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Teaching-learning based optimization approach for solar cell model parameter identification

Abstract. *Constructing a high-performance photovoltaic (PV) system refers to extracting the characteristics of solar cell models. A population-based algorithm with a parameter-free design called Teaching and Learning Based Optimization (TLBO), inspired by the way teachers teach in the classroom, is proposed in this paper to identify the unknown electrical parameters of different solar cell models i.e., a single diode and a dual diode. The main objective is to extract the optimal parameters of PV system. To evaluate the proposed TLBO, we compared it to the fundamental genetic algorithm (GA), Particle Swarm Optimization (PSO), and other approaches in the literature. The results revealed a strong performance of the developed method. The results revealed the strong performance of the developed TLBO method and outperformed other optimization techniques with a high degree of accuracy in the objective function. In addition, the efficiency of the results is supported by the excellent agreement between the data of a commercial silicon R.T.C France solar cell and the simulated results under all circumstances.*

Streszczenie. *Konstrukcja wysokowydajnego systemu fotowoltaicznego (PV) odnosi si˛e do wydobycia cech modeli ogniw słonecznych. W niniejszej pracy zaproponowano algorytm oparty na populacji z konstrukcj˛a bez parametrów zwany Teaching and Learning Based Optimization (TLBO), zainspirowany sposobem nauczania przez nauczycieli w klasie, w celu identyfikacji nieznanych parametrów elektrycznych ró˙znych modeli ogniw słonecznych tj. pojedynczej diody i podwójnej diody. Głównym celem jest wydobycie optymalnych parametrów systemu PV. Aby oceni´c proponowany TLBO, porównali ´smy go z podstawowym algorytmem genetycznym (GA), Particle Swarm Optimization (PSO) i innymi podej´sciami w literaturze. Wyniki ujawniły siln˛a wydajno´s´c opracowanej metody. Wyniki ujawniły siln˛a wydajno´s´c opracowanej metody TLBO i przewy˙zszaj˛a inne techniki optymalizacji z du˙z˛a dokładno´sci˛a funkcji celu. Dodatkowo, skuteczno´s´c wyników jest poparta doskonał˛a zgodno´sci˛a pomi˛edzy danymi komercyjnego krzemowego ogniwa słonecznego R.T.C France a wynikami symulacji we wszystkich okoliczno´sciach.* ***(Optmalizacja systemu fotowoltaicznego oparta na metodzie uczenia się - identyfikacja parametr ów modelu)***

Keywords: Parameter extracting, Photovoltaic, Teaching learning based algorithm (TLBO), Optimization
Słowa kluczowe: Ekstrakcja parametrów, fotowoltaika, algorytm oparty na uczeniu (TLBO), optymalizacja

Introduction

Since the industrial era, fossil fuels have had an attractive return because of their ease of transport and storage. Furthermore, the promotion of the production of these energies covering the strong demographic growth, urbanisation and ecological development permanently releases large quantities of carbon dioxide in the air, a greenhouse gas [1].

These negative environmental effects trap heat in our atmosphere, causing global warming. In this regard, ecosystem sustainability has encouraged the development of renewable energy sources with minimal emissions and great efficiencies. However, due to a large amount of sunshine, solar energy remains a promising and crucial alternative while minimising environmental impacts [2]. In this context, current trends aim to ensure the efficiency of the design of photovoltaic (PV) devices.

Based on a non-linear model concept, PV generators provide voltage and power in response to environmental changes [3]. Improving this system's overall efficiency requires optimising the solar cells' energy supply, which depends on the types of diversification of the generation [4].

In the literature, three different connection configurations are proposed for PV models, including either a single diode model (1-DM), a double diode model (2-DM) or a three diode model (3-DM) [5]. They are designed to model the actual behavior of PV panels. To this end, the identification of PV parameters plays a crucial role in the design and optimisation process of a PV system. Moreover, due to the appearance of current-voltage (I-V) curves, their estimation becomes a difficult task.

In this regard, the literature introduces several methods for extracting the ideal PV cell characteristics from such a complicated design, which considerably improves the accuracy. These methods are often such as analytical [6], deterministic [7], and intelligent techniques [8].

