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Research paper

Estimation of single-diode and two diode solar cell parameters by equilibrium optimizer method

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ABSTRACT

One of the difficulties encountered in the designing of solar photovoltaic systems is to find a model that accurately reproduces the behaviour of the system under various production conditions. The accuracy of this model depends on the identified parameters which are mainly based on the optimization technique performed and the objective function employed. The algorithm used here is the equilibrium optimizer. This one allows to identify the decision variables of the one and two diodes models of the RTC France solar cell which will allow us to minimize the objective function. The optimization strategy used here is based on the experimental data which are measured under a known temperature and irradiation level. The root mean square error between the measured and estimated current data sets, which is widely used in the literature, is adapted to evaluate the effectiveness of the method. The results obtained by calculating the mean square error by the equilibrium optimizer method for each model, are then compared with those obtained by methods identified in the literature under the similar conditions. It is found that the presented method presents results that are the closest to the real behaviour of a photovoltaic solar cell. It presents a result that minimizes the objective function enormously. Thus, we evaluate for the model with one diode the mean square error to 9.8604E−4 and 9.83532E−4 for the model with two diodes. This method reproduces better the behaviour of a photovoltaic solar cell than other methods listed in the literature. Moreover it presents a fast convergence towards the optimal solution. This allows us to validate the algorithms presented here to estimate the parameters of a photovoltaic solar cell.

1. Introduction

The lifestyle, population boom and the evolution of technology, have pushed man to develop devices, equipment and systems increasingly big and voracious in energy. With this ever-increasing demand for electricity around the world, although at a slower pace than in the early 2000s, it has become necessary and even imperative to explore new sources of energy. Estimated at less than 12% in 2018, the production of electricity from solar energy is one of the most rentable alternatives currently being explored, as it has a much lower environmental hazard than fossil fuels (Newell et al., 2019). The production of this form of energy is estimated to be at least 42% by 2050, with exploitation in energy production processes as well as in desalination processes (Mostafa et al., 2020). The governmental measures on the one hand and the fall in the cost of the photovoltaic module by more than 40% on the other hand have participated in the popularization in the world of photovoltaic solar systems (PV), whose central element is the photovoltaic panel (Charfi et al., 2018). A photovoltaic solar panel is a generator that converts solar energy into electrical energy. Its production is strongly dependent on the irradiance that can be predicted (Meng et al., 2021) and the temperature of the medium (Atmaca and Pektemir, 2020). It consists of several entities associated in series and in parallel called solar cells. The accuracy of these solar cells in the PV system is evaluated using an accurate model based on measured current–voltage data (Khatib et al., 2013).

To reproduce the actual electrical behaviour of PV solar cells, an appropriate mathematical model is needed that is relevant under all conditions. In the literature, various models are proposed to simulate this. These usually have a diode as a central element. Thus, three circuits are mainly used in the electrical modelling of the PV cell: the single diode model (SDM) (Xiao et al., 2004), the double diode model (DDM) (Ishaque et al., 2011) and more recently introduced for industrial type applications the three diode model (TDM) (Khanna et al., 2015).

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The DDM and TDM are the best models because they are more detailed and accurate at low irradiance (Chin et al., 2015). The main drawbacks of the previous models are the identification of the model parameters, where there is a set of parameters that must be identified first until it presents the best accuracy for the model. The selection of values representing the best combination of parameters for a solar cell or PV module is usually treated as an optimization problem by defining an objective function to be minimized. This optimization problem generates a complex multivariate search space. The main problems of conventional methods are slowness and accuracy, especially when the number of unknown parameters increases (Allam et al., 2016). The need for a more efficient technique to deal with the above problems is increasing considerably. The use of metaheuristic algorithms, are increasingly used in the solution of optimization problems. These methods have recently seen considerable progress in the estimation of the parameters of PV models. In the following paragraph, the metaheuristic algorithms used to estimate the parameters of unknown models are illustrated.

Oliva et al. in their work (Oliva et al., 2017), the Artificial Bee Colony (ABC) improved by chaotic maps instead of random numbers to avoid newly generated random solutions were developed to find the unknown parameters of PV models. Merchaoui et al. in their work (Merchaoui et al., 2018) proposed the Particle Swarm Optimization (PSO) improved by adaptive mutation strategy to improve the premature convergence problem to solve this crucial task. Chin and Salam proposed in Chin and Salam (2019), the use of Coyote Optimization Algorithm (COA) which is inspired by the social norms of coyotes to ensure the sustainability of their species to extract the unknown parameters from the one and two diode models. Gnetchejo et al. used in Gnetchejo et al. (2019a), the Enhanced Vibrating Particle System algorithm as a method to extract the intrinsic parameters of the one and two diode model of a photovoltaic module. Kumar et al. use in Kumar et al. (2020), in order to estimate the parameters of a SDM, DDM and TDM of a silicon RTC France cell from the slime mould algorithm (SMA) which models its behaviour of a eukaryote searching for a food source. Qais et al. in their work (Qais et al., 2020) uses the Harris Hawk Optimizer, a method inspired by the cooperative behaviour and hunting style of Harris Hawks, to extract parameters from a three-diode model. Ridha et al. use in Ridha (2020) an algorithm inspired by the widespread foraging strategy of Marine Predators Algorithm boosted with Lambert-W function (MPALW). With this method, they extracted the parameters of a PV cell for an SDM, DDM model refining the accuracy and stability of the error.

The work of Faramarzi et al. (2020) proposed an algorithm, the Equilibrium Optimizer (EO). This method inspired by the control volume mass balance models used to estimate the dynamic and equilibrium states, showed its superiority over known algorithms, recent algorithms and has similarities with high performance optimizers. This is due to its generation rate which reinforces the exploration and exploitation capacity and especially allows to avoid local minima. In order to use the previously presented models in an optimal way, there are unknown parameters in the mathematical models that need to be extracted accurately to obtain better performance of the solar cell. In the following subsections, the mathematical models of SDM and DDM will be illustrated in detail. Regarding TDM, it will be solved in our future work.

