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Chaotic Generator and Artificial Ecosystem-Based Optimization for Accurate Modeling of Photovoltaic Cell Parameters

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Abstract: Accurate modeling of solar cells depends on precise determination of photovoltaic (PV) cell parameters. This study proposes a new optimization algorithm combining a chaotic generator with Artificial Ecosystem-based Optimization (AEO) to obtain accurate current-voltage and power-voltage curves for PV cells and modules with different technologies. The algorithm determines unknown model parameters such as generated photocurrent, saturation current, series resistance, shunt resistance, and ideality factor. Performance assessment demonstrates that the proposed optimization algorithm, when coupled with a chaotic-based search sequence, outperforms many prominent optimization algorithms in terms of robustness and accuracy in extracting PV parameters. Moreover, detailed results indicate the superior performance of the two-diode model in determining the correct values for the model parameters. Researchers and practitioners can efficiently extract PV parameters by utilizing the proposed optimization algorithm, benefiting from its robustness and accuracy. The algorithm's effectiveness is demonstrated through comparative analysis and evaluation of its performance against other optimization methods.

Index Terms: Chaotic sequence AEO algorithm,Optimization, Parameter extraction, Photovoltaic, Single and double diode models.

1. Introduction

Solar energy has gained significant importance as a renewable energy source due to its availability, sustainability, and abundance. The discovery by French scientist Edmond Becquerel in 1839 of the photovoltaic (PV) effect, which allows the transformation of solar energy into electrical energy using PV materials, marked the beginning of solar technology. Since then, the utilization of sunlight to generate electric currents has become increasingly popular due to its remarkable advantages [1].

Solar energy accounted for 43% of the worldwide generation capacity in 2018, making it a prominent player among other power-generating methods. The solar panel, which relies on the PV effect, is the pivotal component for converting solar energy into electrical energy. The projected growth of PV-generated electricity is expected to surpass 720TWh, with an increase of more than 22% in 2019 [2].

To optimize investments and improve cost-effectiveness for industrial-scale applications, accurate models representing the performance of PV panels are essential. These models include maximum power point tracking (MPPT) techniques, power converters, controller design, grid integration, and fault detection [3, 4]. Mathematical modeling of the electrical activity of PV cells/modules is necessary to simulate their I-V (current-voltage) and P-V (power-voltage) curves.

Different PV models, including the one-diode model (1DM), two-diode model (2DM) [5], and three-diode model (3DM) [6], have been studied extensively for PV system modeling. Each model requires the calculation of specific cell characteristics, such as the diode ideality factor (n), photocurrent (Iph), reverse saturation current (I0), shunt resistance (Rsh), and series resistance (Rs) [7-10]. The 1DM, 2DM, and 3DM models involve the extraction of five, seven, and nine parameters, respectively.

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There are three main types of methods developed for parameter extraction from PV data sheets or experimental data: iterative approaches (numerical), non-iterative approaches (analytic), and optimization approaches (AI). Iterative methods are commonly used in literature for solving the nonlinear problems associated with PV models [11]. Non-iterative methods involve approximations and simplifications to derive explicit equations for determining model parameters, typically based on critical points on I-V characteristic curves [12, 13].

Often inspired by nature, optimization algorithms are utilized to estimate model parameters and overcome limitations associated with differentiability, convexity, and sensitivity to initial parameter values. The Artificial Ecosystem-based Optimization (AEO) algorithm, described in [14], is a simple yet effective optimization algorithm for addressing constrained and unconstrained optimization problems. Compared to conventional techniques, the AEO algorithm offers simplicity, enhanced avoidance of local optima, versatility, and gradient-free optimization. Other heuristic methods used for PV parameter estimation include the self-adaptive ensemble-based differential evolution (SEDE) [15], enhanced JAYA algorithm (IJAYA) [16], mimetic adaptive differential evolution (MADE) [17], and modified JAYA algorithm [18].

Additionally, various strategies have been employed to enhance existing algorithms, such as the artificial bee colony method with teaching-learning (TLABC) [19], backtracking search algorithm with multiple learning (MLBSA), leader particle swarm optimization method with enhancement (ELPSO) [20], a combination of the grey wolf optimizer and cuckoo search (GWOCS) [21], the enhanced teaching-learning based optimization (ETLBO) [22], the enhanced Levy flight bat algorithm (ELBA) [23], the improved teaching-learning based optimization (ITLBO) [24], the enhanced Harris Hawks optimization (EHHO) [25], and the differential evolution algorithm with self-guidance (SGDE) [26].

These algorithms often rely on pseudo-random sequence generators. However, recent studies have shown that incorporating chaotic sequences with inherent determinism and unpredictability into optimization algorithms can yield significant improvements. Chaotic sequences can be used as generators of random bits, offering advantages in terms of security, wireless transmission, spread-spectrum communication, and encrypted connections. Chaotic sequence generators, such as the Lorenz, Rossler, Chua, and Linz Sprott types, have been developed and applied in various applications, including parameter extraction of PV cells and modules.

Previous studies have utilized different methods, such as the specialized parallel computing particle (NPSOPC) method [27], for parameter extraction. While many optimization algorithms have proven effective, there is still a need for novel algorithms that can further improve accuracy and overall effectiveness, particularly in reducing the range of error, as stated by the no-free-luch (NFL) theorem in [28].

