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Parameter identification of solar cells using artificial bee colony optimization

Diego Oliva [a], Erik Cuevas [b,*], Gonzalo Pajares [a]

[a] Dpt. Ingeniería del Software e Inteligencia Artificial, Facultad Informática, Universidad Complutense, 28040 Madrid, Spain
[b] Departamento de Electrónica, Universidad de Guadalajara, CUCEI, Av. Revolución 1500, Guadalajara, Jal, Mexico

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ABSTRACT

In order to improve the performance of solar energy systems, accurate modeling of current vs. voltage (*I*−*V*) characteristics of solar cells has attracted the attention of various researches. The main drawback in accurate modeling is the lack of information about the precise parameter values which indeed characterize the solar cell. Since such parameters cannot be extracted from the datasheet specifications, an optimization technique is necessary to adjust experimental data to the solar cell model. Considering the *I*−*V* characteristics of solar cells, the optimization task involves the solution of complex non-linear and multi-modal objective functions. Several optimization approaches have been proposed to identify the parameters of solar cells. However, most of them obtain sub-optimal solutions due to their premature convergence and their difficulty to overcome local minima in multi-modal problems. This paper proposes the use of the ABC (artificial bee colony) algorithm to accurately identify the solar cells' parameters. The ABC algorithm is an evolutionary method inspired by the intelligent foraging behavior of honey bees. In comparison with other evolutionary algorithms, ABC exhibits a better search capacity to face multi-modal objective functions. In order to illustrate the proficiency of the proposed approach, it is compared to other well-known optimization methods. Experimental results demonstrate the high performance of the proposed method in terms of robustness and accuracy.

1. Introduction

The increase in the cost of fossil fuels and their probable depletion, air pollution, global warming phenomenon, and severe environmental laws have resulted in renewable energy sources gaining the attention of many nations to produce electricity. Solar energy is one of the most promising renewable sources that is currently being used worldwide to contribute to meeting rising demands for electric power. It has been reported that solar PV (photovoltaic) is the fastest growing power-generation technology in the world, with an annual average increase of 50% between 2004 and 2011 [1]. PV is not only capable of directly converting solar energy to electricity but also is an emission-free distributed generation unit that would supply power at the load site.

Solar cell accurate modeling has received significant attention in recent years [2–6]. The modeling of PV cells consists in two steps: the mathematical model formulation and the accurate estimation of their parameter values. For the mathematical model, the Current vs. Voltage (*I*−*V*) characteristics that rule the behavior of a solar cell is considered. Several approaches have been proposed in order to model such a behavior from different point of views [7–12].

In practical terms, there exist two equivalent electronic circuits that model the behavior of a solar cell. Such circuits are known as SD (single diode) and DD (double diode) models [13]. Irrespective of the model selected, it is necessary to estimate or identify all its parameters such as photo-generated current, diode saturation current, series resistance, and diode ideality factor. Depending on the model (SD or DD), two different sets of parameters must be identified: five for the SD and seven for the DD. The main problem is to identify the optimal parameter values which, when applied to the selected model, produce the best possible approximation to the experimental data obtained by the true solar cell [13].

The methods employed to solve the problem of PV parameter identification can be divided in two groups: deterministic and heuristic. Some examples of deterministic methods involve methods such as least squares [14], Lambert W-functions [15], and the iterative curve fitting [16]. Deterministic techniques impose several model restrictions such as convexity and differentiability in

* Corresponding author. Tel.: +52 33 1378 5900x7715.
E-mail addresses: doliva@ucm.es (D. Oliva), erik.cuevas@cucei.udg.mx, cuevas@inf.fu-berlin.de (E. Cuevas), pajares@ucm.es (G. Pajares).

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order to be correctly applied [24]. Therefore, they are very sensitive to the initial solution, and most often lead to local optima. As an alternative to deterministic-based techniques, the problem of PV parameter identification has also been handled through heuristic methods. In general, they have demonstrated that they deliver better results than those based on deterministic approaches considering accuracy and robustness [12,13,17–27]. In the literature, several heuristic approaches have been proposed in order to solve the problem of solar cell parameter identification. Such methods include GA (genetic algorithms) [17,18,24], PSO (particle swarm optimization) [12,19], SA (simulated annealing) [20], HS (harmony search) [13], BFA (Bacterial Foraging Algorithm) [21], TBLO (teaching-learning based optimization) [23] and BMO (bird matting optimization) [27]. Although heuristic methods present a higher probability of obtaining a global solution in comparison with deterministic ones, they have important limits [18]. In case of GA and PSO, they maintain a trend that concentrates toward local optima, since their elitist mechanism forces premature convergence [28,29]. Such a behavior becomes worse when the optimization algorithm faces multi-modal functions [30,31]. On the other hand, due to the fact that SA and HS are single-searcher algorithms, their performance is sensitive to the starting point of the search, having a lower probability to localize the global minimum in multi-modal problems than population algorithms such as GA and PSO [32,33]. Therefore, GA, PSO, SA, and HS present a bad performance when they are applied to multi-modal and noisy objective functions.

In order to identify the PV parameters as an optimization problem, it is necessary to define an objective function. Such an objective function is built by using experimental data extracted from I–V measurements of the solar cell. Since experimental data contain noise as a consequence of an imperfect data collection process, the objective function obtained presents high multi-modal and noisy characteristics [34,35]. Under these circumstances, most of the heuristic approaches present a bad performance [36].