The analytical method has the benefit of requiring only the manufacturer's data sheet and executing quickly. They solve explicit analysis by using three key operating points known as the remarkable points of the I-V curve at standard test conditions(STC), such as short-circuit current (Isc) and open-circuit voltage (Voc), and maximum power point (MPP). However, the accuracy of the acquired results may be affected by the considered approximations and assumptions. Likewise, an inappropriate choice of initial conditions affects the accuracy and convergence of the solutions [9]. For this reason, the evolutionary numerical technique is widely used to extract these parameters because of its precision and reliability in terms of performance. These methods are based on point-by-point curve fitting, which reduces the discrepancy between the experimental data and the simulated values using the most appropriate evolutionary algorithms [10]. On the other hand, deterministic methods suffer from convergence problems in case of inappropriate starting point either increase the processing effort or yields a local optimum solution.

For this purpose, Evolutionary-based algorithms, are soft computing approaches based on the notion of global optimisation, depending on whether or not they are inspired by nature. Some of them are mostly employed, such as genetic algorithm, particle swarm optimisation (PSO) [11], Modified whale optimization algorithm (MWOA) [5], and others [12, 13] Among metaheuristic algorithms, Teaching and Learning Optimization (TLBO) is a novelty employed, whose population-based algorithm reproduces a classroom environment to optimise a given objective function [14]. This algorithm requires only two common parameters: the population size and the maximum number of generations. TLBO has been widely used for various real-world optimisation problems, including multi-objective optimisation problems [15] and engineering optimisation [16] due to its simplicity, efficiency, and ease of implementation. For this purpose, TLBO is used to determine the unknown parameters of 1-D and 2-D models. TLBO can detect the characteristics of commercial silicon R.T.C. France PV cells, demonstrating its validity and applicability, followed by a comparison of the performance of the proposed TLBO method with that of well-known techniques used to extract PV parameters.

Nomenclature		Abbreviations	
$I_{ph}(A)$	Photocurrent	TLBO	Teaching Learning Based Optimization
$I_D(A)$	Diode's current	TLBO-ABC	Hybrid algorithm based on Artificial Bee Colony and TLBO
$I_s(A)$	Reverse saturation current	MWOA	Modified Whale Optimization Algorithm
$I_{s1}(A)$	First diode reverse saturation current	CWOA	ChaoticWhale Optimization Algorithm
$I_{s2}(A)$	Second diode reverse saturation current	LWOA	Levy Whale Optimization Algorithm
$R_s(\Omega)$	Series resistor	CSSA	Chaotic Salp Swarm Algorithm
c $R_{sh}(\Omega)$	Shunt current	RUN	RUNge Kutta optimizer
n	Diode ideality factor	PSO	Particle Swarm Optimization
n_1	First diode ideality factor	GA	Genetic Algorithm
n_2	Second diode ideality factor		

Modeling of the PV Cell

Many literature reviews aim to understand the physical behavior of a PV cell to obtain an efficient design for PV systems.The 1-DM is the one that is used the most frequently due to its simplicity and ability to balance accuracy and simplicity. However, 2-DM is recommended for improved depiction accuracy.

1 and 2 Diode Model

The electrical equivalent model of a 1-DM and 2-DM PV cell is shown in Fig. 1 [5].
Kirchhoff's rule is used to express this model in Eq. 1:

$$I_{cell} = I_{ph} - I_D - (\frac{V_D}{R_{sh}}), \quad (1)$$

Where
I_{ph} and I_D stand for the current generated by a PV cell and a diode, respectively; R_{sh} represent the shunt resistor and V_D is the voltage across the diode.
The conventional equation below depicts a basic diode with a characteristic $(I - V)$ curve:

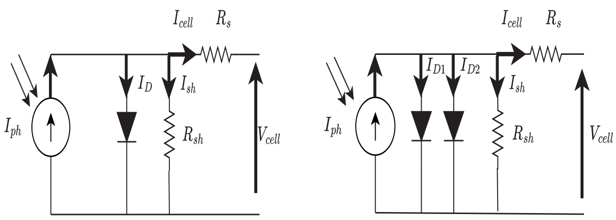
$$I_D = I_s(e^{\frac{qV_D}{nKT}} - 1), \quad (2)$$

The diode's ideality factor, represented as n, is determined by the type of semiconductor material and the fabrication design.
T indicates the PV cell temperature, expressed in kelvin and must be taken into account for a more accurate modeling of the PV cell.
The charge of electron is $q = 1.6 * 10^{-19} Coulomb$.
K is the Boltzmann constant and it is equal to $1.35 * 10^{-23}(J/K)$.