In summary the main contributions of this work can be named as follows:

- Adaptation of the EO algorithm for the extraction of SDM and DDM parameters;
- Testing the proposed work on the well-known dataset, namely the commercial solar cell R.T.C France.
- Compare the proposed method with a number of algorithms to verify its effectiveness, where it could outperform some algorithms and achieve the same results for others in the best case.

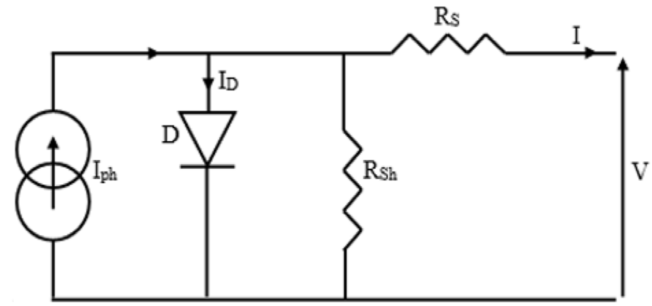

Fig. 1. Single diode model PV cell.

The remaining sections of this manuscript are organized as follows; Section 2 presents and describes the theory related to the single-diode electrical model of the photovoltaic (PV) cell. In Section 3, the metaheuristic method used in the estimation of the PV cell parameters are briefly discussed. In Section 4, we will present the results of our work and end with a conclusion.

2. Models of the photovoltaic cell

In order to simulate the current–voltage characteristic of the PV cell, mathematical models are required. These models allow to estimate analytically the intrinsic parameters of the cell.

2.1. Single-diode model

The PV cell consists of two layers of differently doped semiconductors, whose P–N junction is exposed to light (Jordehi, 2016). Without the presence of solar radiation, the PV cell operates as a single P–N junction diode whose I–V curve is given by the Shockley equation. When irradiation is present, the P–N junction absorbs photon from the incident light and produces an electron–hole pair. This creates a potential difference across the P–N junction (Kumari and Babu, 2012). This phenomenon is called photovoltaic effect and the current resulting from it is called photocurrent (Mahmoud et al., 2011). The association of this current with the Shockley equation, allows to establish an elementary description of a PV solar cell. The circuit resulting from this association is known in the literature as the ideal model of a PV solar cell. This model does not take into account the losses due to the resistance between the silicon and the surface of the electrodes, but also those due to the leakage current of the P–N junction.

However, in order to materialize these losses and to get closer to reality, a series resistor (R_S) and a shunt resistor (R_{Sh}) are integrated in the ideal model to reproduce the real characteristic of the PV solar cell (Ayang et al., 2019). Thus, we obtain a single diode model (SDM). The diode, in the circuit, functions as a rectifier, and an additional parameter is used to account for its non-physical ideal character (Elsheikh et al., 2019). This model is simple to implement in many optimization experiments. However, the problem with this model is that it has parameters and an optimal configuration must be estimated to minimize its average error.

The SDM model is widely used in several studies because it is close to reality (Arani et al., 2013). Fig. 1 shows the circuit of a single diode model (SDM) of a PV solar cell.

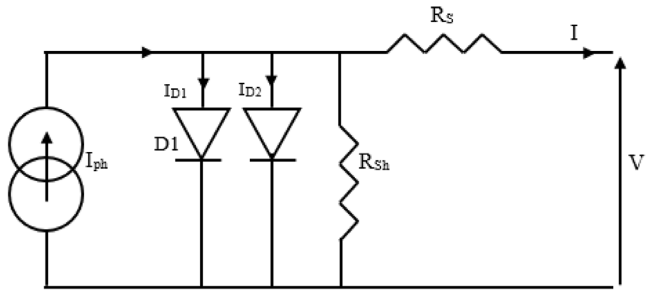

Fig. 2. Double diode model of a PV cell.

This model closer to reality than the ideal model, requires the knowledge of five important parameters namely the photocurrent (Iph), the idealist factor (a), the saturation current of the diode (I_0), the series resistance (R_S) and the shunt resistance (R_{Sh}). Thus, the equation from the latter is presented as follows:

$$I = I_{ph} - I_0\left(e^{\frac{-q\,(V+IR_S)}{aKT}} - 1\right) - \frac{(V + IR_S)}{R_{sh}} \tag{1}$$

The one-diode model is considered a good model for PV cells. However, despite the improved performance, previous studies have reported that its accuracy deteriorates at low irradiances, especially near open circuit voltage (Javed et al., 2019).

2.2. Double diode model

The SDM intrinsically neglects the recombination current loss in the depletion region. Taking this loss into account, especially at open circuit voltage, leads to a more accurate solution (Lim et al., 2015). Thus, the double-diode model (DDM) as shown in Fig. 2, uses one diode as a rectifier while the other is applied to design the recombination current (Niu et al., 2014).

The analysis of Fig. 2, allows us to establish the following equation:

$$I = I_{ph} - I_{01}\left(e^{\frac{q(V+IR_S)}{a_1KT}} - 1\right) - I_{02}\left(e^{\frac{q(V+IR_S)}{a_2KT}} - 1\right) - \frac{V + IR_S}{R_{Sh}} \tag{2}$$

This model presented above requires the knowledge of seven parameters which are the photocurrent (I_{ph}), the ideality factor of diode 1 (a_1), the ideality factor of diode 2 (a_2), the saturation current of diode 1 (I_{01}), the saturation current of diode 2 (I_{02}), the series resistance (R_S) and the shunt resistance (R_{Sh}).