In this paper, an alternative approach using the ABC (artificial bee colony) [37] method for determining the parameters of a solar cell is presented. The ABC is an evolutionary algorithm inspired by the intelligent behavior of honey bees. The performance of the ABC has been compared to other evolutionary methods such as GA and PSO [38,39]. The results have shown that ABC produces optimal solutions when it faces multi-modal and noisy optimization problems. Such characteristics have motivated the use of ABC to solve different types of engineering problems within several fields [40–45]. One relevant advantage of the ABC method is that it does not follow a local strategy for computing new solutions. Instead, the ABC method uses a set of operators to build solutions from random operations avoiding falling into local optimal.

ABC consists of three essential components: food source positions, nectar amount, and several honey-bee classes. Each food source position represents a feasible solution for the problem under consideration. The nectar amount for a food source represents the quality of such a solution (represented by a fitness value). Each bee class symbolizes one particular operation for generating new candidate food source positions (i.e., candidate solutions). The ABC algorithm starts by producing a randomly distributed initial population (food source locations). After initialization, an objective function evaluates whether such candidates represent an acceptable solution (nectar amount) or not. Guided by the values of such an objective function, candidate solutions are evolved through different ABC operations (honey-bee types) until a termination criterion is met.

This paper presents the use of ABC to accurately estimate the parameter of solar cells. In the approach, the estimation process is considered as an optimization problem. The proposed approach encodes the parameters of the solar cell as a candidate solution. An objective function evaluates the matching quality between a candidate solution and the experimental data. Guided by the values of this objective function, the set of encoded candidate solutions is evolved by using the operators defined by ABC so that the parameters that produce the best possible approximation to the I–V measurements obtained by the true solar cell can be found. In order to illustrate the proficiency of the proposed approach, it is compared to other well-known optimization methods. Experimental evidence shows that ABC exhibits no sensitivity to noisy conditions and high performance in terms of robustness and accuracy.

The remainder of the paper is organized as follows. In Section 2, the problem of solar cell identification is defined. Section 3 describes the ABC algorithm. In Section 4, the problem of solar cell identification is translated to an optimization task. Section 5 presents the experimental results and comparisons. In Section 6, the conclusions are stated, finally an appendix with the ABC algorithm is presented.

2. Solar cell modeling

The modeling of PV cells consists in two steps: the mathematical model formulation and the accurate estimation of their parameter values. In general, there exist two models: SD (single diode) and DD (double diode) [13]. In this section these models are described and their objective functions are formulated.

2.1. Double diode model (DD)

Solar cells are ideally modeled considering a photo-generated (I_{ph}) current source which is shunted with a rectifying diode. However, in practical terms, the current source I_{ph} is shunted by another diode which models the space charge recombination current and other non-idealities. The model of solar cells also includes a resistor connected in series with the cell shunt elements [13]. Fig. 1 shows the equivalent circuit for the DD model.

According to Fig. 1, the cell terminal current is computed as follows:

$$I_t = I_{ph} - I_{d1} - I_{d2} - I_{sh}, \tag{1}$$

where I_t is the terminal current, I_{ph} the photo-generated current,I_{d1},I_{d2} is the first and second diode currents whereas I_{sh} is the shunt resistor current. In order to appropriately model the solar cell, there is used the Shockley diode equation; hence, Eq. (1) is rewritten as it is shown in Eq. (2).

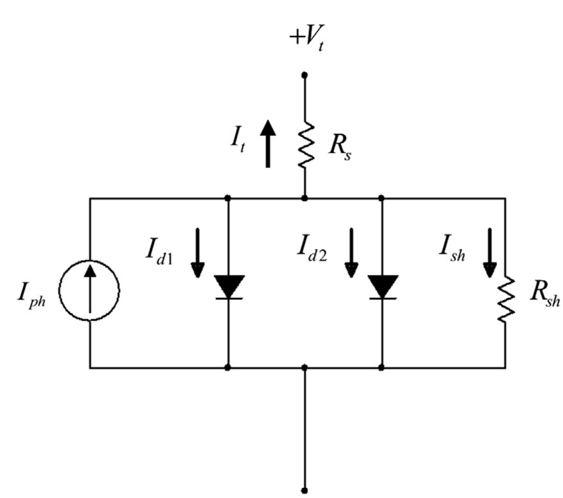

Fig. 1. Double diode model of solar cells.

$$I_t = I_{ph} - I_{sd1}\left[\exp\left(\frac{q(V_t + R_s \cdot I_t)}{n_1 \cdot k \cdot T}\right) - 1\right] - I_{sd2}\left[\exp\left(\frac{q(V_t + R_s \cdot I_t)}{n_2 \cdot k \cdot T}\right) - 1\right] - \frac{V_t + R_s \cdot I_t}{R_{sh}}, \quad (2)$$

where I_{sd1} and I_{sd2} are the diffusion and saturation current, respectively. V_t is the terminal voltage whereas the series and shunt resistances are represented by R_s and R_{sh} respectively. According to the Shockley diode equation, $q = 1.602 \times 10^{-19}$ (coulombs) is the magnitude of charge on an electron, $k = 1.380 \times 10^{-23}$ (J/K) is the Boltzmann constant, n_1 and n_2 are the diffusion and recombination diode ideality factors, respectively. Finally, T is the cell temperature (K). Therefore, Eq. (2) has seven unknown parameters (R_s, R_{sh}, I_{ph}, I_{sd1}, I_{sd2}, n_1, and n_2). An accurate identification of such parameters allows projecting the optimal performance of a solar cell, for that reason the estimation process is an important task.