$$V_D = V_{cell} + R_s I_{cell}, \quad (3)$$

Hence

$$I_{cell} = I_{ph} - I_s(e^{\frac{qV_D}{nKT}} - 1) - (\frac{V_D}{R_{sh}}), \quad (4)$$



(a) (b)

Fig. 1. Equivalent electrical circuit cell: (a) 1-DM, (b) 2-DM

Applying Kirchhoff's law yields for the 2-DM equivalent circuit, the following description the produced current becomes [5]:

$$\begin{aligned} I_{cell} &= I_{ph} - I_{s1}(e^{\frac{qV_D}{n_1KT}} - 1) - ... \\ &I_{s2}(e^{\frac{qV_D}{n_2KT}} - 1) - (\frac{V_D}{R_{sh}}), \end{aligned} \quad (5)$$

Where I_{s1}, I_{s2} are the diffusion and saturation currents of the first and second diode, n_1 and n_2 are the ideality factors of the two diodes, respectively.
1-DM and 2-DM contend with the following unknown parameters:
$X_1 = [I_{ph} \quad I_s \quad n \quad R_s \quad R_{sh}]$
$X_2 = [I_{ph} \quad I_{s1} \quad I_{s2} \quad n_1 \quad n_2 \quad R_s \quad R_{sh}]$

PV module model

A PV module is composed of many solar cells linked in both series and parallel as shown in Fig. 2.

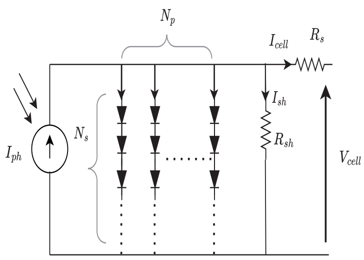


Fig. 2. Equivalent electrical circuit of PV module

The 1-DM and 2-DM PV module equations are represented by Eq.6 and 7, respectively [5].

$$\begin{aligned} I_{cell} = N_p I_{ph} - N_p I_s(e^{q\frac{N_pVcell + N_sR_sIcell}{N_sN_pnKT}} - 1) - ... \\ (\frac{N_pV_{cell} + N_sR_sI_{cell}}{N_sR_{sh}}), \end{aligned} \quad (6)$$

(7)
$$\begin{aligned} I_{cell} = N_p I_{ph} - N_p I_{s1}(e^{q\frac{N_pV_{cell} + N_sR_sI_{cell}}{N_sN_pn_1KT}} - 1) - ... \\ N_p I_{s2}(e^{q\frac{N_pV_{cell} + N_sR_sI_{cell}}{N_sN_pn_2KT}} - 1) - (\frac{\cancel{N_pVcell + N_sRsIcell}}{N_sR_{sh}}), \end{aligned}$$

Objective function

A desirable electrical model of the PV cell should match the actual output characteristic as closely as possible. Adopting a cost function for minimization.
The root mean square (RMSE) is selected for this investigation between the PV model parameter vector and the experimentally measured parameter vector of the PV model is used as an objective function for optimization to determine the five unknown parameters of the 1-DM and the seven unknown

parameters of the 2-DM.

$$RMSE(X) = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(I_m^i - I_c^i(V_m^i, I_m^i, X))^2}, \tag{8}$$

Where
X: represent the extracted parameters vectors for the 1-DM and 2-DM models.
N: describes the amount of data measured.
V_m^i and I_m^i are the i^{th} measured voltage and current.
I_c^i is the i^{th} calculated current according to the cell model utilized from Eq.6 and 7.

TLBO

In this part, the fundamental principle of TLBO is briefly explained [17]; a new population-based meta-heuristic technique inspired by teacher-student interaction is considered. This approach has two essential components: the teacher and the learners.
In general, the teacher is regarded as the most knowledgeable person in a class who imparts his or her expertise to better the overall grade or performance of the class. When instructed by a teacher of great quality, students can attain higher results more rapidly. In addition, learners can learn by engaging and communicating with each other, which can also contribute to their progress. The full operational process of TLBO can be summarized in two phases: the teacher and the learner.
The "teacher phase" consists of acquiring knowledge from the teacher. While the "learner phase" refers to learning through interaction between students.