Table 1. Comparison of Different Optimization techniques from the literature

Method	Merits	Demerits
GWOCS	Effective global search capability Robustness to handle multimodal functions Easy implementation Low computational cost Good balance between exploration and exploitation	The convergence rate can be slow Requires fine-tuning of parameters May suffer from premature convergence
ELBA	Explores search space efficiently Fast convergence rate Suitable for continuous and discrete optimization problems Flexibility in handling complex functions	Complexity increases with dimensionality Sensitive to parameter settings May get trapped in local optima Requires careful handling of parameters
EHHO	An effective balance between exploration and exploitation	Suffers from stagnation in some cases Parameter selection is critical

	Global search capability Adaptive search strategy Robust performance in noisy environments	It may not be suitable for high-dimensional Suffers from stagnation in some cases Parameter selection is critical It may not be suitable for high-dimensional problems It may require fine-tuning for convergence
NPSOPC	Efficiently handles high-dimensional optimization problems Faster convergence rate compared to standard particle swarm optimization (PSO)algorithms Effective in parallel computing	Can suffer from premature convergence Needs fine-tuning of parameters Higher computational cost Not well-suited for multimodal problems Complexity increases with dimensionality
SGDE	Efficiently handles large-scale problems The self-adaptive mechanism for parameter control Low computational cost Versatile, suitable for different problem types	Complex implementation Requires a large population size The convergence rate may vary for different problem types It can be computationally intensive for complex problems

From the provided Table I comparing various optimization algorithms, it can be observed that each algorithm has its own merits and demerits. However, one research gap that emerges is the need for an optimization algorithm with a fast convergence rate and the ability to effectively handle high-dimensional optimization problems while maintaining a good balance between exploration and exploitation. Several algorithms mentioned in the table show promise in one or more of these aspects, but none seem to excel in all the desired criteria simultaneously.
For instance, the Specialized Parallel Computing Particle (NPSOPC) method efficiently handles high-dimensional problems and exhibits a faster convergence rate than standard PSO algorithms. However, it is not well-suited for multimodal problems, and its complexity increases with dimensionality. On the other hand, the Enhanced Levy Flight Bat Algorithm (ELBA) shows promise in efficiently exploring search spaces and boasting a fast convergence rate. Still, it suffers from sensitivity to parameter settings and may get trapped in local optima.

A. Research Gap and Novelty

Addressing this research gap would involve developing a novel optimization algorithm that combines the strengths of existing approaches while mitigating their respective limitations. The ideal algorithm should efficiently handle high-dimensional optimization problems and multimodal functions, exhibit a fast convergence rate, and perform robustly in noisy environments. Moreover, it should require minimal fine-tuning of parameters and apply to various types of problems, including continuous and discrete optimization. Such an algorithm would significantly improve optimization and enable more efficient and reliable solutions to complex real-world problems. Research efforts should focus on striking the right balance between exploration and exploitation, adaptively adjusting parameter settings, and reducing the computational complexity to create a versatile and powerful optimization approach.

B. Research Objectives

The study's primary objective is to determine the parameters of one and two-diode solar PV models by combining a chaotic map with the improved Artificial Ecosystem-based Optimization (AEO) algorithm. The study aims to address the research gap by proposing a new algorithm that enhances the traditional AEO algorithm and incorporates chaotic sequences to improve accuracy and reduce error.

C. Contributions

1. Enhancement of AEO Algorithm: The study contributes to the field by enhancing the traditional AEO algorithm through parameter adjustments that govern the exploratory and exploitative phases. The suggested algorithm achieves appropriate balancing by using a logistic equation to reduce the search space.
2. Incorporation of Chaotic Sequences: The study introduces the incorporation of chaotic sequences, known for their inherent determinism and unpredictability, into the optimization algorithm. By utilizing chaotic systems' sensitivity to initial conditions, the proposed method introduces a new solution during the AEO updating phase, leading to significantly improved Root-Mean-Square-Error (RMSE) values.
3. Comparative Analysis: The study compares the proposed optimization algorithm against other popular optimization algorithms and techniques. This analysis helps evaluate the effectiveness of the proposed strategy and demonstrates its outperformance in terms of resilience and accuracy in extracting PV parameters.
4. Accuracy Improvement in Parameter Extraction: The detailed data analysis confirms that the two-diode PV model provides more accurate estimates of the model's parameters. The proposed optimization algorithm, incorporating a chaotic search sequence, contributes to achieving this improved accuracy.

In light of the abovementioned objective and addressed contribution, the paper's main findings demonstrate that the suggested Logistic Chaotic Artificial Ecosystem-based optimization algorithm (LCAEO), incorporating a chaotic search sequence, outperforms many conventional techniques regarding resilience and accuracy in extracting PV parameters. Detailed data analysis also confirms that the two-diode PV model provides more accurate estimates of the model's parameters.

The remaining sections of this paper are organized as follows: Section 2 provides an overview of the one-diode model (1DM) and two-diode model (2DM) used for solar PV modeling. Section 3 explains the basics of the LCAEO optimization algorithm and describes the method for estimating PV parameters using a chaotic sequence generator. Section 5 presents simulation findings and comparisons. Section 6 concludes the paper, summarizing the essential findings and contributions of the study.

2. Photovoltaic Cell/Module Models

The literature reports the use of different various methods for simulating PV cells/modules. The equivalent circuit model (ECM) is one of the techniques often employed in research projects [1]. The significant benefit of utilizing this model is the simplicity and ease of integration into the most widely used electrical tools, such as MATLAB [2].

The Shockley equation below describes the I-V characteristic:

$$I_D = I_0 \left[\exp\left(\frac{qV_D}{nkT}\right)\right] \tag{1}$$

The external circuit starts to conduct charge carriers, which produces an electrical current I_{ph}designated as a photocurrent. Consequently, the ideal model (the initial model of the PV cell) is created as a parallel-connected current generator and diode. The output current I of the ideal cell is described as follows with the addition of I_{ph} to Eq. (1):

$$I = I_{ph} - I_D = I_{ph} - I_0 \left[\exp\left(\frac{qV_D}{nkT}\right)\right] \tag{2}$$

Generating series resistance should consider the losses brought on by the materials and the connections' resistance. As a result, the output current of the revised model is formulated, where the output current and voltage are, respectively, I and V.

$$I = I_{ph} - I_0 \left[\exp\left(\frac{q(V+IR_S)}{nkT}\right) - 1\right] \tag{3}$$

Despite its ease of use, the earlier model was less accurate since it ignored the leakage current that occurs in the PV cell.

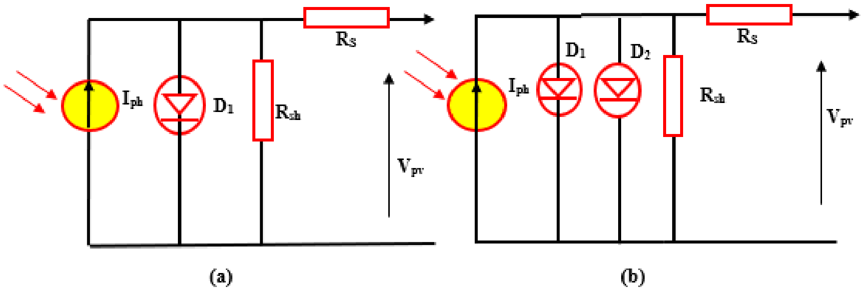

Figure 1. Schematics of a PV cell:(a)1DM,(b)2DM.