2.2. Single diode model (SD)

In a solar cell, the diffusion (I_{sd1}) and saturation (I_{sd2}) currents are different and independent. In the SD model, both currents are combined by using a non-physical ideality factor n [13,17,20]. This model, shown in Fig. 2, is widely used for modeling solar cells due to its simplicity. Different to the DD, the SD model has only five parameters to be identified.

Under the SD model, Eq. (2) is reduced to the following equation:

$$I_t = I_{ph} - I_{sd}\left[\exp\left(\frac{q(V_t + R_s \cdot I_t)}{n \cdot k \cdot T}\right) - 1\right] - \frac{V_t + R_s \cdot I_t}{R_{sh}} \quad (3)$$

Consequently, the parameters to be identified are R_s, R_{sh}, I_{ph}, I_{sd}, and n. In Table 1 are presented the range values for each parameter, notices that such ranges are used for both SD and DD.

2.3. Parameter identification of a solar cell as an optimization problem

The problem of modeling solar cells consists in accurately identifying the parameters of Eqs (2) and (3). In the proposed approach, the problem of parameter identification is considered as an optimization problem where it is sought the parameter set that produces the best approximation to the I–V measurements obtained by the true solar cell. Therefore, it is necessary to define an objective function that evaluates the matching quality between a candidate parameter set and the experimental data. In this paper, the problem of solar cell modeling is approached considering the SD (Eq. (3)) as well as the DD (Eq. (2)) model. Thus, Eqs (2) and (3) must be rewritten in order to reflex the difference with regard to experimental data. Thereby, for the DD model, the error function is defined as follows:

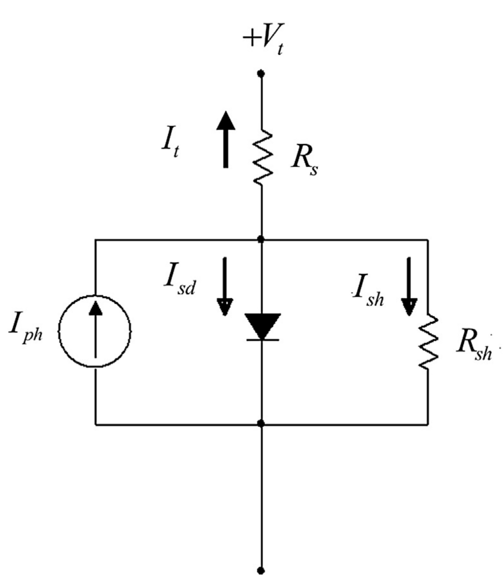

Fig. 2. Single diode model of solar cells.

Table 1
Upper and lower range of the solar cell parameters.

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

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

whereas for the SD model such function is formulated as Eq. (5).

$$f_{SD}(V_t, I_t, \mathbf{x}) = I_t - I_{ph} + I_{sd}\left[\exp\left(\frac{q(V_t + R_s \cdot I_t)}{n \cdot k \cdot T}\right) - 1\right] + \frac{V_t + R_s \cdot I_t}{R_{sh}} \quad (5)$$

In both functions (f_{DD} and f_{SD}), the values of V_t and I_t are experimentally collected from the solar cell. $\mathbf{x}$ is a vector that contains the model parameters, where $\mathbf{x} = [R_s, R_{sh}, I_{ph}, I_{sd1}, I_{sd2}, n_1, n_2]$ is the model parameters for DD and $\mathbf{x} = [R_s, R_{sh}, I_{ph}, I_{sd}, n]$ for SD. Eqs (4) and (5) allow to evaluate the model quality of the candidate parameter set $\mathbf{x}$, assessing the difference between the real value I_t and the computed by the identified model. Therefore, the parameter estimation is a process that minimizes the difference between the measured data and the calculated current by adjusting the model parameters$\mathbf{x}$. Considering that the number of experimental data is N, the objective function can be formulated by the RMSE (root mean square error) as:

$$\mathrm{RMSE}(\mathbf{x}) = \sqrt{\frac{1}{N}\sum_{c=1}^{N}\left(f_M^c(V_t^c, I_t^c, \mathbf{x})\right)^2}, \quad (6)$$

where M is the model type DD or SD.

As it is formulated in Eq. (6), the objective function is built by using experimental data, extracted from I–V measurements of the solar cell. The experimental data could be also obtained from the solar cell datasheet. Since experimental data contain noise as a consequence of an imperfect data collection process, the objective function obtained presents high multi-modal and noisy characteristics [34,35]. Under these circumstances, most of the heuristic approaches present a bad performance [36].

3. Artificial bee colony algorithm

In this paper, an alternative approach that uses the ABC (artificial bee colony) [37] method for determining the parameters of a

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solar cell is introduced. The ABC is an evolutionary algorithm inspired by the intelligent behavior of honey-bees. The ABC algorithm has demonstrated to produce optimal solutions when it faces multi-modal and noisy optimization problems.

The ABC algorithm assumes the existence of a set of operations that may resemble some features of the honeybee behavior. For instance, each solution within the search space includes a parameter set representing food source locations. The "fitness value" refers to the food source quality that is linked to the food's location. The process mimics the bee's search for valuable food sources yielding an analogous process for finding the optimal solution.

