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Research Article

Harris Hawk Optimization Combined with Differential Evolution for the Estimation of Solar Cell Parameters

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In a dynamic shift, lowering reliance on fossil fuels and greenhouse gas emissions is now a top goal. This is accomplished through expanding the usage of renewable energy. Solar photovoltaic (PV) energy is now more than ever at the heart of many cities' policies. Improving the efficiency of PV systems is a current research goal. The key challenge in rectifying complex systems is to establish a model that correctly reproduces the system's dynamic behaviour. The goal function and optimization method utilised are indicative of the model parameters' correctness. This paper presents a mix of differential evolution (DE) and Harris hawk optimisation (HHO). The suggested technique estimates the parameter vector that minimises the objective function to the greatest extent possible. This is for the many diode models. The procedure is validated using experimental data acquired at a known temperature and irradiance. The root mean square error (RMSE) is used to assess the method's effectiveness. A comparison is made between the objective function of the hybrid approach presented in this publication and previously authorised methods. The strategy utilised is as straightforward as many others stated in our predecessors' publications, and this applies to both models analysed. When compared to the simple version of the Harris hawk optimizer, this approach allows for more experimentation.

1. Introduction

Energy production, mostly based on fossil fuels, has created a number of concerns in recent years, putting it at the centre of worldwide debate [1]. Long-term, this pattern of energy production will result not only in the depletion of fossil resources but also in a slew of environmental issues [2]. As a result, several governments have chosen to progressively forgo fossil fuels in order to move toward so-called renewable sources, which have the major benefit of being limitless [3].

Solar energy has a promising aspect in comparison to others because of its accessibility and availability [4]. Despite the extreme sensitivity of these systems to external factors [5], it is mostly employed in power generating [6]. As a result, accurate photovoltaic cell models are critical for optimising and controlling PV systems [7]. To represent the electrical behaviour of the PV solar cell, a mathematical model is typically using a single diode [8], the double diode [9], and even the three diode [10]. All these models take into consideration the various environmental conditions, for the proper operation of the different models. The accuracy of PV models is mostly determined by unknown factors. The selection of values indicating the ideal combination of parameters for a solar cell or PV module is often treated as an optimization problem with a reduced objective function. Because of its multidimensional and complicated presentation, traditional approaches have significant constraints in terms of both speed and quantity of variables [7]. The demand for a more effective means of dealing with the aforementioned difficulties is continuously increasing. To tackle optimization problems, metaheuristic algorithms are increasingly being used [7]. The demand for a more effective means of dealing with the aforementioned difficulties is continuously increasing. To tackle optimization problems, metaheuristic algorithms are increasing and can be used.

The modified artificial bee colony (MABC) was established by Jamadi et al. in their study [11], to prevent freshly generated random solutions and to identify unknown parameters of solar cell models. To determine the unknown parameters of solar cell models, Abd Elaziz and Oliva presented [12] and used the improved opposition-based whale optimization algorithm instead of random numbers to prevent freshly created random solutions. Gnetchejo et al. proposed in [13] a GAMS method to solve the estimation's problem of the solar cells. The Manta-ray foraging optimizer method was utilised by El-Hameed et al. in [14], to identify the intrinsic characteristics of the three diode model of a solar module. The bald eagle search method was used by Nicaire et al. in [15], to extract the intrinsic parameters of the one and two diode model of a solar cell and photovoltaic module. In [16], Ndi et al. estimate single and double diode model parameters using the equilibrium optimizer approach, which is inspired by models used to analyze dynamic and equilibrium states.

Heidari et al. [17] proposed the Harris hawk optimizer (HHO) technique. This method resembles the participative hunting behaviour of Harris' hawks in the wild. The method calls for numerous hawks to approach a prey, generally a rabbit, from different directions in order to catch it off guard. The HHO is based on the surprise assault of Harris' hawks and consists of two stages: exploration and exploitation. This technique has yielded intriguing results in parameter estimation [18]. The HHO technique has local search restrictions during the exploration phase. Hybridization, utilising mainly analytical approaches, is a frequent solution for overcoming these restrictions. This approach has proven to be effective in a variety of applications, including internet data clustering [19], power flow [20, 21], cybersecurity [22], mechanism [23], and even in the estimate of diode model parameters [24, 25]. Despite providing excellent results for extracting parameters from the diode model, metaheuristic methods have several drawbacks. BES, for example, is extremely sensitive to beginning settings, HHO has sluggish convergence, and EO has fragile stability. In this work, the Harris hawk optimizer (HHO) approach is used in conjunction with differential evolution (DE) to estimate the parameters of single and double diode models that fully replicate the genuine behaviour of a solar cell. The upgrade consists of including a differential evolution exploration phase to increase the exploration capabilities of HHO. As a consequence, the Harris hawk optimization algorithm, when combined with the differential evolution (HHODE) approach, gives methods for exploring and employing the Harris hawk optimization algorithm, which has been upgraded with the potential of differential evolution.