To produce a straightforward and precise model (called the one-diode model), a shunt resistance Rsh is inserted into the prior model (Figure 1(a)). Calculation of the output current is performed based on Figure 1(a) using additional components and Kirchhoff's rule as follows:

$$I = I_{ph} - I_0\left[\exp\left(\frac{q(V+IR_S)}{nkT}\right) - 1\right] - \frac{V+IR_S}{R_{sh}} \tag{4}$$

Recombination indicates a critical loss in a real PV cell inadequately represented by a single diode. To account for the effects of composite current loss, the one-diode model is expanded to include a second diode. Figure 1(b) shows the analogous circuit for the two-diode model. As a result, the I-V characteristic is:

$$I = I_{ph} - I_{01}\left[\exp\left(\frac{q(V+IR_S)}{n_1kT}\right) - 1\right] - I_{02}\left[\exp\left(\frac{q(V+IR_S)}{n_2kT}\right) - 1\right] - \frac{V+IR_S}{R_{sh}} \tag{5}$$

Where I_{01} and I_{02}designate respectively diffusion and saturation currents.n_1 and $n_2$designatethe ideality factor for diffusion and recombination diodes,

The 1DM and 2DM can be mathematically formulated, respectively, considering the scenario of a PV module constituted of Ns cells connected in serial and N_p cells connected in parallel.

$$I = N_pI_{ph} - N_pI_0\left[\exp\left(\frac{q(V+(N_s/N_p)IR_S)}{nN_skT}\right) - 1\right] - \frac{V+(N_s/N_p)IR_S}{(N_s/N_p)R_{sh}} \tag{6}$$

$$I = N_pI_{ph} - N_pI_{01}\left[\exp\left(\frac{q(V+(N_s/N_p)IR_S)}{nN_skT}\right) - 1 - N_pI_{02}\left[\exp\left(\frac{q(V+(N_s/N_p)IR_S)}{n_2N_skT}\right) - 1\right]\right] - \frac{V+(N_s/N_p)IR_S}{(N_s/N_p)R_{sh}} \tag{7}$$

A. Roposed Optimization Method

The fitness value to be minimized is often defined using root mean squared deviation (RMSD). The fitness function (FF) is given in equation (8), and RMSD can be calculated using it (9). The proposed PV models are evaluated by comparing the differences between real and estimated PV current values. To ensure fair comparisons with previous studies, the same FF is used.

$$RMSD = \sqrt{\frac{\sum(I_m(k)-I_e(k))^2}{N_m}}, \forall k \in N_m \tag{8}$$

$$FF = min(RMSD) \tag{9}$$

whereI_m and I_e describes the measured and estimated values obtained by the suggested models, respectively, Nm signifies the number of points measured. Notably, the Newton-Raphson numerical iterative approach is used to derive $I_e$values for each observed voltage point by solving (6) and (7) for 1DM and 2DM, respectively.

The FF shown in (9) is subjected to various min/max restrictions of the model's unknown parameters. Additionally, Io1 Io2 and n1 n2 are adopted for 2DM.

3. AEO With A Logistic Chaotic Sequence

Recently, there has been a trend to replace randomness in heuristic algorithms with chaotic maps to exploit chaotic randomization's dynamic and statistical characteristics [27]. As a result, the random numbers rj,i in the updated solution of the equationare replaced with a logistic chaotic sequence Cj,i." as follows:

$$Y_{j,k,i} = Y_{j,k,i} + C_{jj}\left(Y_{j\,\mathrm{pest}\,,i} - Y_{j,\,\mathrm{worst}}\right) \qquad (10)$$

The logistic chaotic sequence is given by:

$$C_{z+1} = 4C_z(1 - C_z) \qquad (11)$$

where C1 is randomly generated within the range [0, 1], which is chosen to be equal to 0.8, and C_z is the result of the z_{th} chaotic iteration.

In the suggested optimization technique, the primary goal is to estimate the parameters of the PV cell/module by adjusting the variables for the 1DM and 2DM. This is done to minimize the RMSE value.

4. Logistic Chaotic AEO Optimization Algorithm

The Figure 2 Shows the Flowchart of the estimation of the parameters using the LCAEO method.

Table 2. Measured voltage and current computed and utilized in this investigation

N	RTCFrancesilicon[3]		PhotoWattModulePolycrystalline[3]	
	$V_{measured}$	$I_{measured}$	$V_{measured}$	$I_{measured}$
1	-0.2057	0.764	0.1248	1.0315
2	-0.1291	0.762	1.8093	1.03
3	-0.0588	0.7605	3.3511	1.026
4	6.0538	1.018	4.7622	1.022
5	0.0646	0.76	6.0538	1.018
6	0.1185	0.759	7.2364	1.0155
7	0.1678	0.757	8.3189	1.014
8	0.2132	0.757	9.3097	1.01
9	0.2545	0.7555	10.2163	1.0035
10	0.2924	0.754	11.0449	0.988
11	0.3269	0.7505	11.8018	0.963
12	0.3585	0.7465	12.4929	0.9255
13	0.3873	0.7385	13.1231	0.8725
14	0.4137	0.728	13.6983	0.8075
15	0.4373	0.7065	14.2221	0.7265
16	0.459	0.6755	14.6995	0.6345
17	0.4784	0.632	15.1346	0.5345
18	0.496	0.573	15.5311	0.4275
19	0.5119	0.499	15.8929	0.3185
20	0.5265	0.413	16.2229	0.2085
21	0.5398	0.3165	16.5241	0.101
22	0.5521	0.212	16.7987	-0.008
23	0.5633	0.1035	17.0499	-0.111
24	0.5736	-0.01	17.2793	-0.209
25	0.5833	-0.123	17.4885	-0.303
26	0.59	-0.21		