3.1. Biological profile

The minimal model for a honeybee colony consists of three classes: employed bees, onlooker bees and scout bees. The employed bees will be responsible for investigating the food sources and sharing the information with recruit onlooker bees. They, in turn, will make a decision on choosing food sources by considering such information. The food source having a higher quality will have a larger chance to be selected by onlooker bees than those showing a lower quality. An employed bee, whose food source is rejected as low quality by employed and onlooker bees, will change to a scout bee to randomly search for new food sources. Therefore, the exploitation is driven by employed and onlooker bees while the exploration is maintained by scout bees.

3.2. Description of the ABC algorithm

Similar to other swarm-based approaches, the ABC algorithm is an iterative process. It starts with a population of randomly generated solutions or food sources. The following three operations are applied until a termination criterion is met [39]:

1. Send the employed bees.
2. Select the food sources using the onlooker bees.
3. Determine the scout bees.

3.2.1. Initializing the population

The first step of the algorithm is to initialize the population of N_{p} food sources. Every food source is a d-dimensional vector containing the parameters values to be optimized. Such values are randomly and uniformly distributed between a bounded space.

$$\begin{aligned} &x_{i,j} = l_j + \mathrm{rand}(0,1)\cdot(u_j - l_j),\\ &j = 1,2,\ldots,d;\quad i = 1,2,\ldots,N_{\mathrm{p}}, \end{aligned} \tag{7}$$

where $x_{i,j}$ is a food source, the index i corresponds to i-th food source and j is the j-th dimension of the search space. l_j and u_j are the lower and the upper bound in each dimension. The indexes i and j will be used under the same definition in the remainder section.

3.2.2. Send employed bees

The employed bees are used to generate new solutions; the number of this kind of bees is equal to the number of food sources. According with the literature [37,38] the entire population is divided in two ($N_{\mathrm{p}}/2$), one part corresponds to the employed bees and the rest to the onlooker bees. This division operates as part of the search strategy, for that reason, it needs to be applied for all problems where ABC is employed as optimization tool.

$$\begin{aligned} &B_{i,j} = x_{i,j} + \phi_{i,j}\left(x_{i,j} - x_{k,j}\right),\quad \forall\ i \neq k\\ &k \in \mathrm{rand}\{1, N_{\mathrm{p}}\},\quad j \in \{1,2,\ldots,d\} \end{aligned} \tag{8}$$

The parameter $\phi_{j,i}$ is a random value selected between $[-1,1]$, i is an index that corresponds to the i-th food source and j is the dimension problem index, then to generate the new source food using the employed bee operator, in a randomly way is selected a k food source in the j dimension. If a parameter of an employed bee food source$B_{i,j}$ exceeds the boundaries, it should be adjusted in order to fit the appropriate range. After this process, it is calculated the fitness value associated with each solution. The fitness value is used to evaluate the quality of a food source. For a minimization problem it can be obtained using the following expression:

$$fit_i = \begin{cases} \dfrac{1}{1+J_i} & \text{if}\ \ J_i \geq 0 \\ 1+\mathrm{abs}(J_i) & \text{if}\ \ J_i < 0 \end{cases} \tag{9}$$

where J_i is the objective function value with regard to the candidate solution $\mathbf{x}_i$. In our context, J_i represents the RMSE (Eq. (6)) value associated to a candidate model $\mathbf{x}_i$. The next process consist in apply a greedy selection between the values of the employed bee food sources contained in $\mathbf{B}_i$ and the initial food sources vector $\mathbf{x}_i$, that means: if the nectaramount (fitness value) of $\mathbf{B}_i$ is better, then the solution $\mathbf{x}_i$ is replaced by $\mathbf{B}_i$ otherwise, $\mathbf{x}_i$ is preserved.

3.2.3. Select the food sources by the onlooker bees

In order to describe the onlooker phase, first it is necessary to explain that the number of onlooker bees corresponds to the food source number. In this way the food sources are modified several times depending on the fitness value (Eq. (9)). For a food source could be selected, it is necessary to obtain a probability factor that is computed based on the fitness.

$$\mathrm{Prob}_i = \frac{\mathrm{fit}_i}{\sum_{i=1}^{N_p}\mathrm{fit}_i} \tag{10}$$

Here, fit_i corresponds to the fitness value of the i-th food source and is related to the objective function of the food source$i$. If the fitness of a food source increases, then the probability of be selected by an onlooker is bigger. When a food source is selected a new value is obtained using Eq. (2), its fitness is computed and the greedy process is applied to modify (or not) its position.

3.2.4. Determine scout bees

The final step is the scout bee process. Here the bees are applied if a food source i cannot be improved through a predetermined trial "limit" number, then the food source is considered to be abandoned and instead to be modified by and onlooker bee, is modified by a scout bee using Eq. (7). The predefined "*limit*" is a counter assigned to each food source and is incremented when the fitness is not improved.