2.3. Objective function

To realize the optimum models, the fundamental aim is to find the optimal parameters in each model. The purpose is to minimize the variance between the measured and estimated current.

The function of error for SDM and DDM are giving by Eqs. (3) and (4) are respectively (Jordehi, 2016):

$$F(V_m, I_m) = I_m - I_{ph} + I_0\left(e^{\frac{-q\,(V_m+I_mR_S)}{aKT}} - 1\right) + \frac{(V_m + I_mR_S)}{R_{sh}} \tag{3}$$

$$F(V_m, I_m) = I_m - I_{ph} + I_{01}\left(e^{\frac{-q(V_m+I_mR_S)}{a_1KT}} - 1\right) + I_{02}\left(e^{\frac{-q(V_m+I_mR_S)}{a_2KT}} - 1\right) + \frac{V_m + I_mR_S}{R_{Sh}} \tag{4}$$

Here, the optimization problem is described as locating the parameters of the solution vector [I_{ph} I_0 R_S R_{Sh} a] for SDM and [I_{ph} I_{01} R_S R_{Sh} a_1 I_{02} a_2] for DDM that minimize the mean error between the model-estimated current and the measured current. Thus, for a set of M samples used, the root mean square error (RMSE) is given by:

$$\mathrm{Min}(F(V, I)) = \sqrt{\frac{\sum_{j=1}^{M}\left[I_m(j) - I_e(j)\right]^2}{M}} \tag{5}$$

where j is a selection variable, Ie (j) is the estimated current from the chosen model, and Im (j) is the measured current obtained from the manufacturer or experimentally by several measurements.

3. Equilibrium optimizer algorithm

The equilibrium optimizer (EO) method, is a metaheuristic algorithm inspired by physics, which simulates the equilibrium behaviour on a volume controller (Faramarzi et al., 2020). In other words, it measures over a period of time the flow of particles into and out of a section through a volume controller using a mass equation on that section and attempts to find the state that establishes an equilibrium between the volume at the inlet and that at the outlet. EO uses a group of individuals (particles) that simulate the concentration vector of the mass on the volume, where each concentration vector represents a solution to the optimization problem.

Like most metaheuristic algorithms, the EO method starts the optimization process by distributing the individuals in the search space of the optimization problem using the formula:

$$\overrightarrow{P_i} = \overrightarrow{H_{min}} + \left(\overrightarrow{H_{max}} - \overrightarrow{H_{min}}\right) * \vec{r} \qquad (i = 1, 2 \ldots N) \tag{6}$$

where Pi is the position vector of the ith particle, $\overrightarrow{H_{max}}$, $\overrightarrow{H_{min}}$ are respectively the upper and lower bounds imposed by the problem. $\vec{r}$ is a random vector and N the number of particles.

EO searches for the state that will come to realize the equilibrium of the system. When it reaches this state, it can reach the solutions of the problem.

At the beginning of the optimization process, the equilibrium state is unknown so EO takes four best generated particles as the equilibrium solutions of the system. To these, a fifth value is added which is the average of the previous values. The EO method is carried out in two phases namely:

- The exploration, during which the first generated values are used to improve this phase.
- Exploitation, where the fifth value is mainly used to improve the exploitation capacity.

One of the important elements of the EO method uses its equilibrium reservoir vector defined by:

$$\overrightarrow{p_{eq,rés}} = \left[\overrightarrow{p_{eq(1)}}, \overrightarrow{p_{eq(2)}}, \overrightarrow{p_{eq(3)}}, \overrightarrow{p_{eq(4)}}, \overrightarrow{p_{eq(moy)}}\right] \tag{7}$$

The exponential term F allows for an equilibrium between the different phases of the EO. The latter at the beginning of the optimization process searches for the solution using large steps that decreases as the iterations grow. $\vec{\lambda}$ is a randomly generated vector in [0, 1].

$$\vec{F} = e^{-\vec{\lambda}(t-t_0)} \tag{8}$$

where t decreases with the iteration increment through formula (9):

$$t = \left(1 - \frac{it}{T_{iter}}\right)^{a_2*\left(\frac{it}{T_{iter}}\right)} \tag{9}$$

where it is the current iteration, T_{iter} is the total number of iterations and a_2 a constant used mainly used throughout the operation phase. Another constant that manages the exploration phase is a!. This is used in formula (10):

$$\vec{t_0} = \frac{1}{\vec{\lambda}} \ln\left(-a_1 \mathrm{sign}\left(\vec{r} - 0.5\right)\left(1 - e^{-\vec{\lambda}t}\right)\right) + t \tag{10}$$

Thus by substituting Eq. (10) into (8), we obtain:

$$\vec{F} = \left(a_1 \mathrm{sign}\left(\vec{r} - 0.5\right)\left(e^{-\vec{\lambda}t} - 1\right)\right) \tag{11}$$

When a_1 is high, the exploration phase stronger and the exploitation phase weaker. And conversely, when a_2 is high, exploitation is stronger and exploration is weaker. sign $\left(\vec{r} - 0.5\right)$ is the result of the combination of exploration and exploitation. To improve this exploitation phase, in addition to the previous term, the generation rate ($\vec{K}$) is used which is determined as follows:

$$\vec{K} = K_0 e^{-\vec{\lambda}(t-t_0)} \tag{12}$$

where K_0 is the initial value given by Eq. (13):

$$\vec{K_0} = \overrightarrow{KCP} * (\vec{P_{eq}} - \vec{\lambda}\,\vec{P}) \tag{13}$$

$$\overrightarrow{KCP} = \begin{cases} 0.5 * r_1 & r_2 \geq \beta \\ 0 & r_2 < \beta \end{cases} \tag{14}$$

where r_1 and r_2 are random values in [0, 1], KCP is a vector that is constructed by repeating the same value resulting from Eq. (14). In this equation, KCP is defined as the control parameter of the generation rate. This includes a possibility of the contribution of the generation term to the update process. The probability of this contribution is determined by another term called generation probability (β). $\vec{P_{eq}}$ is a vector taken at random from $\overrightarrow{P_{eq,rés}}$.