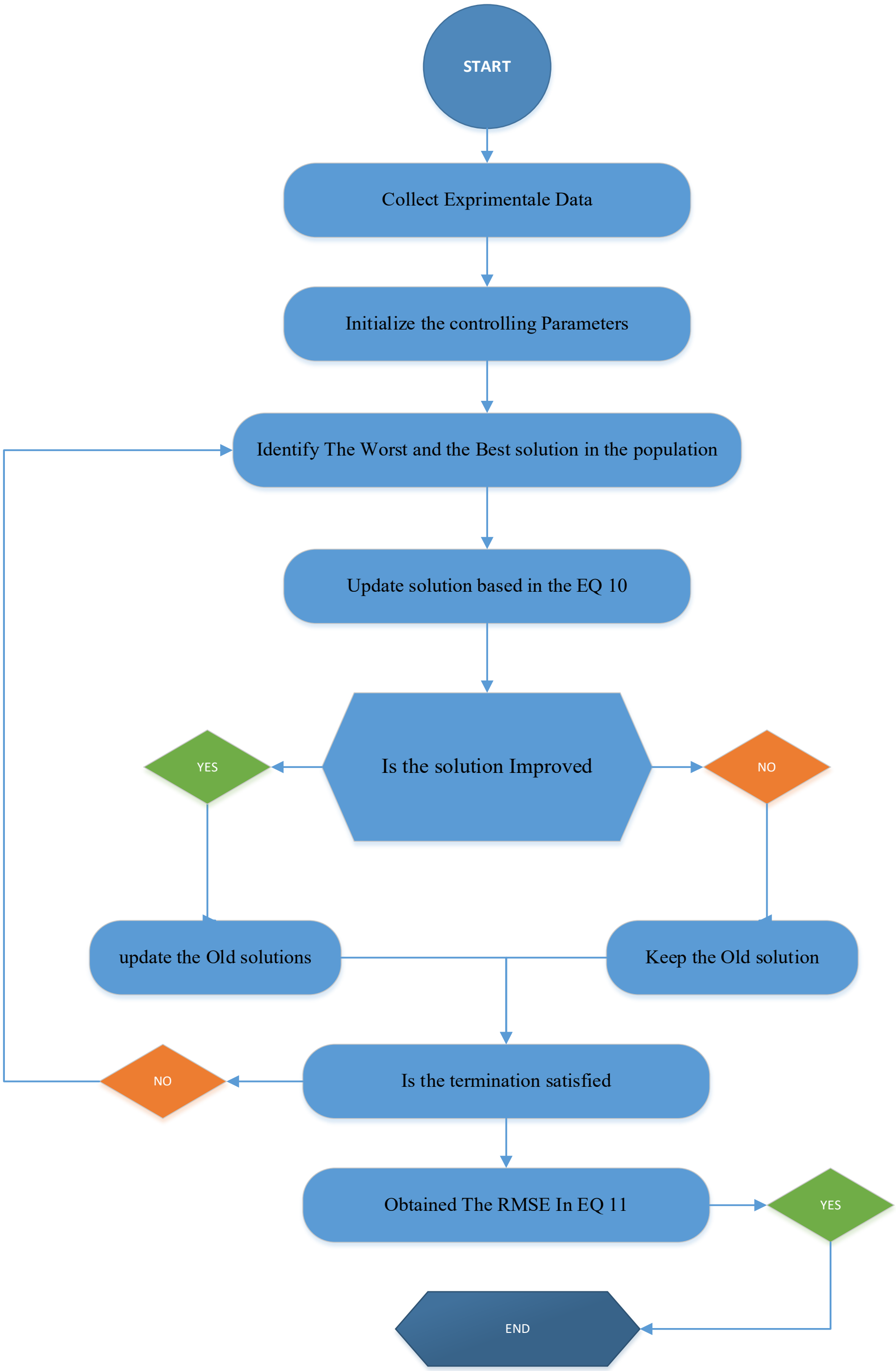

Figure 2. Flowchart of the estimation of the parameters using the LCAEO method.

Table 3. Measured voltage and current computed and utilized in this investigation

PV system	I_{sc} (A)	V_{oc} (V)	I_{mp} (A)	V_{mp} (V)	N_s
RTC France Cell	0.760	0.5728	0.69119	0.45	1
PhotoWatt Module	1.030	16.778	0.9120	12.6490	36

5. Simulation and Result

The algorithm was implemented under a Matlab/Simulink environment to estimate the I-V and P-V characteristics of the France silicon PV cell and PhotoWatt module, for which the experimental measurements of the I-V pairs are listed in Table II. Table III illustrates the chosen limitations for all parameters for comparison with the other methods. Also utilized for a fair comparison are 1000 iterations and 10 populations. The suggested LCAEO simulation results are compared to several very recently established algorithms' most accurate PV parameter findings, including EHHO[25], SGDE[26], ELBA[23], NSPSOPC [27], SGDE [26], GWOCS[21]. Table IV shows the parameters of the RTC France Cell &PhotoWatt Module.

Table 4. Parameters of RTC France Cell &PhotoWatt Module

Parameter	**RTC France cell**		**PhotoWatt Module**	
	Min	Max	Min	Max
Iph[A]	0	1	0	2
I_0 [µA]	0	1	0	50
n x N_s	1	2	1	50
R_s [Ω]	0	0.5	0	2
R_{sh} [Ω]	0	100	0	2000

A. Experimental versus simulated curves for the RTC France silicon cell (1DM)

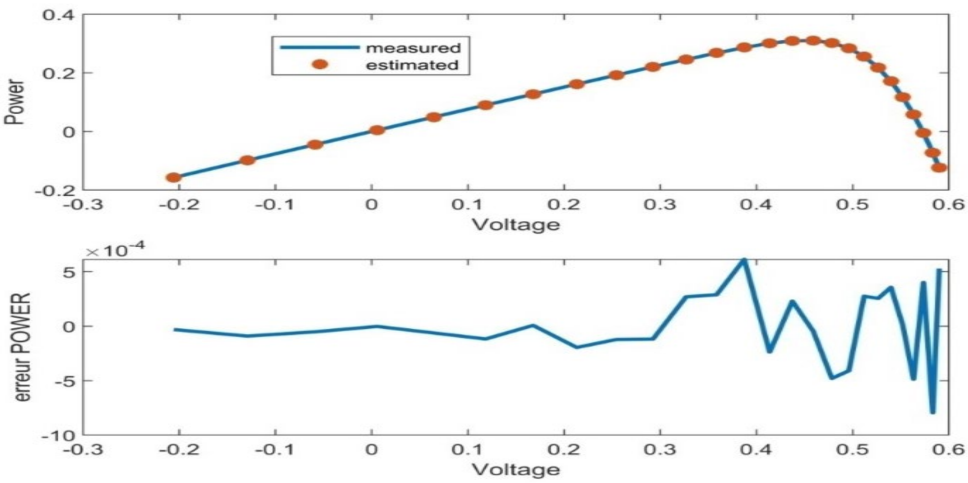

Figure 3. Comparisons between the experimental data and estimated data obtained by LCAEO for RTC-FRANCE:P-V and IAEpower–V characteristics.