In short, we provide a unique estimate technique for single diode model (SDM) and double diode model (DDM) parameters that integrates Harris hawk optimization and differential evolution. Differential evolution is being utilised to improve the Harris hawk optimization technique's exploitation experience. We are testing the proposed work on a well-known dataset, the R.T.C France commercial solar cell dataset, and in the best case, we will be able to compare the proposed method with a number of algorithms to verify its effectiveness, where it may outperform some algorithms while achieving the same results as others. The following section of this manuscript presents the generalities related to the PV solar cell model.

The paper is organised as follows: first, we offer generalities about the PV cell model, and then we detail the approach suggested in this study. This will be followed by a summary of the method's outcomes and, finally, a conclusion.

2. Models of PV Cell and Objective Function

One of the most widely used models in the literature is the model with the single diode. This model is widely utilised in research because of its behaviour, which is closer to that of a solar cell than the ideal model, and its mathematical computation simplicity [26]. Kirchhoff's theorem may be used to represent the current I at the solar cell's output in the following equation:

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

where I_0 is the saturation current, the ideality factor is n, the Boltzmann constant is K, the electron charge is q, the cell temperature is T in kelvin, the series resistance is R_S, and the shunt resistance is R_{Sh}. According to equation (1), there are five parameters that must be precisely predicted in order to acquire the greatest performance from solar cells. This parameter is $[I_{ph}\ I_0\ R_{Sh}\ R_S\ n]$.

Figure 1 gives us a simplified representation of this model.

Aside from the model with single diode, the model with double diodes is also often used in literature due to its ability to include the recombination limitations of the previously mentioned model [6]. The equation of this model is given by the following equation:

$$\begin{aligned} I = I_{ph} &- I_{01}\left(e^{-q(V+IR_S)/n_1KT} - 1\right) \\ &- I_{02}\left(e^{-q(V+IR_S)/n_2KT} - 1\right) - \frac{(V + IR_S)}{R_{Sh}}, \end{aligned} \tag{2}$$

where I_{01} and n_1 denote the current diffusion and ideality factor, respectively, for the first diode; I_{02} and n_2 represent the saturation current and ideality factor, respectively, of the second diode. Based on equation (2), the parameters of this double diode model (DDM) to be estimated are $[I_{ph}\ I_{01}\ I_{02}\ R_{SH}\ R_S\ n_1\ n_2]$.

Figure 2 gives us the simplified representation of the model with two diodes.

The mathematical statistical tool we set to reassure ourselves of the optimal estimation of the intrinsic parameters

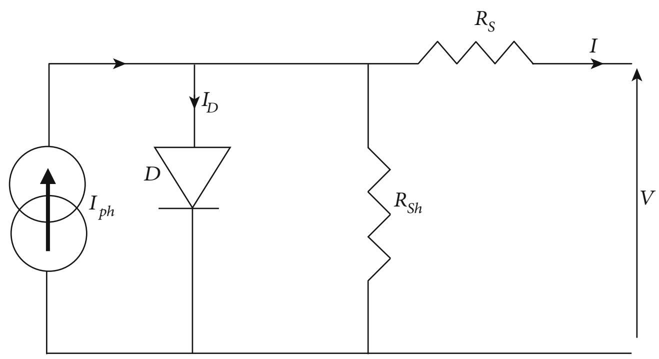

Figure 1: Representation of the solar cell model with a single diode.