4. Parameter identification of solar cells using ABC

4.1. Problem statement

The proposed approach encodes the parameters of the solar cell as a candidate solution. The representation of such a candidate solution (food source) depends on the model type: DD or SD. Therefore, each food source uses seven elements for the DD formulation and five for the SD model, as decision variables within the optimization algorithm. Thus, the estimation task is faced as an optimization problem which can be stated as follows:

$$
\begin{array}{lll}
\text{minimize :} & RMSE(\mathbf{X}), \quad \mathbf{X} = \left[\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_{N_\text{p}}\right], & \mathbf{x}_i = \left[\mathbf{x}_{i,1}, \mathbf{x}_{i,2}, \ldots, \mathbf{x}_{i,d}\right] \quad d \in [5, 7], \\
\text{subject to :} & \begin{array}{c} d = 5\ (\text{SD}) \\ 0 \le x_{i,1}(R_\text{s}) \le 0.5 \\ 0 \le x_{i,2}(R_\text{sh}) \le 100 \\ 0 \le x_{i,3}\left(I_\text{ph}\right) \le 1 \\ 0 \le x_{i,4}(I_\text{sd}) \le 1 \\ 1 \le x_{i,5}(n) \le 2 \end{array} & \begin{array}{c} d = 5\ (\text{SD}) \\ 0 \le x_{i,1}(R_\text{s}) \le 0.5 \\ 0 \le x_{i,2}(R_\text{sh}) \le 100 \\ 0 \le x_{i,3}\left(I_\text{ph}\right) \le 1 \\ 0 \le x_{i,4}(I_\text{sd1}) \le 1 \\ 0 \le x_{i,5}(I_\text{sd2}) \le 1 \\ 1 \le x_{i,6}(n_1) \le 2 \\ 1 \le x_{i,7}(n_2) \le 2 \end{array}
\end{array}
\tag{11}
$$

where N_p and d are the population size and the number of dimensions, respectively.

4.2. Computational approach

The proposed algorithm has been implemented considering the two different solar cell models (SD and DD) whereas its efficiency is evaluated using de RMSE criterion. As optimization technique, the ABC method is used to solve the problem of parameter identification defined by Eq. (11). The computational procedure of the proposed approach can be summarized into the Algorithm 2.

Algorithm 2. *Computational approach.*

1:	Read the N experimental data values of V_t and I_t. Then, Store them in the vector $\mathbf{ED} = \left[ED_1, ED_2, \ldots ED_N\right]$, $ED_i = \left[V_t^i, I_t^i\right]$.
2:	Initialize the ABC parameters: $c_{\max}$ (maximum iteration number), $limit$ (limit to declare an abandoned solution), d (number of dimensions) and N_p (population size).
3:	Initialize the population $\mathbf{X}$ of N_p random candidate solutions with d dimensions depending on the solar cell model (d=5 for SD and d=7 for DD).
4:	Evaluate the initial population with regard to the objective function
5:	Set cycle to 1
6:	**repeat**

7:	**for** each employed bee
	{
	Produce new solution v_i by using Eq. (8)
	Calculate the value fit_i (Eq. (9))
	Apply greedy selection process
	}

8:	Calculate the probability values Prob_i for the produced solutions by Eq. (10)

9:	**for** each onlooker bee
	{
	Select a solution i depending on Prob_i
	Produce new solution v_i
	Calculate the value fit_i
	Apply greedy selection process
	}

10:	**if** (a candidate solution does not change in more than $limit$ iterations) **then** replace it with a new random solution produced by a scout using Eq. (7)
11:	Memorize the best solution so far
12:	cycle = cycle + 1
13:	**until** cycle = $c_{\max}$

5. Experimental results

In order to prove the performance of the proposed approach, the algorithm has been tested using a commercial silicon solar cell (from the R.T.C. Company of France) under the STC (standard test conditions), with a diameter of 57 mm. During the data collection process, it is considered that the solar cell operates under the following operating conditions: 1 sun (1000W/m^2) at $T = 33°\text{C}$; however, in order to test the performance of the ABC method four more temperatures have been included $T = 25°\text{C}$, $T = 50°\text{C}$, $T = 75°\text{C}$ and $T = 100°\text{C}$. In this section, two different results are presented. In the first part, the proposed approach is employed to

Table 2
Parameter setup for the ABC algorithm.

c_{max}	N_p	*limit*
10,000	150	$N_p \cdot d$

Table 3
Extracted parameter after applying ABC for SD and DD.

Parameter	Double diode	Single diode
$R_s(\Omega)$	0.0364	0.0364
$R_{sh}(\Omega)$	53.7804	53.6433
$I_{ph}(\mathrm{A})$	0.7608	0.7608
$I_{sd}(\mu\mathrm{A})$	–	0.3251
$I_{sd1}(\mu\mathrm{A})$	0.0407	–
$I_{sd2}(\mu\mathrm{A})$	0.2874	–
n_1	1.4495	–
n_2	1.4885	–
n	–	1.4817
RMSE	9.861 E-04	9.862 E-04

extract the cell parameters using the single and double diode models. Finally, in the second part, the results of the ABC-based approach are compared with other well-known similar approaches.

In order to conduct such experiments, the ABC is configured considering the parameter values shown in Table 2. Once they have been determined after intensive tests, they are kept for all experiments.

The parameter *limit* is computed as$N_p \cdot d$, where N_p and d are the population size and the number of dimensions, respectively. In the experiments, the stop criterion is the maximum iteration numberc_{max}. However, if the fitness value for the best candidate solution remains unspoiled in 10% of the total number of c_{max}, then the algorithm is stopped.

5.1. ABC experimental results

This experiment presents the results of the proposed approach when it is employed to extract the cell parameters considering the single and double diode models. To this end, 26 measurements from the physical solar cell are collected. Such samples, shown in Table 4 represent the experimental data set; this set is extensively used in the related literature. Here, it has been selected to maintain compatibility to similar works reported in the literature. The extracted parameters for the SD and DD model are shown in Table 3.