Eq. (15) gives the update of the EO method. This one is given by:

$$\vec{p} = \vec{p_{eq}} + -\left(\vec{p_{eq}} - \vec{p}\right) * \vec{F} + \frac{\overrightarrow{K}}{\vec{\lambda} * V} * (1 - \vec{F}) \tag{15}$$

where $\vec{K}$ is defined in Eq. (12), $\vec{F}$ in Eq. (11) and V is equal to one (see Fig. 3).

4. Results

In this section, we present the results obtained using the equilibrium optimizer method to estimate the intrinsic parameters of the PV cell diode models. To observe the effectiveness of the proposed algorithm, a commercial silicon solar cell R.T.C France was operated under test conditions of 1000 W/m2 irradiance and 33 °C temperature, this for SDM and DDM to obtain the measured current–voltage. For efficiency verification, we used 26 pairs of measured current–voltage (I–V) data, shown in Table 3 for SDM and DDM, which have been used frequently in the literature. We used commercial solar silicon from R.T.C France in our comparison because measured I–V values of actual solar cells were available and allowed us to make a fair comparison with all other algorithms. Table 1 shows the upper and lower bounds, for each unknown parameter in each PV model, as shown in the table. The software tool used to estimate the intrinsic parameters of the PV cell is Matlab 2016a. The computing tasks are implemented on a laptop with Intel Core i5-3437U @1.9 GHz CPU, 8GB RAM and windows 10 64-bits operating system.

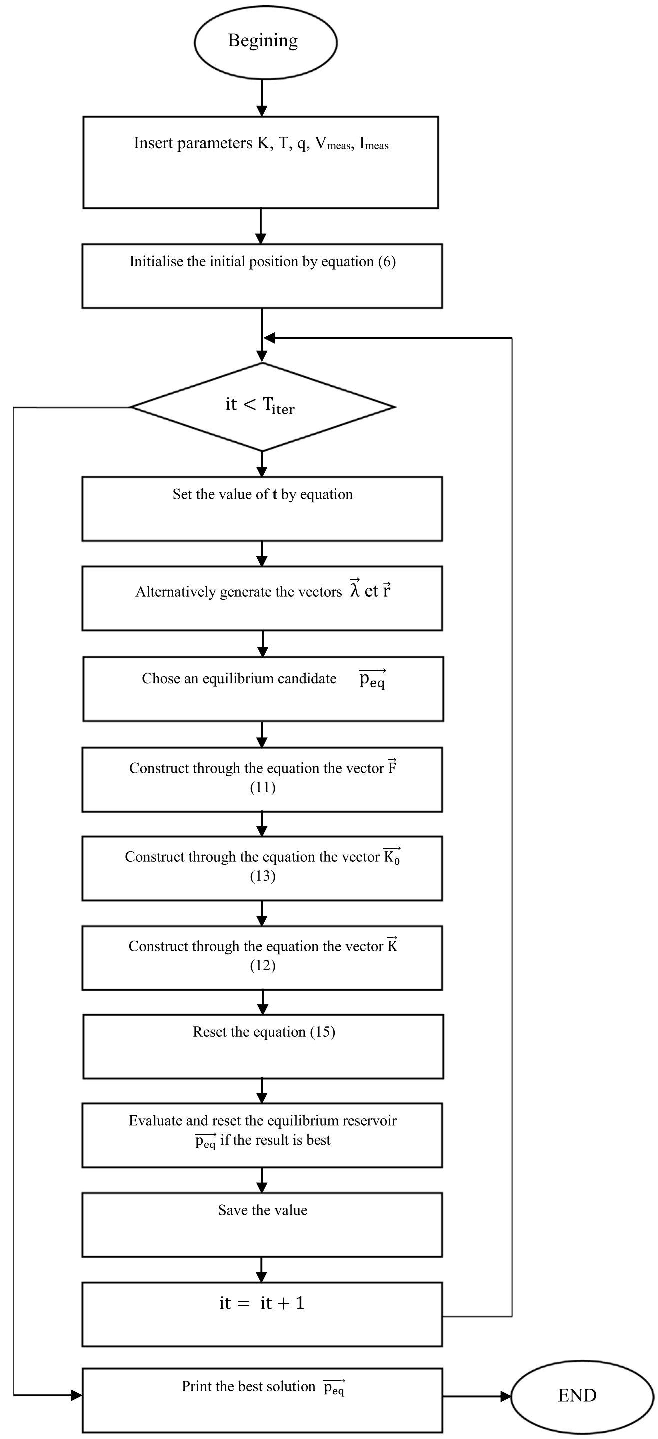

Fig. 3. EO method Organigram.

Table 1
Lower and upper bounds.

Parameters	Lower bounds	Upper bounds
I_{ph} (A)	0	1
I_{01}, I_{02} (μA)	0	10^{-6}
R_s (Ω)	0	0,5
R_{sh} (Ω)	0	100
a_1, a_2	1	2

Table 3
Experimental values of the output voltage and current of an RTC France.