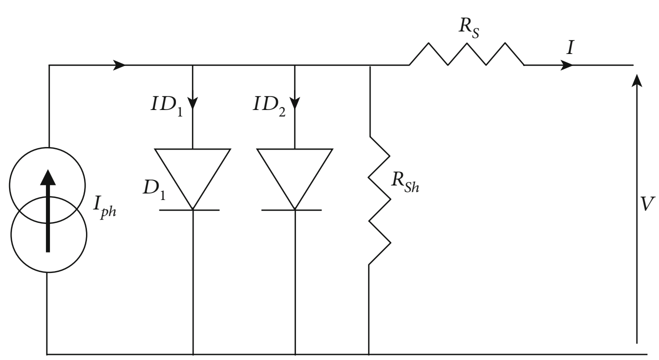

Figure 2: Representation of the solar cell model with double diodes.

of the cell generating an estimated current close to the measured value is the root mean square error (RMSE). This is given by the following equation [27]:

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{j=1}^{M}\left[I_m(j) - I_e(j)\right]^2}{M}}. \tag{3}$$

$Ie\,(j)$ is the estimated current from the chosen model, and Im (j) is the measured current either from the manufacturer or empirically through many measurements.

3. Harris Hawk Optimization Associated with Differential Evolution

3.1. Harris Hawk Optimization (HHO). The Harris hawk optimizer approach (abbreviated HHO) is an algorithm that is based on the cooperative behavior and hunting style of wild Harris hawks [17]. The strategy aims at attacking a prey, usually a rabbit, by several hawks coming from different directions, in order to surprise it. The HHO is built on two steps: exploration and exploitation and is designed after the Harris hawk surprise assault.

HHO's method can be broken down into two stages, which can be modeled through mathematical equations that present and simulate the process.

Harris's hawks always perch on a branch to watch and identify their prey during phase 1, which is an exploring phase. The equation is the mathematical expression for the latter:

$$X_{t+1} = \begin{cases} X_{\mathrm{rand}} - r_1.\left|X_{\mathrm{rand}} - 2r_2.X_t\right| & q_1 \geq 0.5, \\ X_{\mathrm{rabbit}} - X_{\mathrm{mean}} - r_3\left(LB + r_4(UB - LB)\right) & q_1 < 0.5, \end{cases} \tag{4}$$

where q_1 is a random number taken between [0, 1], X_t and X_{t+1} are the current and next positions of the Harris hawk, respectively, X_{rand} is a random position taken by the Harris hawks, X_{mean} is the average of all positions taken by the Harris hawks, X_{rabbit} is the position of the rabbit, LB and UB are the lower and upper bounds, respectively, t is the running iteration, and r_1, r_2, r_3, and r_4 are random values taken between [0, 1]. The leakage energy is important in the HHO method as it is the transition element between phase 1 and phase 2. This energy decreases gradually during the leakage and is given by the following equation:

$$E = 2E_0\left(1 - \frac{t}{T_{iter}}\right), \tag{5}$$

where E is the escape energy, which fluctuates between [-2, 2], E_0 is the beginning energy, which varies between [-1, 1], T_{iter} is the maximum number of iterations, and t is the current iteration. If the energy level is high ($|E| \geq 1$), the Harris hawks are on the prowl for escaping prey: this is the exploration phase. If this energy is low ($|E| < 1$), the Harris' hawks are attempting to pursue the exhausted fleeing rabbits: this is the exploitation phase, which corresponds to the second phase.

Phase 2 is an exploitation phase in which the Harris hawks use surprise attacks to chase away the encircled fleeing rabbits. The technique used in this level depends on the level of energy left in the fleeing rabbits and the headquarters of the Harris hawks. This escape energy can be symbolized by a random value r, between [0, 1]. Thus, the type of siege will depend here on the remaining energy of the fleeing rabbit's r and the escape energy E.

(i) If $|E| \geq 0.5$ and $r \geq 0.5$, this demonstrates that the rabbits still have the ability to flee. Harris' hawks gently circle them to tire them out before attacking them. The siege is carried out carefully in this case, as shown by the following equation:

$$X_{t+1} = X_{\text{rabbit}} - X_t - E|JX_{\text{rabbit}} - X_t|, \tag{6}$$

where $J = 2(1 - r_5)$ and r_5 a random number taken between [0, 1].

(ii) If $|E| \geq 0.5$ and $r < 0.5$, the siege then proceeds smoothly, with quick and gradual dips. This suggests that the rabbits have enough energy and that Harris' hawks are employing complex techniques to chase away evading rabbits. This strategy is described by the following equation:

$$Y = X_{\text{rabbit}} - E|JX_{\text{rabbit}} - X_t|, \tag{7}$$

$$Z = Y + SxLF(D), \tag{8}$$

$$X_{t+1} = \begin{cases} Y & si\, F(Y) < F(X_t), \\ Z & si\, F(Z) < F(X_t). \end{cases} \tag{9}$$