Since the SD model has five parameters and DD seven parameters, there are parameters not available for one or other model in Table 4. The inexistence of such parameters is represented by the symbol (–). In order to evaluate the accuracy of the identified model, four different performance indexes have been employed: The relative errorR_{error}, the MAE (median absolute error) and its respective NMAE (normalized MAE), the NRMSE (normalized RMSE), the MBE (median bias error) and the NMBE (normalized median bias error).

The relative error R_{error} evaluates the difference between the measured current $I_{t-measured}$ and the calculated by the respective model$I_{t-calculated}$. R_{error}, is calculated by:

$$R_{error} = \frac{I_{t-measured} - I_{t-calculated}}{I_{t-measured}} \times 100 \tag{13}$$

The MAE (median absolute error) and its respective NMAE (normalized MAE) are computed using Eqs. (14) and (15), the value of N corresponds to the number of experimental data (for this work $N = 26$).

$$\mathrm{MAE} = \sum_{i=1}^{N} \frac{|I_{t-measured} - I_{t-calculated}|}{N} \tag{14}$$

Table 4
Terminal ($V_t - I_t$) measurements and relative error values for: double and single diode models.

Data	$V_t(V)$ Measured	$I_t(A)$ Measured	$I_{t-calculated}(A)$ ABC double diode model	R_{error} ABC double diode model	Normalized $NR_{error}(\%)$ ABC double diode model	$I_{t-calculated}(A)$ ABC single diode model	R_{error} ABC single diode model	Normalized $NR_{error}(\%)$ ABC single diode model
1	−0.2057	0.7640	0.7640	−9.2908 E-05	36.8310	0.7641	−0.0001	36.6608
2	−0.1291	0.7620	0.7626	−0.0006	22.8277	0.7626	−0.0006	22.6153
3	−0.0588	0.7605	0.7613	−0.0008	18.1264	0.7613	−0.0008	17.95165
4	0.0057	0.7605	0.7601	0.0003	47.2470	0.7601	0.0003	47.4202
5	0.0646	0.7600	0.7590	0.0009	61.7485	0.7590	0.0009	62.1258
6	0.1185	0.7590	0.7580	0.0009	62.0349	0.7580	0.0009	62.4765
7	0.1678	0.7570	0.7571	−0.0001	36.5502	0.7571	−0.0001	36.8073
8	0.2132	0.7570	0.7561	0.0008	59.6029	0.7561	0.0008	60.1225
9	0.2545	0.7555	0.7550	0.0004	48.8006	0.7550	0.0004	49.2543
10	0.2924	0.7540	0.7536	0.0003	46.9719	0.7536	0.0003	47.4304
11	0.3269	0.7505	0.7513	−0.0008	17.2776	0.7513	−0.0008	17.4642
12	0.3585	0.7465	0.7473	−0.0008	18.3219	0.7473	−0.0008	18.5101
13	0.3873	0.7385	0.7401	−0.0016	0	0.7401	−0.0016	0
14	0.4137	0.7280	0.7273	0.0006	54.4874	0.7273	0.0006	54.9849
15	0.4373	0.7065	0.7069	−0.0004	28.2650	0.7069	−0.0004	28.5214
16	0.4590	0.6755	0.6752	0.0002	45.2437	0.6752	0.0002	45.6933
17	0.4784	0.6320	0.6307	0.0012	70.0782	0.6307	0.0012	70.8228
18	0.4960	0.5730	0.5718	0.0011	65.8199	0.5718	0.0011	66.6002
19	0.5119	0.4990	0.4995	−0.0005	24.8089	0.4995	−0.0005	25.2670
20	0.5265	0.4130	0.4136	−0.0006	23.4270	0.4136	−0.0006	23.8922
21	0.5398	0.3165	0.3175	−0.0010	14.2999	0.3175	−0.0010	14.6298
22	0.5521	0.2120	0.2121	−0.0001	34.7889	0.2121	−0.0001	35.1718
23	0.5633	0.1035	0.1022	0.0012	68.7767	0.1022	0.0012	69.2431
24	0.5736	−0.0100	−0.0087	−0.0012	7.57006	−0.0086	−0.0013	7.13579
25	0.5833	−0.1230	−0.1255	0.0025	100	−0.1254	0.0024	100
26	0.5900	−0.2100	−0.2085	−0.0014	2.6948	−0.2084	−0.0015	1.41935

Table 5
Performance indexes for: double and single diode models.

Model	RMSE	NRMSE (%)	MAE	NMAE (%)	MBE	NMBE (%)
Double diode	9.8619 E-04	62.53	8.2918 E-04	−0.47	5.8807 E-07	1.19872
Single diode	9.8629 E-04	62.70	8.3034 E-04	−0.49	−1.5448 E-06	1.21547

$$\mathrm{NMAE} = \sum_{i=1}^{N} \frac{|I_{t-\text{measured}} - I_{t-\text{calculated}}|/I_{t-\text{measured}}}{N} \tag{15}$$

The normalized RMSE is defined as follows:

$$\mathrm{NRMSE}(\mathbf{x}) = \frac{\mathrm{RMSE}}{\max(I_{t-\text{calculated}}) - \min(I_{t-\text{calculated}})}, \tag{13}$$