Rank	Measured data		Rank	Measured data	
	$V_{measured}$ (V)	$I_{measured}$ (A)		$V_{measured}$ (V)	$I_{measured}$ (A)
1	−0.2057	0.764	14	0.4137	0.728
2	−0.1291	0.762	15	0.4373	0.7065
3	−0.0588	0.7605	16	0.459	0.6755
4	0.0057	0.7605	17	0.4784	0.632
5	0.0646	0.76	18	0.496	0.573
6	0.1185	0.759	19	0.5119	0.499
7	0.1678	0.757	20	0.5265	0.413
8	0.2132	0.757	21	0.5398	0.3165
9	0.2545	0.7555	22	0.5521	0.212
10	0.2924	0.754	23	0.5633	0.1035
11	0.3269	0.7505	24	0.5736	−0.01
12	0.3585	0.7465	25	0.5833	−0.123
13	0.3873	0.7385	26	0.59	−0.21

4.1. Results of the EO method for SDM

A Single-diode model was implemented, to estimate the parameters of the R.T.C France cell.

The results obtained by the EO method for a single-diode model of the R.T.C France cell under the above conditions, as well as those from previous work under the same test conditions, are shown in Table 2.

We used 26 pairs of measured I–V data, shown in Table 3 for SDM and DDM, which have been used frequently in the literature.

The algorithm is run 20 times on SDM and the best value of the error (RMSE) is calculated with the extracted parameters values and presented in Table 2. This table shows that our proposed algorithm is superior to many other compared algorithms in terms of RMSE. Therefore, our proposed algorithm is competitive with these algorithms on SDM. It is found that the EO method presents more accurate results than many optimization techniques such as the Pattern Search (PS) method, Modified Particle Swarm Optimization (MPSO) method, Bee Pollinator Flower Pollination Algorithm (BPFPA), Opposition Based Whale Optimization Algorithm (OBWOA), Evaporation Rate based Water Cycle Algorithm (ER-WCA), Heterogeneous Comprehensive Learning Particle Swarm Optimization (HCLPSO) and Multi-Verse Optimizer (MVO). This superiority can be explained thanks to its generation rate, which improves the exploration and exploitation capacity of this method. However, these results obtained are less accurate than the parameters obtained from the Marine Predator Algorithm (MPA) due to the diversity of the population.

Figs. 4 and 5 show the Power–Voltage (P–V) curve and I–V characteristics of the photovoltaic cell, derived from the measured data (blue curve) and the estimated intrinsic parameters of the cell (red curve) under the test conditions mentioned above. Fig. 6 shows the convergence of the method to the optimal solution after 1000 iterations. The results from these figures show that our algorithm could significantly extract the values of the parameters that could concretely predict the measured curve.

4.2. Results of the EO method for DDM

In order to estimate the parameters of the DDM model implemented in this section, we will keep the conditions quoted above. The lower and upper bounds are those in Table 1. Also, as described in SDM, the algorithm on DDM is run 20 times independently and the best value of RMSE (RMSE = 9.83532E−4) as well as the values of its parameters are presented in Table 4.

Inspection of Table 4, shows that the EO method presents much more accurate results in terms of RMSE minimization than any of the optimization methods cited here. This shows that the algorithm we propose here rivals and outperforms the method based on the Enhanced Vibrating Particle System Algorithm (EVPS), Combinatorial Particle Swarm Optimization (CPSO) method, Harmony Search (HS) method, Innovative Global Harmony Search (IGHS) method, Artificial Bee Colony Optimization (ABCO) method to name a few.

In Figs. 7 and 8, we present the P–V and I–V characteristics after implementing the estimated parameters in the Matlab/Simulink model of the PV cell. We thus obtain an estimated curve which presents many points of agreement with the curve obtained from the measured parameters. The inspection of this figure notifies us that the proposed algorithm was able to estimate the measured parameters in a significant way.

This results due to its generation rate which reinforces the exploration and exploitation capacity and especially allows to avoid local minima. However, this method has some problems. The premature convergence of the method to solutions that turn out to be local optima, and the second one being the diversity of the population until all members of the population focus on the best regions.

Fig. 9 shows the convergence of the method to the optimal solution after 2000 iterations.

The results from these figures show that our algorithm could significantly extract the values of the parameters that could concretely predict the measured curve.

5. Conclusion

The energy of renewable resources is a very important subject that must be found to solve many problems such as the environment and energy consumption. This form of energy can solve many problems related to the current production scheme essentially based on fossil fuels. The solar energy by its availability and its simplicity in its implementation, is considered the best alternative to solve the problems related to fossil fuels. To build solar cells, three different types based on the number of diodes are proposed, namely SDM, DDM and TDM. But these models were needed to find the correct value of some unknown parameters in the mathematical calculations in order to get better accuracy. Thus, in this paper, a new and powerful metaheuristic algorithm, namely the equilibrium optimizer, has been proposed to extract these unknown parameters. To verify the effectiveness of our proposed work, we compared it with a number of recent robust algorithms. The results of the comparison show that the superiority and competitiveness of our algorithms, the RMSE being 9.8604E−4 for the SDM and 9.83532E−4 for the DDM. These values are less than the RMSE values obtained using many other algorithms used by previous authors. The algorithm used in this work has a minimal objective function compared to other methods identified in the literature. For future work, it is recommended to improve the characterization of faults occurring on solar panels in operation, taking into account the technology of these panels and using the optimization method proposed in this work.

CRediT authorship contribution statement

Francelin Edgar Ndi: Methodology, Software, Investigation, Writing – original draft, Writing – reviewing and editing. **Steve Ngoffe Perabi:** Conceptualization, Validation, Project administration. **Salome Essiane Ndjakomo:** Supervision, Project administration. **Gregoire Ondoua Abessolo:** Data curation, Software. **Ghislain Mengounou Mengata:** Visualization.

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.

Table 2
Comparison between the different estimation tools for a R.T.C France PV cell.