(iii) If $|E| < 0.5$ and $r \geq 0.5$, the siege is then challenging. The bunnies are tired, and the Harris hawks have surrounded them and made a surprise attack. Equation (10) represents the strategy here:

$$X_{t+1} = X_{rabbit} - E|X_{rabbit} - X_t|. \tag{10}$$

(iv) If $|E| < 0.5$ and $r < 0.5$, the siege becomes tougher with fast, gradual dips. This indicates that the rabbits are weary, and Harris' hawks barely encircle the fleeing rabbits before annihilating the prey with a surprise attack

$$Y = X_{\text{rabbit}} - E|JX_{\text{rabbit}} - X_{\text{mean}}|, \tag{11}$$

$$Z = Y + SxLF(D), \tag{12}$$

$$X_{t+1} = \begin{cases} Y & si\, F(Y) < F(X_t), \\ Z & si\, F(Z) < F(X_t). \end{cases} \tag{13}$$

3.2. Differential Evolution (DE). Differential evolution (DE) is a sophisticated stochastic optimization approach that is very simple to understand. It is mainly based on the mutation process which is a key element to explore the areas of the search space [28]. DE relies on the differences between pairs of randomly selected objective vectors. It is this process that makes it efficient and more powerful.

Mutation, crossover, and selection processes enhance the random solutions. Like a result, it is commonly given as follows:

(i) Initialization

The initialization procedure consists at generation $t = 1$, to randomly generate the population $x_i^t = \{(x_{i,1}^t, x_{i,2}^t, \cdots, x_{i,D}^t)|i = 1, 2, 3, \cdots, N\}$ with D being the dimension of the decision variable and N the population size. After initialization, there follows in turn a mutation, then crossover, and finally, selection.

(ii) Mutation

At generation t, the algorithm creates a mutant vector $\{v_i^t = (v_{i,1}^t, v_{i,2}^t, \cdots, v_{i,D}^t)|i = 1, 2, 3, \cdots, N\}$ for each vector x_i^t by mutation operation. Depending on how the vector v_i^t is generated, there are five frequently used mutation strategies, among which equation (14):

$$: v_i^t = x_{r1}^t + F.\left(x_{r2}^t - x_{r3}^t\right), \tag{14}$$

$$: v_i^t = x_{\text{best}}^t + F.\left(x_{r1}^t - x_{r2}^t\right), \tag{15}$$

$$- : v_i^t = x_i^t + F.\left(x_{\text{best}}^t - x_i^t\right) + F.\left(x_{r1}^t - x_{r2}^t\right), \tag{16}$$

$$\frac{\text{DE/best}}{2} : v_i^t = x_{\text{best}}^t + F.\left(x_{r1}^t - x_{r2}^t\right) + F.\left(x_{r3}^t - x_{r4}^t\right), \tag{17}$$

$$: v_i^t = x_{r1}^t + F.\left(x_{r2}^t - x_{r3}^t\right) + F.\left(x_{r4}^t - x_{r5}^t\right), \tag{18}$$

where r_1, r_2, r_3, r_4, and r_5 represent random quantities taken from the set $\{1, 2, \cdots, N\}$, x_{best}^t denotes the best individual of a population at generation t. The difference vector is boosted by the scaling factor F, which is greater than zero.

(iii) Crossover

After mutation, the DE algorithm performs the crossover which consists of generating a test vector $\{u_i^t = (u_{i,1}^t, u_{i,2}^t, \cdots, u_{i,D}^t)|i = 1, 2, 3, \cdots, N\}$ from v_i^t and x_i^t. This crossover method is defined by the following equation:

$$u_{i,j}^t = \begin{cases} v_{i,j}^t & \text{rand}_j(0, 1) \leq CR\, o\text{u}\, j = j_{\text{rand}}, \\ x_{i,j}^t & ailleurs, \end{cases} \tag{19}$$

