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Self-adaptive Teaching-Learning-Based Optimization with Reusing Successful Learning Experience for Parameter Extraction in Photovoltaic Models

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Abstract: This paper proposes a self-adaptive teaching-learning-based optimization with reusing successful learning experience (RSTLBO) to accurately and reliably extract parameters of different photovoltaic (PV) models. The key novelties of RSTLBO are: 1) Learners adaptively choose teacher or learner phase based on a selection probability according to their performance, balancing exploration and exploitation; 2) Successful learner experiences are reused to enhance search capability. Experiments on single diode, double diode and PV panel models demonstrate that RSTLBO achieves higher accuracy and faster convergence than state-of-the-art methods like P-DE, TLBO, GOTLBO, etc. Specifically, RSTLBO obtains the minimum *RMSE* across all models, outperforms compared methods in statistical results, and exhibits fastest convergence in almost all cases. The self-adaptive probability selection and experience reuse make RSTLBO effective for PV parameter extraction.

Keywords: learning experience; optimization; parameter extraction; photovoltaic model; teaching-learning-based optimization

1 INTRODUCTION

Renewable energy sources have received increasing attention due to environmental pollution, climate change, and global warming caused by the extensive use of fossil energy in the past [1]. Among renewable energy sources, such as wind, solar, nuclear, tidal, geothermal, and biomass, solar energy is considered as one of the most promising energy sources due to its wide availability and cleanliness [2]. Among solar power generation, photovoltaic (PV) system as a widely used technology has attracted much attention in recent years because of its ability to convert solar energy directly into electrical energy [3]. As for the PV system, its electrical energy conversion performance is very much dependent on the selection of the PV model [4, 5]. The three most commonly used PV models in practice are single diode, double diode, and PV panel model [6]. No matter which PV model is selected, some unknown parameters crucial for the performance of the model must be extracted. However, it is not an easy task to extract these unknown parameters in a PV model because the equivalent circuit equations of these PV models have highly nonlinear, implicit, and multivariate characteristics, which greatly increase the difficulty of extraction. Therefore, there is an urgent need for a feasible optimization approach to accurately and reliably extract the parameters of PV models. In recent years, many scholars have proposed various optimization methods to extract the parameters of the PV model, which can be summarized into three categories: analytical methods, deterministic methods and heuristic methods. The analytical method mainly reduces the number of unknown parameters by analyzing the equivalent equations in the model and combining some special key points in the data set, such as short-circuit current points, open-circuit voltage points and maximum power points. This method is relatively simple and can quickly extract the unknown parameters of the model, but it requires complex derivations and pre-assumptions, which may reduce the accuracy of the extracted parameters to some extent [7]. Deterministic methods carry out parameter extraction by giving an initial guess value in advance and then by methods such as gradient. These methods are simple and easy to implement, but the results obtained are highly dependent on the initial guess value and can easily fall into local optimality [8]. In addition, these methods have strict requirements on the objective function of the model, such as differentiability and convexity, but it is often difficult to satisfy the equivalent equations of the PV model, which leads to the easy acquisition of poor quality solutions when using these methods. Heuristic methods [9], [11], which are intelligent optimization algorithms inspired by natural phenomena, overcome the shortcomings of the previous two types of methods, do not have any requirements on the objective function and are simple to implement, and are considered to be promising alternatives for parameter extraction of PV models. In recent years, a large number of heuristics have been used for PV model parameter extraction, such as Genetic Algorithm (GA) [12], Simulated Annealing (SA) [13, 14], Particle Swarm Optimization (PSO) [15, 16], Differential Evolution (DE) [17], Artificial Bee Swarm Optimization (ABSO) [18], Whale Optimization Algorithm (WOA) [19, 20], Cuckoo Search (CS) [21], JAYA Algorithm (JAYA) [22-24], and Backtracking Search Algorithm (BSA) [25, 