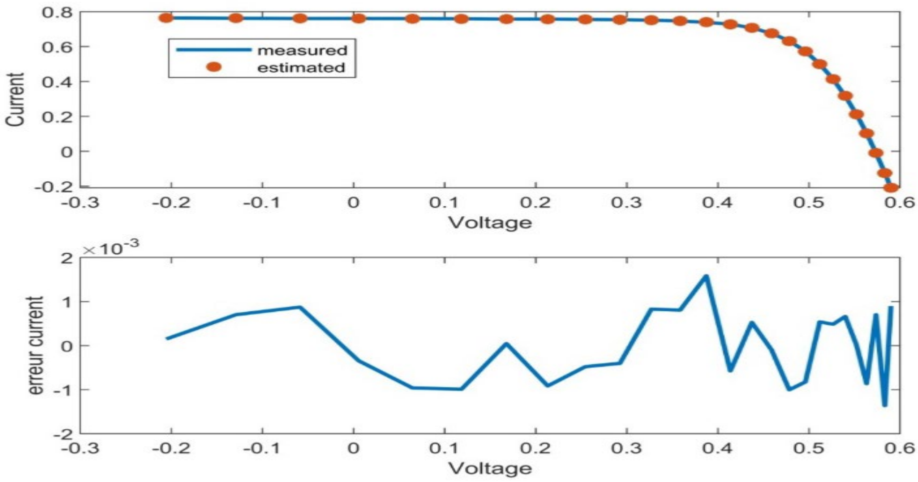

Figure 4. Comparisons between the experimental data and estimated data obtained by LCAEO for RTC-FRANCE:I-V and $IAE_{CURRENT}$ –V characteristics.

Figures 3 and 4 compares the experimental data and estimated data obtained by LCAEO for RTC-FRANCE (1DM) P-V & I-V Characteristics, respectively.

Table 5. The Best RTC France PV cell solution by LCAEO and other algorithms (1DM)

Model	Variables	LCAEO (proposed)	EHHO[25]	SGDE[26]	ELBA[23]	NPSOPC[27]
SDM	I_{ph}[A]	0.760788	0.76078	0.76078	0.76078	0.7608
	I_0 [μA]	0.310691	0.323	0.32302	0.32302	0.3325
	n x N_s	1.47727	1.48124	1.48118	1.48119	1.4814
	R_s [Ω]	0.036546	0.03638	0.03638	0.03638	0.03639
	R_{sh} [Ω]	52.8899	53.74282	53.71853	53.71852	53.7583
	RMSE[10^{-4}] W	7.72985	9.8602	9.860219	9.860219	9.8856

The LCAEO model performs better than the other models (EHHO, SGDE, ELBA, NPSOPC) based on the values presented in the table V. The LCAEO model consistently exhibits minor deviations from the valid values across various variables. For instance, the LCAEO model predicts Iph (A) with remarkable accuracy, showing a value of 0.760788, which is very close to the actual value of **0.76078**. In contrast, the other models show slightly more significant discrepancies, ranging from **0.76078** to **0.7608**. Similarly, the LCAEO model accurately estimates I_0 (μA) with a value of **0.310691**, whereas the other models have higher values, leading to less accurate predictions. Moreover, the LCAEO model closely matches the actual value of n x Ns, further supporting its precision.

Additionally, the LCAEO model demonstrates better agreement with the proper values for the parameters Rs (Ω) and Rsh (Ω). Its values of **0.036546** and **52.8899**, respectively, are close to the true values, while the other models exhibit slightly more significant differences. Furthermore, the LCAEO model exhibits the lowest RMSE value of **7.72985 x 10^-4**, indicating its overall better fit to the actual data than the other models. In conclusion, the LCAEO model's ability to consistently predict the variables with higher accuracy and its lower RMSE value supports its superiority over the other models, making it a favorable choice for the given dataset.

B. Experimental versus simulated curves for the RTC France silicon cell (2DM)

Figure 5 and 6 compares experimental and estimated data obtained by LCAEO for RTC-FRANCE (1DM) P-V & I-V Characteristics, respectively.

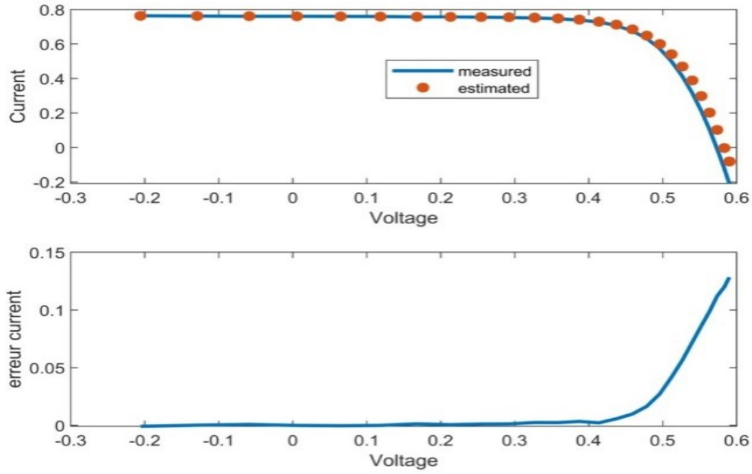

Figure 5. Comparisons between the experimental dand estimated data Obtained by LCAEO for RTC-FRANCE:P-V and IAEpowercharacteristics

