBO, ABC, IGHS, ABSO, SA, CSO and MABC. The performance of the proposed algorithm has been evaluated based on its robustness and accuracy. The results show that the performance of the CIABC algorithm is close to the results of STLBO and CSO for SD and DD models, whereas, it is better than all other algorithms. Moreover, the effects of chaotic Tent map are compared with other different chaotic maps and its performance is better than other maps in both the SD and DD models.

In addition, the proposed CIABC was used to identify the parameters of PV panels based on polycrystalline material, and it gives results better than two other methods. In future work, we will implement other interesting models for solar cells. Also, some other modifications will be introduced, extending the use of this optimization algorithm for renewable energy problems.

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Author Contributions: All authors contributed equally to this work. Diego Oliva proposed the idea of solving the problem of parameter estimation of solar cells. He developed the code of the objective function and searched for the datasets. He also wrote Section 2 and part of the Introduction. Ahmed A. Ewees proposed the modification in the onlooker phase of the ABC as well as combined the chaotic theory with ABC programmatically. He developed part of the experiments and described the proposed approach and part of the implementation. Mohamed Abd El Aziz, proposed the use of chaos in the ABC, he also helped to implement the objective function for using the dataset number 2. He collaborated in writing the experiments and part of the implementations. Aboul Ella Hassanien, contributed to validate the experiments and wrote a part of the introduction. He also collaborated in checking the technical information of the paper. Marco Peréz Cisneros, assisted with the reviewer comments, especially those related to the physical meaning of the parameters. He collaborated in the introduction modification, validating the results and checking the English style.

Conflicts of Interest: The authors declare no conflict of interest.

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