Algorithms	Year	I_{ph} (A)	I_0 (μA)	R_s (Ω)	R_{sh} (Ω)	a	RMSE (10^{-4})
EO		**0.7607597037**	**0.32628893**	**0.03634099**	**54.206594**	**1.482193**	**9.8603**
MPA (Yousri et al., 2020)	2020	0.76079	0.31072	0.036546	52.8871	1.4771	7.7301
HCLPSO (Yousri et al., 2019)	2019	0.76079	0.31062	0.036548	52.885	1.4771	11.2009
BPFPA (Gnetchejo et al., 2019b)	2019	0.7600	0.3106	0.0366	57.7151	1.4774	12.536
ER-WCA (Gnetchejo et al., 2019b)	2019	0.760776	0.322699	0.036381	53.69100	1.481080	9.8609
OBWOA (Merchaoui et al., 2018)	2018	0.76077	0.3232	0.0363	53.6836	1.5208	11.417
MPSO (Kler et al., 2017)	2018	0.760787	0.310683	0.036546	52.88971	1.475262	73.3007
MVO (Ali et al., 2016)	2016	0.7616	0.32094	0.0365	59.5884	1.5252	1268.0
PS (AlHajri et al., 2012)	2012	0.7617	0.9980	0.0313	64.10236	1.6000	149.36

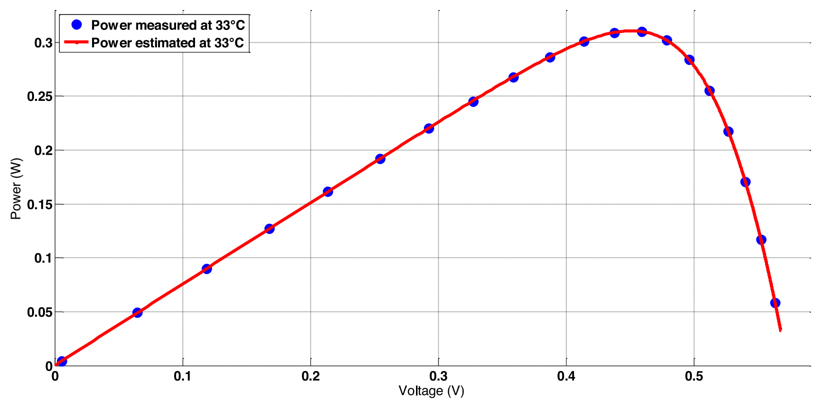

Fig. 4. P–V characteristic of the SDM model of an RTC France. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

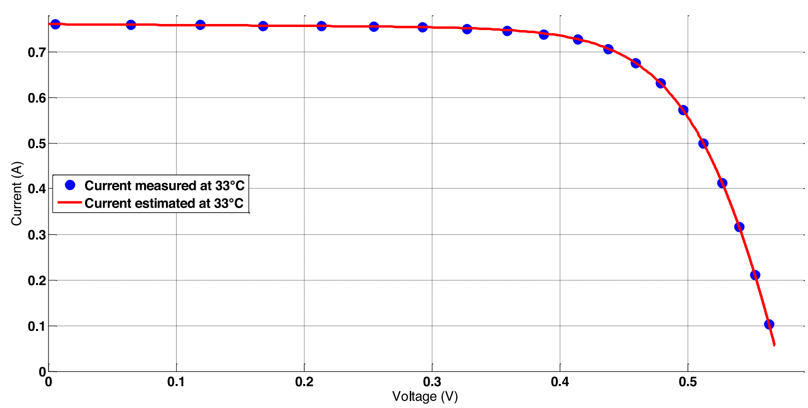

Fig. 5. I–V characteristic of the SDM model of an RTC France. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

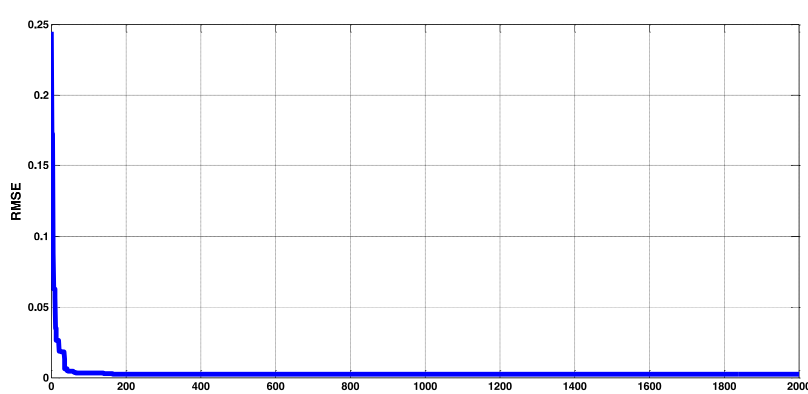

Fig. 6. Convergence of the EO method to the optimal solution.

Table 4
Comparison between the different estimation tools for a PV R.T.C. cell in France.

Algorithms	I_{ph} (A)	I_{01} (μA)	I_{02} (μA)	R_s (Ω)	R_{sh} (Ω)	a_1	a_2	RMSE (10^{-4})
EO	0.76792	0.39999	0.26605	0.03659	54.17614	2.0000	1.46451	**9.83532**
EVPS (Gnetchejo et al., 2019a)	0.7607	0.29749	0.2504	0.0363	55.8827	1.4749	1.9726	9.8510
IGHS (Askarzadeh and Rezazadeh, 2012)	0.76079	0.97310	0.16791	0.03690	56.8368	1.92126	1.42814	9.8635
ABC (Wang et al., 2015)	0.7609	2.6900	2.8198	0.03690	56.8368	1.4670	1.8722	10
ABCO (Oliva et al., 2014)	0.7608	0.0407	0.2874	0.0364	53.7804	1.4495	1.4885	9.861
HS (Askarzadeh and Rezazadeh, 2012)	0.7616	0.12564	0.25470	0.03562	46.8269	1.49439	1.49989	12.6
CPSO (Nunes et al., 2018)	0.762321	0.297108	0.710454	0.035601	45.547533	1.476035	1.998103	13.0565