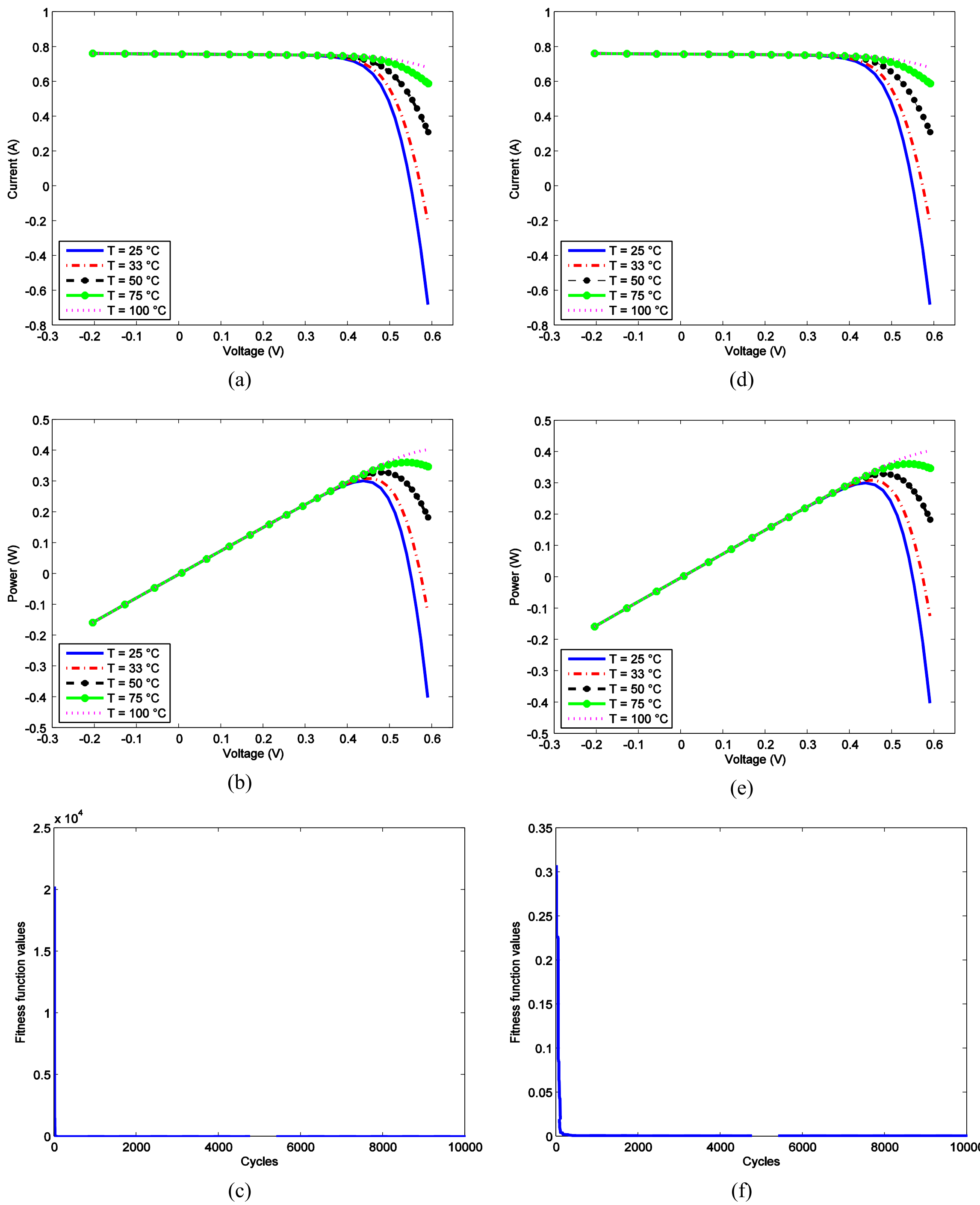

Fig. 3. For the DD model: (a) Measured voltage vs. ABC computed current for different temperatures, (b) Measured voltage vs. ABC-power at different temperatures, (c) *RMSE* evolution. SD model: (d) Measured voltage vs. ABC computed current for different temperatures, (e) Measured voltage vs. ABC-power at different temperatures, (f) *RMSE* evolution.

where $\min(I_{t-\text{calculated}})$ and $\max(I_{t-\text{calculated}})$ are the minimum and maximum values of $I_{t-\text{calculated}}$ over the existent N samples.

Finally, the MBE (median bias error) and the NMBE (normalize MBE) are computed as follows:

$$\text{MBE} = \sum_{i=1}^{N} \frac{(I_{t-\text{measured}} - I_{t-\text{calculated}})}{N} \tag{16}$$

$$\text{NMBE} = \frac{\text{MBE}}{\max(I_{t-\text{calculated}}) - \min(I_{t-\text{calculated}})} \tag{17}$$

Table 5 presents the results of the experiment. Such results include the experimental data (V_t and I_t), the obtained results ($I_{t-\text{calculated}}$), the respective relative errors (R_{error}) and their normalized values for both models.

In Table 5 are presented the values of RMSE, NRMSE (normalized RMSE), MAE, NMAE, MBE and NMBE (normalized MBE) for the proposed approach based on ABC.

Considering the model parameters of Table 4, it is possible to obtain the power ($P = I \times V$) characteristics of the solar cell. Fig. 3 shows the graphs or current vs. voltage at different temperatures ($T = 25°\text{C}$, $T = 50°\text{C}$, $T = 75°\text{C}$ and $T = 100°\text{C}$), the power, and the fitness values for the double and single diode models.