Initialization step

Before beginning the TLBO algorithm, the parameters listed below must be initialized:
- determining the number of decision m;
- the population size N_p;
- the termination criterion ϵ;
- the maximum number of iterations T;
- the admissible lower and upper bound values for each variable Xj_{lb} and Xj_{ub};
- initial solutions X_{jk}^1 are selected at random using equation 9:

$$X_{jk}^1 = rand(0,1) * (Xj_{ub} - Xj_{lb}) + Xj_{lb} \tag{9}$$

Teacher phase

During the teacher phase, these different steps are applied:
- a teacher is chosen from the population by selecting the student with the highest level of physical fitness $X_{jk_{best}}^i (j = 1, ..., m, k = 1, ..., N)$;
- calculate the mean result of the students M_j^i and the difference mean d_{jk}^i are as follows for each subject:

$$M_j^i = \frac{\sum_{k=1}^{N} X_{jk}^i}{N} \tag{10}$$

$$D_{jk}^i = r(X_{jbest}^i - t_f M_j^i) \tag{11}$$

Where
r is a random number from 0 to 1 and t_f is random number from 1 to 2;
- each existing solution is updated as follows:

$$Xnew_{jk}^i = X_{jk}^i + D_{jk}^i \tag{12}$$

- a greedy selection is performed between the old and new solution $(X_{jk}^i, Xnew_{jk}^i)$ to retain the optimal solution.

Learner phase

Students attempt to develop themselves through interaction with one another. The student X_A choose at random to connect with and learn from the student X_B. This phase is divided into the subsequent steps:
- choose randomly q pairs of solutions where $F_A^i \neq F_B^i$, where F_A^i and F_B^i are the fitness values of X_A and X_B, respectively;
- in the case of a minimization issue, update the answers for each pair using the following equations:

$$Xnew_{jA}^i = X_{jA}^i + r(X_{jA}^i - X_{jB}^i), if F_A^i < F_B^i \tag{13}$$

$$Xnew_{jA}^i = X_{jA}^i + r(X_{jB}^i - X_{jA}^i), if F_B^i < F_A^i \tag{14}$$

- A greedy selection is performed between the old and new solutions in order to retain the optimal solution.

The TLBO method's flowchart, seen in Fig. 3, illustrates its several stages.

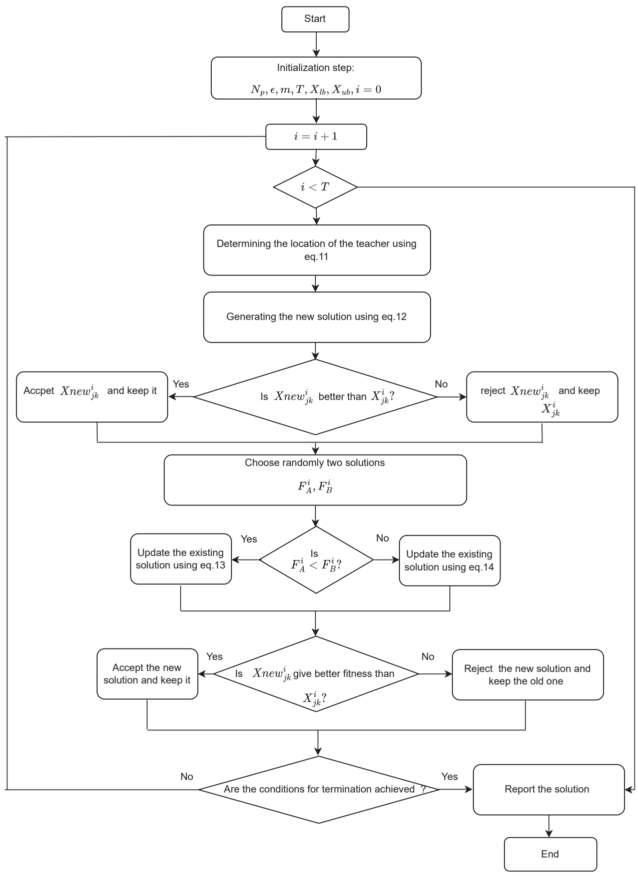


Fig. 3. Flow chart of the TLBO algorithm

Application to the parameter identification of PV module 1-D and 2-D models

To demonstrate the performance of the TLBO technique, the unknown parameters of two PV models, including 1-D and 2-D models, are extracted. In this paper, the simulation uses a commercial R.T.C France silicon solar cell with a $57mm$ diameter. The system at solar radiation and $33°C$ temperature has collected the data for the solar cell. Each parameter's search limitations are listed in Table 1.
In addition, the efficiency of the TLBO technique is compared