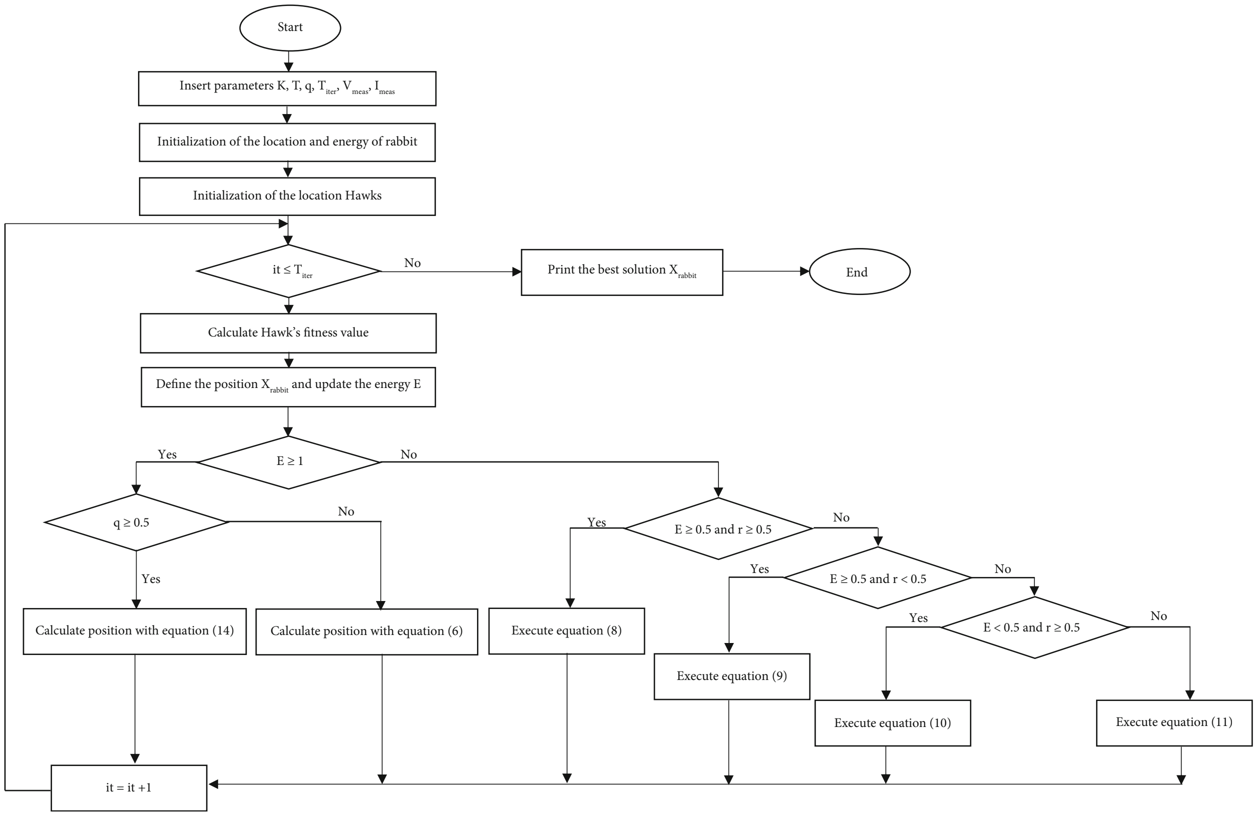

Figure 3: Flowchart HHODE algorithm.

where rand_j is a random quantity taken between [0, 1], CR the crossover rate which is the probability that $u_{i,j}^t$ copies $x_{i,j}^t$ or $v_{i,j}^t$, and j_{rand} an integer quantity taken at random in the interval $[1, D]$.

The Harris's hawk examines and finds its prey in a hunting area during the exploration phase, due to its keen vision. This is not always simple, since it might take many minutes or even hours. DE mutation operators are introduced into the exploration phase as a result of this scenario. At this step of HHO, each Hawk is put in a random spot and waits for the prey to be detected in one of two scenarios. Thus, the hybrid HHODE algorithm manages a global population shared between HHO and DE.

Figure 3 shows the flowchart of this method proposed.

4. Results

The suggested algorithm's efficiency was compared to that of a commercial R.T.C France silicon solar cell. Irradiance of 1000 W/m^2 and a temperature of 33°C are the test parameters for this encounter. The simulation's results are the average of 20 runs. The number of iterations to reach the termination condition is set at 3000. Experiments were run on a machine with an Intel Core i5-3437U@1.9GHz CPU, 8 GB RAM, and Windows 10-64 bits installed. MATLAB R2013a was used to develop the suggested approach.

The boundaries are specified in order to identify the unknown PV cell characteristics. Table 1 gives all the bounds (lower and upper) of this simulation. The lower and upper bounds used here are the same as those used in works found in the literature, such as [6, 15, 18] and others. Thus, we have the photocurrent which varies between [0 1] (A), the diode's saturation current [0 1] (μA), the ideality factor [1 2], the series resistance [0 0.5] (Ω), and the shunt resistance [0 100] (Ω).