Fig. 3 presents the results obtained by the proposed approach considering the two diode models and five different temperatures. Form Fig. 3, it is possible to analyze that the ABC-based approach obtains better models producing an accurate approximation to experimental data; however, the influence of the temperatures evidently modifies the current values in the model. This fact affects directly the power values. Besides, the evolution of the optimization process shows that the proposed method allow to find appropriate solar cell models in a reduced number of generations.

5.2. Comparisons with other approaches

In order to demonstrate the performance of the proposed approach, its results have been compared to those produced by other similar implementations reported in the literature, for solar cell modeling. The methods used in the comparison are: HS (harmony search) () [13], PSO (particle swarm optimization) [12], GA (genetic algorithms) [18] and BFA (Bacterial Foraging Algorithm) [21]. In the comparison, all the algorithms have been executed 35 times so that it can be computed their averaged *RMSE* values and their respective mean values and STD (standard deviation). Tables 6 and 7 present the results obtained from this analysis, for the DD and SD model, respectively.

Table 6 presents the comparison analysis for the double diode model. From the results, it is possible to see that the ABC-based algorithm present better performance than other approaches. The Mean corresponds to the average values of the RMSE after 35 independent experiments. The STD value can be interpreted as a stability index which reflects the algorithm capacity to produce the same result when it is executed several times. Likewise, Table 7 shows the comparison analysis for the single diode model. The results show that the proposed algorithm performs better in comparison with the HS, PSO GA and BFA algorithms in terms of the averaged *RMSE* and STD values.

Table 6
Comparison results for the DD model.

Parameter	ABC	HS	PSO	GA	BFA
$R_s (\Omega)$	0.0364	0.0354	0.0325	0.0364	0.0351
$R_{sh} (\Omega)$	53.7804	46.8269	43.1034	53.7185	60.0000
I_{ph} (A)	0.7608	0.7617	0.7623	0.7608	0.7609
I_{sd1} (μA)	0.0407	0.1245	0.4767	0.0001	0.0094
I_{sd2} (μA)	0.2874	0.2547	0.0100	0.0001	0.0453
n_1	1.4495	1.4943	1.5172	1.3355	1.3809
n_2	1.4885	1.4998	2.0000	1.4810	1.5255
RMSE	9.861 E-04	0.0013	0.0166	0.3604	0.0012
Mean	0.0010	0.0683	0.0715	0.0229	0.0245
STD	3.285 E-05	0.5111	0.3109	0.0199	0.3697

Table 7
Comparison results for the SD model.

Parameter	ABC	HS	PSO	GA	BFA
$R_s (\Omega)$	0.0364	0.0366	0.0354	0.0299	0.0325
$R_{sh} (\Omega)$	53.6433	53.5946	59.0120	42.3729	50.8691
I_{ph} (A)	0.7608	0.7607	0.7607	0.7619	0.7602
I_{sd} (μA)	0.3251	0.3049	0.4000	0.8087	0.8000
n	1.4817	1.4753	1.5033	1.5751	1.6951
RMSE	9.862 E-04	9.510 E-04	0.0013	0.0190	0.029
Mean	0.0010	0.0039	0.2544	0.0551	0.0152
STD	1.497 E-05	0.7268	0.0289	0.0735	0.0586

6. Conclusions

In this paper, the use of ABC (artificial bee colony) to accurately estimate the parameter of solar cells has been presented. In the approach, the estimation process is considered as an optimization problem. The proposed approach encodes the parameters of the solar cell as a candidate solution. An objective function evaluates the matching quality between a candidate solution and the experimental data. Guided by the values of this objective function, the set of encoded candidate solutions is evolved by using the operators defined by ABC so that the parameters that produce the best possible approximation to the *I*–*V* measurements obtained by the true solar cell can be found.

The proposed approach has been compared with other similar techniques proposed in the literature such as HS, PSO GA and BFA. The efficiency of the algorithm has been evaluated in terms of accuracy and robustness. Experimental results provide evidence on the outstanding performance, accuracy and convergence of the proposed algorithm in comparison to such methods.

Although the results offer evidence to demonstrate that the standard ABC method can yield good results on both diode models, the aim of our paper is not to devise an SC algorithm that could beat all currently available methods, but to show that harmony search algorithms can be effectively considered as an attractive alternative for this purpose.

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Appendix

ABC computational procedure

The complete ABC Algorithm can be summarized by the instructions listed in Algorithm 1.

Algorithm 1. *Artificial bee colony method.*

1: Generate the initial population $x_{i,j}$, $j = 1,2,...,d$; $i = 1,2,...,N_p$, Eq. (7).
2: Evaluate the initial population with regard to the objective function
3: Set cycle to 1
4: **repeat**
5: **for** each employed bee
{
Produce new solution v_i by using Eq. (8)
Calculate the value fit_i (Eq. (9))
Apply greedy selection process
}
6: Calculate the probability values Prob_i for the produced solutions by Eq. (10)
7: **for** each onlooker bee
{
Select a solution i depending on Prob_i
Produce new solution v_i
Calculate the value fit_i
Apply greedy selection process
}
8: **if** (there is an abandoned solution) **then** replace it with a new random solution produced by a scout using Eq. (7)
9: Memorize the best solution so far
10: cycle = cycle + 1
11: **until** cycle = maximum iteration number

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