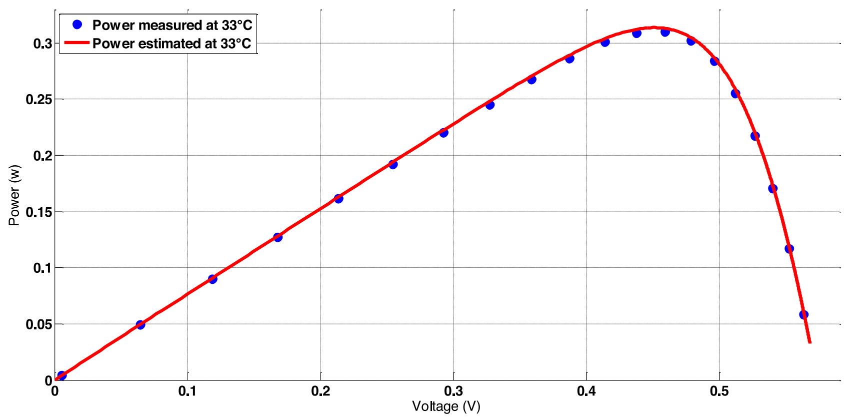

Fig. 7. P–V characteristic of the DDM model of an RTC France.

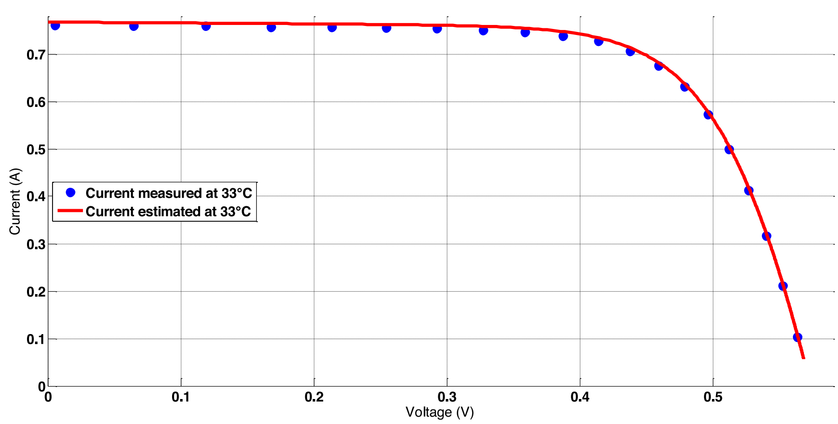

Fig. 8. I–V characteristic of the DDM model of an RTC France.

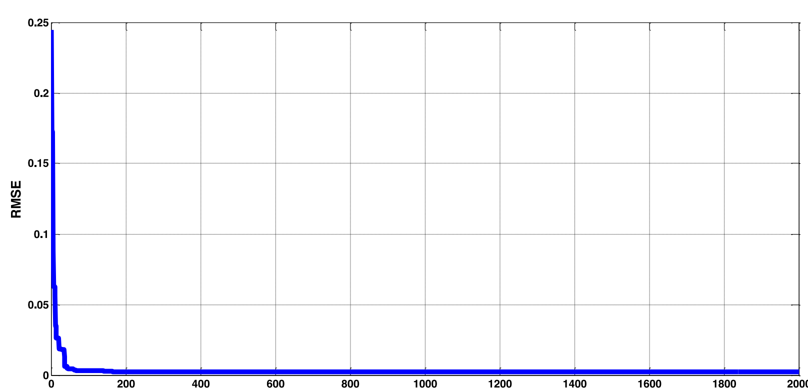

Fig. 9. Convergence of the EO method for a DDM model of RTC France.

References

AlHajri, M., El-Naggar, K., AlRashidi, M., Al-Othman, A., 2012. Optimal extraction of solar cell parameters using pattern search. Renew. Energy 44, 238–245.
Ali, E., El-Hameed, M., El-Fergany, A., El-Arini, M., 2016. Parameter extraction of photovoltaic generating units using multi-verse optimizer. Sustain. Energy Technol. Assess. 17, 68–76.

Allam, D., Yousri, D., Eteiba, M.J., 2016. Parameters extraction of the three diode model for the multi-crystalline solar cell/module using Moth–Flame Optimization Algorithm. Energy Conserv. Manage. 123, 535–548.

Arani, B.O., Mirzabeygi, P., Panahi, M.S., 2013. An improved PSO algorithm with a territorial diversity-preserving scheme and enhanced exploration–exploitation balance. Swarm Evol. Comput. 11, 1–15.

Askarzadeh, A., Rezazadeh, A., 2012. Parameter identification for solar cell models using harmony search-based algorithms. Sol. Energy 86 (11), 3241–3249.

Atmaca, M., Pektemir, İ.Z., 2020. Photovoltaic-thermal system for building application: a case study. Energy Sources A 1–18.

Ayang, A., et al., 2019. Maximum likelihood parameters estimation of single-diode model of photovoltaic generator. Renew. Energy 130, 111–121.

Charfi, W., Chaabane, M., Mhiri, H., Bournot, P., 2018. Performance evaluation of a solar photovoltaic system. Energy Rep. 4, 400–406.

Chin, V.J., Salam, Z., 2019. Coyote optimization algorithm for the parameter extraction of photovoltaic cells. Sol. Energy 194, 656–670.

Chin, V.J., Salam, Z., Ishaque, K., 2015. Cell modelling and model parameters estimation techniques for photovoltaic simulator application: A review. Appl. Energy 154, 500–519.

Elsheikh, A.H., Sharshir, S.W., Abd Elaziz, M., Kabeel, A., Guilan, W., Haiou, Z., 2019. Modeling of solar energy systems using artificial neural network: A comprehensive review. Sol. Energy 180, 622–639.