Table 1: Parameters boundaries of this operation.

Parameters	Lower limits	Upper limits
Photo-current (I_{ph})	0	1
Diode's saturation current (I_0, I_{01}, I_{02})	0	10^{-6}
Series resistance (R_S)	0	0,5
Shunt resistance (R_{Sh})	0	100
Ideality factor (n, n_1, n_2)	1	2

For an efficient verification of our algorithm, we use the measured current and voltage data presented in the work of Easwarakhanthan et al. [29]. This data has been used numerous times in the literature to test algorithms for estimating intrinsic parameters. We use 26 pairs of data from the commercial silicon solar cell from R.T.C France. This data was repeated in the works of researchers such as Niu et al. (2014) in [30], Yuan et al. (2015) in [31], Jamadi et al. (2016) in [11], Oliva et al. (2017) in [32], Merchaoui et al.

Table 2: Comparison of several methods on the single diode model.

Methods	$I_{ph}(A)$	I_0 (μA)	$R_S(\Omega)$	$R_{Sh}(\Omega)$	n	RMSE (10^{-4})
HHODE (proposed)	0.760678	0.365462	0.0340193	71.8144	1.48174	14.664
HHO [18]	0.76143	0.965	0.31311	72.4432	1.6004	21.607
EO [16]	0.7607597037	0.32628893	0.32628893	54.206594	1.482193	9.8603
PO [18]	0.76109	1	0.030904	80	1.6045	21.444
MPSO [34]	0.760787	0.310683	0.036546	52.88971	1.475262	73.3007
MABC [11]	0.760779	0.321323	0.036389	53.39999	1.481385	27.619
BSO [35]	0.76090	0.99996	0.03137	97.35715	1.60455	24.551

Table 3: Comparison of several methods on the double diode model.

Methods	$I_{ph}(A)$	I_{01} (μA)	I_{02} (μA)	$R_S(\Omega)$	$R_{Sh}(\Omega)$	n_1	n_2	RMSE (10^{-4})
HHODE (proposed)	0.76055	0.49894	0.11117	0.0337608	67.9996	1.52949	1.78329	15.978
ASO [18]	0.76186	$11.19*10^{-6}$	0.62307	0.032945	48.5803	1.9098	1.5508	17.564
PO [18]	0.76267	0.27315	$159.8*10^{-6}$	0.05	30	1.5531	1	34.802
SSA [18]	0.76119	0.38853	0.22658	0.036546	67.0463	1.6909	1.467	17.887
SMA [36]	0.76035	0.31574	0.84969	0.035115	67.4807	1.4846	2	9.9715
EO [16]	0.76792	0.39999	0.26605	0.03659	54.17614	2.000	1.46451	9.83532
BES [15]	0.7608	0.2259	0.7493	0.0367	55.4854	1.4510	2.0000	9.8248

(2018) in [9], Gnetchejo et al. (2019) in [6], Ridha (2020) in [33], and Nicaire et al. (2021) in [15]. We did not design an experimental bench but just retrieved the data already available to evaluate our proposed method.

4.1. Case of the SDM. The HHODE approach was compared to six other methods in order to emphasize its performance. HHO [18], the equilibrium optimizer (EO) [16], the political optimizer (PO) [18], modified particle swarm optimization (MPSO) [34], the modified artificial bee colony (MABC) [11], and the brain storm optimization algorithm [35] were all based on these comparable methodologies.

Table 2 shows the results of the suggested hybrid technique for identifying the five parameters of the one-diode model, as well as work done under the same conditions and with the same data. The decision parameter for the validation of our algorithm is the mean square error. It appears from this comparative study that the proposed hybrid method has a much lower root means square error (RMSE = $14.664e-4$) than the basic algorithm, the Harris hawk optimization (RMSE = $21.607e-4$). This demonstrates the superiority of the proposed method over the baseline method with an RMSE closer to zero. From Table 3, we also deduce the superiority of the hybrid HHODE method over methods such as the political optimizer (PO), the modified particle swarm optimization (MPSO), the modified artificial bee colony (MABC), and the brain storm optimization (BSO). This demonstrates a higher level of precision in parameter extraction for the single diode model than the hybrid model of Harris hawk optimization and differential evolution. However, it must be noted that, despite the superiority and established accuracy of the proposed method, it remains less accurate than equally recent algorithms such as the equilibrium optimiser (EO), which presents a root mean square error of the order of $9.803e-4$. The latter presents more accurate and reliable results than the hybrid method we propose.