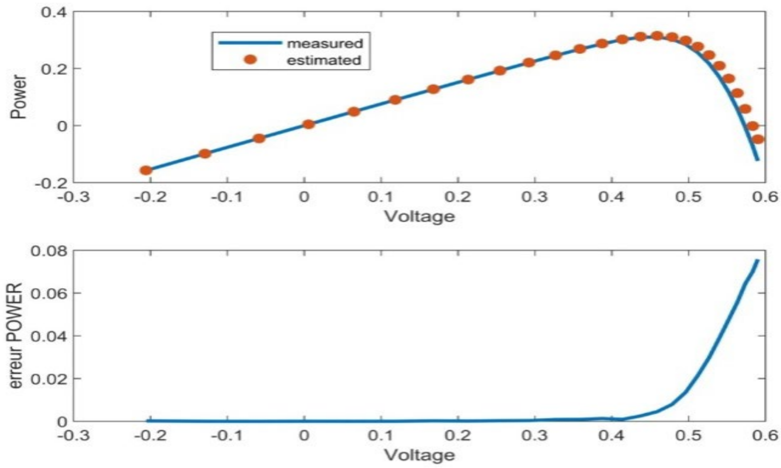

Figure 6. Comparisons between the experimental and estimated data obtained by LCAEO for RTC-FRANCE:I-V and IAECURRENT –V characteristics.

Table 6. The optimal solution for RTC France PV cell by LCAEO and various algorithms (2DM)

Model	Variables	LCAEO	SGDE[26]	ELBA[23]	NPSOPC[27]
DDM	I_{ph}[A]	0.760818	0.76079	0.76078	0.76078
	I_{01} [μA]	0.0926527	0.14582	0.74934	0.25093
	I_{02} [μA]	0.301758	0.73510	0.22598	0.54542
	N1 x N_s	1.99998	1.45536	2.0000	1.45982
	N2 x N_s	1.47499	1.89377	1.45102	1.99941
	R_s [Ω]	0.0365127	0.03722	0.03674	0.03663
	R_{sh} [Ω]	52.8132	54.85897	55.48544	55.1170
	RMSE[10^{-4}] W	7.7134206	7.490069	9.824849	9.82084

The LCAEO model continues to demonstrate its favorable performance compared to the other models (SGDE, ELBA, NPSOPC) in the tableVI. The values presented show that the LCAEO model consistently provides more accurate predictions for the variables. For instance, regarding Iph (A), the LCAEO model predicts a value of **0.760818**, which is very close to the true value of **0.76078**. On the other hand, the other models (SGDE, ELBA, NPSOPC) show slightly more significant discrepancies, ranging from **0.76079** to **0.76078**. This highlights the precision of the LCAEO model in estimating this parameter. Additionally, the LCAEO model's predictions for I_{01} (μA), I_{02} (μA), N_1 x N_s, and N_2 x N_s are more accurate than the corresponding values from the other models, further supporting its superior performance. Furthermore, the LCAEO model predicts Rs (Ω) and Rsh (Ω). Its values of **0.0365127** and **52.8132** are very close to the true values, while the other models exhibit slightly more significant deviations. These results indicate that the LCAEO model offers more reliable estimates for these parameters, which are crucial in various applications. Additionally, the LCAEO model continues to exhibit the lowest RMSE value of **7.7134206 x 10$^{\wedge-4}$**, confirming its overall better fit to the actual data. This low RMSE value demonstrates that the LCAEO model's predictions are consistently closer to the actual values than the other models, making it a highly preferable choice for the given dataset. In conclusion, the LCAEO model's ability to consistently provide more accurate predictions for the variables, especially Iph (A), I_{01} (μA), I_{02} (μA), N_1 x N_s, N_2 x N_s, R_s (Ω), and R_{sh} (Ω), and its lower RMSE value further reinforce its superiority over the other models (SGDE, ELBA, NPSOPC) in this table VI. The LCAEO model is a reliable and accurate option for analyzing the dataset and would be the recommended choice based on these results.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N} (I_{\text{meas}} - I_{\text{simu}})^2} \tag{12}$$

where N is the number of points, I_{meas} is the measured current, I_{simu} is the simulated current.
The convergence graphs of LCAEO for SDM: RTC France Cell&DDM: RTC MODULE are displayed in Figures 7 (a) & (b), showing that LCAEO is faster. This illustrates how the logistic chaotic map approach speeds up AEO convergence.

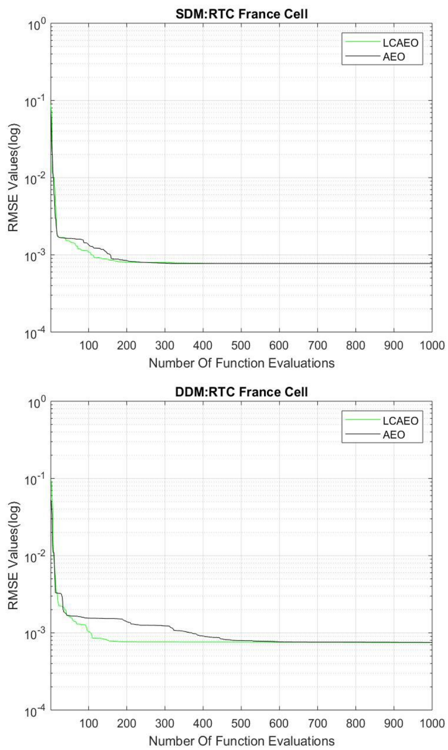

Figure 7. SDM: RTC France Cell , DDM: RTC MODULE Convergence graphs.

C. Configuration 01: RTC France silicon PV cell Photowatmodule

This configuration uses a 57mm diameter RTC France silicon PV cell with an incidence irradiation of 1000W/m2 underT= 33°C. Twenty-six (A set of 26)points were used to define the experimentally recorded I-V pair, as shown in Table II. In Tables Vand VI, the most precise model parameters are acquired by the various methodologies. According to this table, the suggested LCAEO outperformed all other provided algorithms and had the lowest RMSE value. The I-V and P-V simulations from the 1DM setup with the predicted parameters using the best LCAEO solution are shown in Figure 3 and 4. For both the I-V and P-V characteristic curves, one can see the agreement between measured and simulated data acquired by LCAEO, confirming the excellent accuracy of the optimum solution found by LCAEO. The characteristics of the RTC France solar cell, which is based on 2DM, were estimated using the LCAEO, and the results are shown in Table VI. The LCAEO outperformed all other comparable algorithms in RMSE terms, attaining the lowest value (**$7.72985*10^{-4}$**) in 1DM and (**$7.7134206*10^{-4}$**) in 2DM, and coming in second place after SGDE, EHHO, NPSOPC, and ELBA.