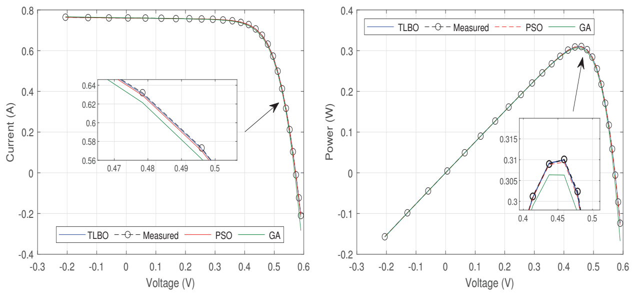
Table 1. Study intervals of estimated parameters

Parameter	Lower bound	Upper bound
$I_{ph}(A)$	0	1
$I_s(\mu A)$, $I_{s1}(\mu A)$, $I_{s2}(\mu A)$	0	1
$R_s(\Omega)$	0	0.5
$R_{sh}(\Omega)$	0	100
n, n_1, n_2	1	2

with some algorithms such as GA, PSO and to previously published results.
The parameters used in this study about the TLBO algorithm are: population size=100 and maximum number of iterations is fixed to 5000.

Results of 1-DM

Table 2 shows the comparative results for 1-DM, including the estimated parameters and RMSE values. According to Table 2, TLBO, MWOA and RUN had the minimum RMSE values highlighted in bold compared to the other algorithms studied which are GA and PSO.
Fig. 4 (a and b) illustrates the extracted parameters were used to recreate the I-V and P-V curves to further validate the estimated results accuracy.



(a) (I, V) curves (b) (P, V) curves

Fig. 4. Comparison between measured and estimated data using the proposed TLBO for 1-D model

As shown in Fig. 4 (a and b), the curves indicate that the PSO algorithm converges slightly more to the actual PV properties than the GA. Furthermore, the estimated data acquired by the proposed TLBO are extremely close to the measured data, which demonstrates the accuracy of the calculated parameters.
Fig. 5 shows the evolution of the objective function RMSE by the three implemented algorithms TLBO, PSO and GA for the 1-DM case.

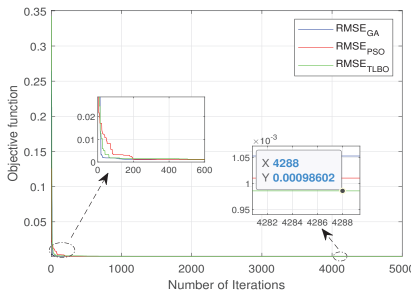
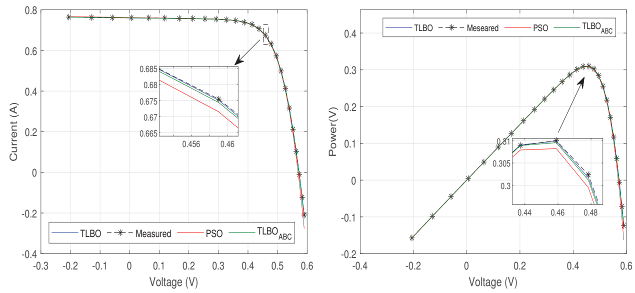


Fig. 5. Variation of RMSE using TLBO, PSO and GA for the 1-DM

It is noticed from Fig. 5, that the TLBO algorithm has a faster convergence speed than the PSO and GA algorithms.

Results of 2-DM

The extracted parameters and the RMSE obtained by different algorithms are summarized in table 3. According to the above table, TLBO continues to perform admirably for the 2-DM.
Based on the performance of TLBO in comparison to both PSO and GA algorithms applied for 1-D model, it is clear that, in terms of optimization precision shown in table 3, TLBO is not only superior to other competing algorithms but also has a strategic advantage over other improved TLBO (TLBO-ABC). Therefore, there is reason to assume that TLBO is a promising method for identifying unknown photovoltaic model parameters.
The characteristic curves of current versus voltage and power versus voltage for the 2-DM are presented in Fig. 6. These curves are reconstructed using the parameters estimated by the TLBO, TLBO-ABC, PSO and the experimental data.



(a) (I, V) curves (b) (P, V) curves

Fig. 6. Comparison between measured and estimated data using the proposed TLBO for 2-D model

By analyzing Fig. 6, it can be seen that the TLBO algorithm has the potential to provide results that exactly approximate the experimentally measured data. Compared to the TLBO-ABC algorithm, which has a lower approximation and to PSO, which remains less accurate.
Fig. 7 depicts the evolution of the RMSE versus the number of iterations for the 2-DM corresponding to the three compared algorithms TLBO,TLBO-ABC and PSO.