Faramarzi, A., Heidarinejad, M., Stephens, B., Mirjalili, S., 2020. Equilibrium optimizer: A novel optimization algorithm. Knowl.-Based Syst. 191, 105190.

Gnetchejo, P.J., Essiane, S.N., Ele, P., Wamkeue, R., Wapet, D.M., Ngoffe, S.P., 2019a. Enhanced vibrating particles system algorithm for parameters estimation of photovoltaic system. J. Power Energy Eng. 7 (08), 1.

Gnetchejo, P.J., Essiane, S.N., Ele, P., Wamkeue, R., Wapet, D.M., Ngoffe, S.P., 2019b. Important notes on parameter estimation of solar photovoltaic cell. Energy Convers. Manage. 197, 111870.

Ishaque, K., Salam, Z., Taheri, H., 2011. Simple, fast and accurate two-diode model for photovoltaic modules. Sol. Energy Mater. Sol. Cells 95 (2), 586–594.

Javed, M.Y., et al., 2019. A comprehensive review on a PV based system to harvest maximum power. Electronics 8 (12), 1480.

Jordehi, A.R., 2016. Parameter estimation of solar photovoltaic (PV) cells: A review. Renew. Sustain. Energy Rev. 61, 354–371.

Khanna, V., Das, B., Bisht, D., Singh, P., 2015. A three diode model for industrial solar cells and estimation of solar cell parameters using PSO algorithm. Renew. Energy 78, 105–113.

Khatib, T., Sopian, K., Kazem, H.A., 2013. Actual performance and characteristic of a grid connected photovoltaic power system in the tropics: A short term evaluation. Energy Convers. Manage. 71, 115–119.

Kler, D., Sharma, P., Banerjee, A., Rana, K., Kumar, V., 2017. PV cell and module efficient parameters estimation using evaporation rate based water cycle algorithm. Swarm Evol. Comput. 35, 93–110.

Kumar, C., Raj, T.D., Premkumar, M., Raj, T.D., 2020. A new stochastic slime mould optimization algorithm for the estimation of solar photovoltaic cell parameters. Optik 223, 165277.

Kumari, J., Babu, C.S., 2012. Mathematical modeling and simulation of photovoltaic cell using matlab-simulink environment. Int. J. Electr. Comput. Eng. 2 (1), 26.

Lim, L.H.I., Ye, Z., Ye, J., Yang, D., Du, H., 2015. A linear method to extract diode model parameters of solar panels from a single I–V curve. Renew. Energy 76, 135–142.

Mahmoud, Y., Xiao, W., Zeineldin, H., 2011. A simple approach to modeling and simulation of photovoltaic modules. IEEE Trans. Sustain. Energy 3 (1), 185–186.

Meng, F., et al., 2021. An intelligent hybrid wavelet-adversarial deep model for accurate prediction of solar power generation. Energy Rep. 7, 2155–2164.

Merchaoui, M., Sakly, A., Mimouni, M.F., 2018. Particle swarm optimisation with adaptive mutation strategy for photovoltaic solar cell/module parameter extraction. Energy Convers. Manage. 175, 151–163.

Mostafa, M., Abdullah, H.M., Mohamed, M.A., 2020. Modeling and experimental investigation of solar stills for enhancing water desalination process. IEEE Access 8, 219457–219472.

Newell, R., Raimi, D., Aldana, G., 2019. Global Energy Outlook: The next generation of energy. Resour. Future 8–19.

Niu, Q., Zhang, L., Li, K., 2014. A biogeography-based optimization algorithm with mutation strategies for model parameter estimation of solar and fuel cells. Energy Convers. Manage. 86, 1173–1185.

Nunes, H., Pombo, J., Mariano, S., Calado, M., De Souza, J.F., 2018. A new high performance method for determining the parameters of PV cells and modules based on guaranteed convergence particle swarm optimization. Appl. Energy 211, 774–791.

Oliva, D., Cuevas, E., Pajares, G., 2014. Parameter identification of solar cells using artificial bee colony optimization. Energy 72, 93–102.

Oliva, D., Ewees, A.A., Aziz, M.A.E., Hassanien, A.E., Peréz-Cisneros, M., 2017. A chaotic improved artificial bee colony for parameter estimation of photovoltaic cells. Energies 10 (7), 865.

Qais, M.H., Hasanien, H.M., Alghuwainem, S., 2020. Parameters extraction of three-diode photovoltaic model using computation and Harris Hawks optimization. Energy 195, 117040.

Ridha, H.M., 2020. Parameters extraction of single and double diodes photovoltaic models using Marine Predators Algorithm and Lambert W function. Sol. Energy 209, 674–693.

Wang, R., Zhan, Y., Zhou, H., 2015. Application of artificial bee colony in model parameter identification of solar cells. Energies 8 (8), 7563–7581.

Xiao, W., Dunford, W.G., Capel, A., 2004. A novel modeling method for photovoltaic cells. In: 2004 IEEE 35th Annual Power Electronics Specialists Conference (IEEE Cat. No. 04CH37551), Vol. 3. IEEE, pp. 1950–1956.

Yousri, D., Abd Elaziz, M., Oliva, D., Abualigah, L., Al-qaness, M.A., Ewees, A.A., 2020. Reliable applied objective for identifying simple and detailed photovoltaic models using modern metaheuristics: Comparative study. Energy Convers. Manage. 223, 113279.

Yousri, D., Allam, D., Eteiba, M., Suganthan, P.N., 2019. Static and dynamic photovoltaic models' parameters identification using chaotic heterogeneous comprehensive learning particle swarm optimizer variants. Energy Convers. Manage. 182, 546–563.