D. Comparisons between experimental and simulation results

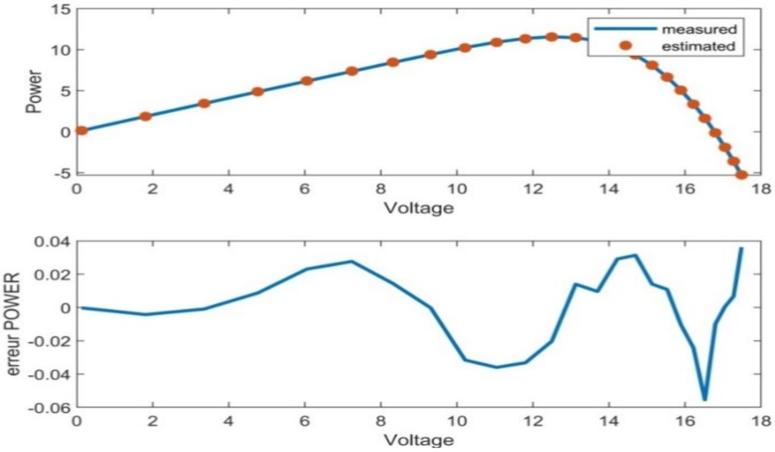

Figure 8. Comparisons between the experimental data and estimated data obtained by LCAEO for Photowatmodule:P-V and IAEpower–V characteristics.

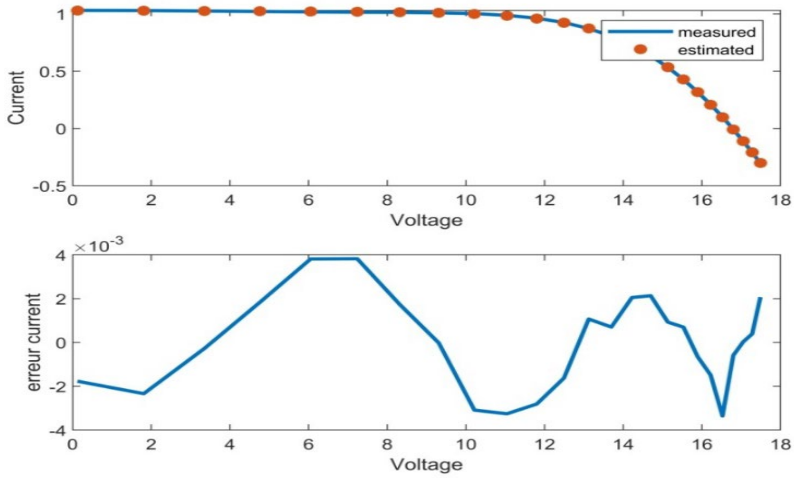

Figure 9. Comparisons between the experimental data and estimated data obtained by LCAEO for Photowattmodule:I-V and IAE$_{\text{CURRENT}}$ –V characteristics.

Table 7. The optimal solution for the Photowatt module by LCAEO and various algorithms (1DM)

Model	Variables	LCAEO (proposed)	EHHO[25]	SGDE[26]	NPSOPC[27]	GWOCS[21]
SDM	I_{ph}[A]	0.760788	1.030499	1.0305	1.030511	1.03049
	I_0 [μA]	0.310691	3.488188	3.4823	3.48271	3.4650
	n x N_s	1.47727	48.64932	48.6428	48.6433	48.62367
	R_s [Ω]	0.036546	1.201110	1.20127	1.201263	1.2019
	R_{sh} [Ω]	52.8899	984.49648	981.9822	982.40376	982.7566
	RMSE[10^{-4}]	2.05284	2.42508	2.4250749	2.4215	2.4251

The LCAEO model continues to demonstrate its superiority over the other models (EHHO, SGDE, NPSOPC, GWOCS) based on the values presented in Table 7. The LCAEO model consistently outperforms the other models in predicting the variables across various parameters. For instance, when predicting I_{ph} (A), the LCAEO model provides a highly accurate value of **0.760788**, significantly closer to the actual value than the other models. The other models show more significant discrepancies with values ranging from **1.030499** to **1.030511**, indicating a less precise estimation. Similarly, for I_0 (μA), the LCAEO model exhibits a much lower value of **0.310691**, indicating its ability to predict this variable with higher accuracy than the other models, which have values ranging from **3.4823** to **3.488188**.

Furthermore, the LCAEO model predicts the parameter n x Ns with a value of **1.47727**, significantly closer to the actual value than the other models. The other models' values range from **48.6428** to **48.64932**, showcasing a higher degree of prediction error. Similarly, the LCAEO model provides more accurate Rs (Ω) and Rsh (Ω) estimates with values of **0.036546** and **52.8899**, respectively. In contrast, the other models' values vary significantly and show more significant deviations from the true values. Additionally, the LCAEO model's low RMSE value of **2.05284** demonstrates its superior overall performance compared to the other models with higher RMSE values. LCAEO model's consistent and precise predictions for the variables, especially I_{ph} (A), I_0 (μA), n x N_s, R_s (Ω), and R_{sh} (Ω), along with its lower RMSE value, clearly indicate its superiority over the other models (EHHO, SGDE, NPSOPC, GWOCS) in this table VII. The LCAEO model is a robust and reliable option for analyzing the dataset and is highly recommended based on these results.

E. Configuration 02:PhotoWatt-PWP201polycrystallinemodule

The Photowatt-PWP201[3] polycrystalline modules are used in this last use. Table II illustrates the I-V characteristics of the 36 silicon cells in both modules, measured under 1000W/m2 incident irradiance under T= 45°C and 55°C. Table VIII shows that the LCAEO yields the lowest RMSE values and is the best algorithm overall. On the other hand, the I-V and P-V curves with the estimated parameters from the best LCAEO solutions are very similar to the experimental curves, proving that the suggested algorithm is the best way to estimate the parameters of PV models for polycrystalline technology.