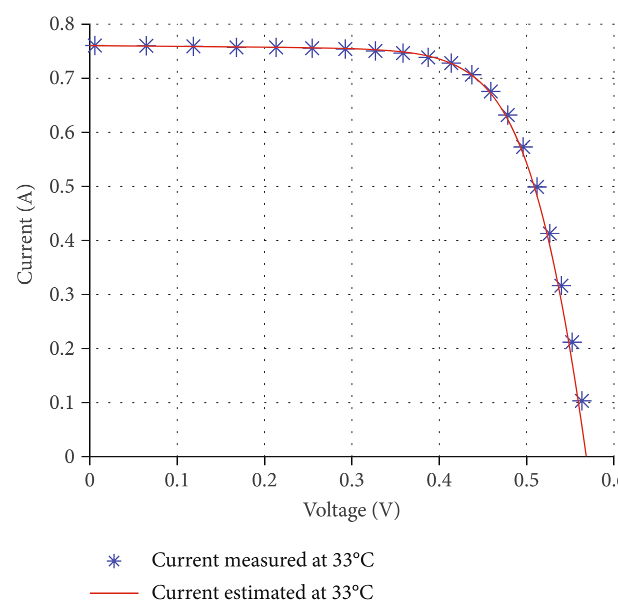

Figure 4: Estimated and measured current curves for the single diode model.

For the R.T.C France solar cell, Figure 4 displays the I-V calculated and measured parameters of the single diode model. The blue dot curve gives us the measured current-voltage characteristic, and the red solid line curve shows the current-voltage characteristic estimated by the HHODE hybrid algorithm under the test conditions mentioned

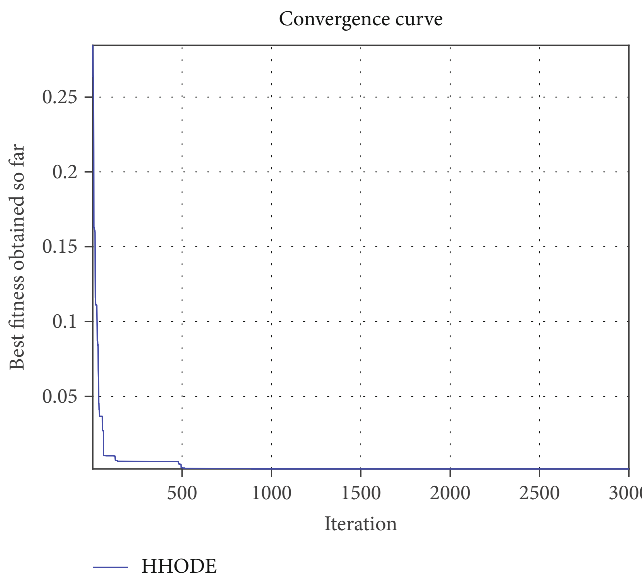

Figure 5: Convergence curve of RMSE.

above. The estimated and measured curves are virtually perfectly superimposed. This is because the difference between the measured and estimated values is nearly zero.

Figure 5 depicts the method's convergence to the best solution after 3000 iterations. After more than 500 iterations, we can see that the approach is rapidly and significantly converged to the ideal answer. The search for the best solution then becomes invariant. The main limitation of this method is that it has a large number of randomly chosen coefficients that very often lead to skipping regions of optimal solutions. The energy that escapes can also quickly alter the convergence to the optimal solutions.

4.2. Case of the Double Diode Model. In order to highlight the performance of the HHODE method, it has been compared to six competitive methods. These compared methods were the basis of the atom search optimization (ASO) [18], the political optimizer (PO) [18], the salp swarm algorithm (SSA) [18], the slime mould algorithm (SMA) [36], the equilibrium optimizer (EO) [16], and the bald eagle search (BES) [15].

The results obtained by the proposed hybrid method for estimating the parameters of the double diode model and work carried out under the same conditions, with the same data, are presented in Table 3. The decision parameter is the same as for the single diode model. The comparative study shows that, for a two-diode model, the proposed hybrid method is more accurate and reliable (RMSE = 15.978$e-4$) than many algorithms found in the literature such as the atom search optimization (ASO), the political optimizer (PO), and the salp swarm algorithm (SSA). Nevertheless, it is interesting to note that despite this noted accuracy in parameter estimation, the HHODE method is less reliable than methods such as the slime mould algorithm (SMA), the equilibrium optimizer (EO), and the bald eagle search (BES) to mention only the latter, which are more advanced than the proposed method.