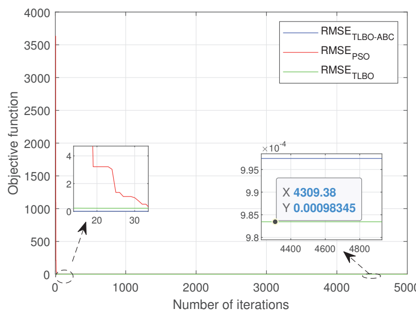


Fig. 7. Variation of RMSE using TLBO, TLBO-ABC and PSO for the 2-DM

As shown in Fig. 7, the TLBO method has a faster convergence rate than the TLBO-ABC and PSO algorithms. This reveals the efficiency of the algorithm for both PV cell models studied.

Conclusion

This paper presents a learning-based optimization approach to identify the unknown parameters of a solar PV system for a commercial R.T.C France (1-DM and 2-DM). This method is compared to other optimization techniques to list the fitness criteria. Thus, the PSO method is easy to implement but requires the tuning of many parameters. In addition, the GA technique may converge prematurely in some complex problems and get stuck in a local position.
In contrast, the learning-based optimization technique requires only two general control parameters: the population

Table 2. A comparison of the results obtained by the TLBO and other methods for the identification of the 1-DM parameter.

Algorithm	$I_{ph}(A)$	$I_s(\mu A)$	$R_s(\Omega)$	$R_{sh}(\Omega)$	n	RMSE
TLBO [17]	0,7608	0,3230	0,0364	53,7190	1,4824	**9.8602E-04**
TLBO-ABC [18]	0.76078	0.32302	0.03638	53.71636	1.48118	9.8602E-04
CSSA [18]	0.7551	0,2267	0.0352	52.4437	1.4475	8.9064E-03
RUN [18]	0.7608	0.3230	0.0364	53.6707	1.4802	**9.8602E-04**
MWOA [5]	0.760773	3.23	0.036375	53.76689	1.48127	**9.8602E-04**
CWOA [19]	0.7605	0.5047	0.0341	51.4778	1.52783	1.5792E-03
LWOA [20]	0.7602	0.4607	0.0350	75.4619	1.5177	1.2352E-03
PSO [14]	0.7607	0.4000	0.0354	59.18	1.5033	1.3e-3
GA [13]	0,7619	0,8089	0,0299	42,3729	1,5751	1.9080E-02

Table 3. A comparison of the results obtained by the TLBO and other methods for the identification of the 2-D parameter.

Algorithm	$I_{ph}(A)$	$I_{s1}(\mu A)$	$I_{s2}(\mu A)$	$R_s(\Omega)$	$R_{sh}(\Omega)$	n_1	n_2	RMSE
TLBO [17]	0,7608	0,2981	0,1792	0,0364	54.1028	1,4756	1.9956	**9.8345E-04**
TLBO-ABC [18]	0.76081	0.42394	0.24011	0.03667	54.66797	1.9075	1.45671	9.8415E-04
CSSA [18]	0.7612	0.2160	0.2627	0.0362	51.1869	1.7437	1.4675	1.050E-03
RUN [18]	0.7608	0,26	0.5580	0.0364	55,3832	1,4634	1.9996	9.8717E-04
MWOA [5]	0.7608	2.6500	3.1200	0.0367	53.3477	1.4638	1.9796	9.8694E-04
CWOA [19]	0.7598	0.2415	0.6000	1.4565	1.9899	0.0367	55.2016	1.789E-03
LWOA [20]	0.7608	0.1667	0.0361	55.2366	1.6086	0.2323	1.4658	1.000E-03
PSO [14]	0.7623	0.4767	0.01	0.0325	43.1034	1.5172	2.000	1.660e-2
GA [13]	0,7608	0,0001	0,0001	0,0364	53,7185	1,3355	1,481	3.60E-03

size and the stopping criterion. Therefore, the effectiveness of the new TLBO optimization method is tested for the two electrical models of solar PV systems by exploring the performance of I-V and P-V characteristics. The simulation results showed that TLBO is more efficient than PSO and GA for the 1-DM system and even better than PSO TLBO-ABC for the 2-DM system.

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