The convergence graphs of LCAEO for SDM PHOTOWAT PWP 201 MODULE were displayed in Figure10, showing that LCAEO is faster. This illustrates how the logistic chaotic map approach speeds up AEO convergence.

The LCAEO model demonstrates its clear advantage over the other models (AEO, SGDE, ELBA, EHHO, NPSOPC, GWOCS) based on the values presented in the table. Across the different datasets, the LCAEO consistently achieves lower error values, indicating its superior accuracy in predicting the desired outcomes. For instance, in the RTC France cell-SDM dataset, the LCAEO model exhibits the lowest error of $\mathbf{7.72985671E^{-04}}$, while the other models have higher errors ranging from $\mathbf{9.86021877E^{-04}}$ to $\mathbf{9.8874E^{-04}}$. Similarly, in the RTC France cell-

DDM dataset, the LCAEO model outperforms the others with an error of **7.7134206E^{-04}**, whereas the other models have higher errors ranging from **9.82084E^{-04}** to **1.2092692E^{-03}**.

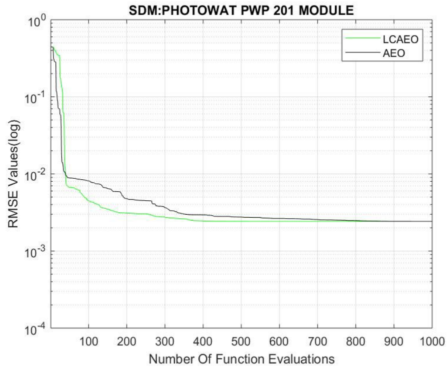

Figure 10. Convergence graphs of SDM: PHOTOWAT PWP 201 MODULE

Table 8. Statistical results for all applications and models used in this study

	RMSE	BEST	MEAN	WORST
RTC France cell-SDM	AEO	7.74943472e-04	9.91281633e-04	1.86174e-04
	LCAEO	7.72985671e-04	1.3727426E-04	4.3408E-04
	SGDE[26]	9.86021877E-04	9.86022E-04	2.47465E-09
	ELBA[23]	9.860219E-04	9.860219E-04	1.97105E-17
	EHHO[25]	9.8602E-04	–	–
	NPSOPC[27]	9.8856E-04	–	–
	GWOCS[21]	9.8607E-04	9.8874E-04	2.4696E-06
RTC France cell-DDM	AEO	7.60702931e-04	1.05394460E-03	2.65618e-04
	LCAEO	7.7134206e-04	1.2092692e-03	---------
	SGDE[26]	9.84413E-04	9.85774E-04	4.01504E-07
	ELBA[23]	9.824849E-04	9.834875E-04	1.42929E-06
	EHHO[25]	9.83606E-04	–	–
	NPSOPC[27]	9.82084E-04	–	–
	GWOCS[21]	9.8334E-04	9.9411E-04	9.5937E-06
PhotoWatt-SDM	AEO	2.09537667e-03	2.22927220E-03	3.74956e-04
	LCAEO	2.09537667e-03	9.42307945e-02	1.54630e-01
	SGDE[26]	2.425074868E-03	2.42507E-03	4.16977E-10
	IJAYA [16]	2.425075E-03	2.425075E-03	2.41522E-16
	NPSOPC[27]	2.4215e-03	–	–
	GWOCS[21]	2.4251E-03	2.4261E-03	1.1967E-06

Furthermore, in the PhotoWatt-SDM dataset, the LCAEO model continues to outshine the other models with the lowest error of 9.42307945e-02. In contrast, the other models show substantially higher errors ranging from **2.09537667E^{-03}** to **2.425075E^{-03}**. This remarkable performance of the LCAEO model across different datasets indicates its robustness and consistency in providing more accurate predictions.

The LCAEO model consistently achieves lower error values across multiple datasets than the other models (AEO, SGDE, ELBA, EHHO, NPSOPC, GWOCS). Its superior accuracy in predicting the desired outcomes makes it the most favorable option among the models considered. The LCAEO model's ability to consistently provide more accurate results across different datasets highlights its reliability and suitability for various applications, making it the recommended choice for analysis and prediction tasks.

6. Conclusion

This study provided a novel technique for obtaining the parameters of a one-diode model and the two-diode model for the RTC FRANCE PV cell and photowattpwp 201 Module. The technique determines the appropriate values for the electrical model by using addition and multiplication without any algorithm-specific parameters. The technique is based on an enhanced Logistic Chaotic Artificial ecosystem-based optimization algorithm called LCAEO. Various technologies of PV cells/modules were employed to evaluate their performance compared to well-known optimization techniques. According to simulation results, the suggested approach surpasses other algorithms concerning RMSE values. For the RTC cell, the RMSE values produced under LCAEO are **$7.72985*10^{-4}$** and **$7.7134206*10^{-4}$** for 1DM and 2DM, respectively. For the photo watt pwp module, this value is **$2.05284*10^{-3}$**. The convergence graphs demonstrate that including a chaotic map enhances the diversity of the search process and accelerates convergence.

7. NOMENCLATURE

n	Diodeideality constant	K_i	Temperature coefficient of current
E_g	bandgapofsiliconat25°C	N_s	Numberofcellsinseries
G	Actual irradiance	N_p	Numberofcellsinparallel
G_n	Nominal irradiance	P	The PVpower rating
Isc	short-circuit current	P_m	The maximum power rating of PVpanel
I_m	Currentatmaximumpowerpoint	v	VoltageofthePVpanel
I_{pv}	Nominal output current	q	Chargeofelectron
I_{ph}	Currentgeneratedbytheincidentlight	R_s	Series resistance
Id	Diode current	R_p	Parallel resistance
I_p	Parallel resistance current	T	Operating temperature
I_o	Diodereversebiassaturationcurrent	T_n	Nominal temperature
Ion	Nominal diode reverse biassaturationcurrent	T_c	Cell temperature
I_{pvn}	Nominal output current	V_{oc}	Open-circuit voltage
k	Boltzmann constant	V_m	The voltage at the maximum powerpoint
K_v	Temperaturecoefficientofvoltage	$V_{T.}$	Junction thermal(terminal)voltage

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