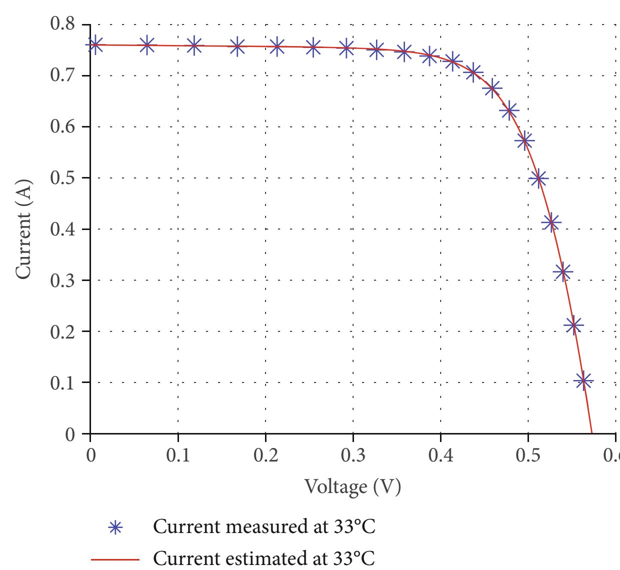

Figure 6: Estimated and measured current curves for the double diode model.

The predicted (red solid line) and experimental (blue dashed line) current-voltage characteristics of the R.T.C. France solar cells for a double-diode model are shown in Figure 6. The blue dot curve represents the observed current-voltage characteristic, whereas the red solid line curve represents the current-voltage characteristic calculated by the HHODE hybrid algorithm under the abovementioned test circumstances. It can be observed that the estimated and measured curves are virtually perfectly superposed. This is because the difference between measured and estimated values is close to zero.

The findings obtained by the HHODE technique, like those obtained by the one-diode model, are subject to some constraints. The fundamental issue is that it contains a large number of randomly generated coefficients, which frequently result in bypassing portions of ideal solutions, and the energy that escapes can quickly change the convergence to optimal solutions.

5. Conclusion

In this work, we provide a new hybrid technique for determining the best values for solar PV cell properties by combining the Harris hawk optimisation (HHO) algorithm with differential evolution (DE). A number of scenarios were created to demonstrate the algorithm's performance, including single and dual diode PV cell models. The current-voltage characteristics of the observed and computed data illustrate the great accuracy of the proposed approach. The accuracy and validity of the PV cell parameter extraction methodology are proven and contrasted using simulation results after 20 tests. It has the advantage of being more accurate than many of the algorithms reported in the literature. The method is validated using real-world data from the commercial RTC France cell. Its accuracy is proven by comparing its RMSE to a variety of metaheuristic techniques. All analysed instances achieve a high level of accuracy ($\mathrm{RMSE} = 14.664e-4$ for SDM and $15.978e-4$ for DDM). As a consequence, a correlation of the simulated I-V curves with the observed characteristics confirms the HHODE's accuracy and application to parameter estimation and problem solving in other power systems.

Nomenclature

CR: Crossover rate
D: Length of dilemma
E: Escape energy
E_0: Initial energy
F: Vector's amplifier
I: Output current of the solar cell
I_e: Estimated current
I_m: Measured current
I_0, I_{01}, I_{02}: Saturation current of the diode
I_{ph}: Photo-current of the solar cell
K: Boltzmann constant
LB: Lower bound
LF: Levy flight
M: Length of the current vector
N: Population size
n, n_1, n_2: Ideality factor
q: Electron charge
r: Remaining energy of the fleeing rabbit
r_1, r_2, r_3, r_4, r_5: Random values
RMSE: Root mean square error
R_S: Series resistance
R_{Sh}: Shunt resistance
T: Temperature
t: Current iteration
T_{iter}: Maximum number of iterations
UP: Upper bound
U_i^t: Test vector
V_i^t: Mutant vector
X_t, X_{t+1}: Current and next position of Harris hawk
X_{rand}: Random position of Harris hawk
X_{mean}: Average of all positions
X_{rabbit}: Position of rabbit
x_i^t: Population
${x_{\mathrm{best}}}^t$: Best individual of a population.

Data Availability

All data are contained in the article.

Conflicts of Interest

The authors state that they have no known rivals, financial interests, or personal ties that may appear to affect the work presented in this paper.

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