26]. These heuristics have obtained more satisfactory results relative to the previous two categories, but they still deserve further exploration in terms of accuracy and reliability. In addition, some heuristic algorithms themselves have many algorithmic parameters, and when these algorithms are utilized for PV model parameter extraction, it is necessary to set the values of these parameters artificially. Once these algorithmic parameter values are not optimal, the performance of the algorithms will be greatly affected. Teaching-Learning-Based Optimization (TLBO) [27] is a heuristic optimization method for solving continuous nonlinear large-scale problems proposed by Rao et al. in 2012. Its main idea comes from the influence of teachers classroom on student teaching. Due to the simplicity, effectiveness and ease of implementation of the algorithm, it and its related variants have been widely used in various fields [28-29], also including the PV model parameter extraction problem studied in this paper. For example, literature [30] proposes a Generalized Oppositional Teaching-Learning Based Optimization (GOTLBO) algorithm to extract the unknown parameters of the PV model, in which the generalized oppositional learning mechanism is combined with a standard teaching-learning-based optimization algorithm, thus the convergence speed can be improved. In order to further accurately extract the parameters of the PV model, a Self-Adaptive Teaching-Learning-Based Optimization (SATLBO) algorithm is proposed in literature [31]. In SATLBO, on the one hand, learners can adaptively select the teacher or learner phase; on the other hand, elite learning strategies and diverse learning methods are introduced to improve the search ability in both phases. Literature [32] proposed a hybrid Teaching-Learning-Based Artificial Bee Colony (TLABC) to optimize the PV model parameters. In TLABC, the authors improved the performance of the algorithm by combining two heuristic algorithms, namely TLBO and Artificial Bee Colony. Literature [6] addresses the shortcomings in standard TLBO algorithm by introducing multi-strategies in both the teacher and learner phases, using different strategies according to the learners own level, thus balancing the exploration and exploitation capabilities of the algorithm. Although these improved algorithms achieved more satisfactory results, there are some limitations, such as the introduction of additional algorithmic parameters for GOTLBO and TLABC, and the lesser accuracy of SATLBO in the double diode model. The purpose of this paper is to design a simple and effective TLBO algorithm without additional algorithmic parameters to accurately and reliably extract the unknown parameters of different PV models. Inspired by the superior performance achieved by TLBO and its variants, this paper proposes an improved teaching-learning-based optimization algorithm, i.e., self-adaptive teaching-learning-based optimization with reusing successful learning experience (RSTLBO). In RSTLBO, on the one hand, learners are able to adaptively choose the appropriate teacher or learner phase according to their own learning level; on the other hand, the search capability of the algorithm is improved by reusing successful learning experience. In addition, RSTLBO does not have any other algorithmic parameters except one algorithmic parameter common to heuristic algorithms, i.e., population size. The main novelties of this paper are summarized as follows:

1) Based on learners performance, a selection probability is proposed, where learners can adaptively choose teacher or learner phase.
2) Successful learner experiences are reused to enhance search capability.

The remainder of the paper is organized as follows. Section 2 presents the equivalent mathematical model of the PV model and its objective function. Section 3 gives a brief introduction to the standard teaching-learning-based optimization algorithm. Section 4 details the adaptive TLBO with reusing successful experiences proposed in this paper. Section 5 gives the experimental results of this paper and their analysis. Finally, section 6 summarizes the whole paper and looks forward to further research ideas in the future.

2 FORMULATION PARAMETER EXTRACTION IN PV MODELS

As mention in Section 1, there are three most common PV models, the single diode model, the double diode model, and the PV panel model. In this section, we provide a brief introduction to these models and the parameter extraction problem in them.

2.1 Single Diode Model

The single diode model, as one of the most commonly used models, has an equivalent circuit model as shown in Fig. 1. As can be seen from the figure, the model mainly contains a light current source, a diode D, and two resistors. Where the output current I_o can be calculated by Eq. (1).

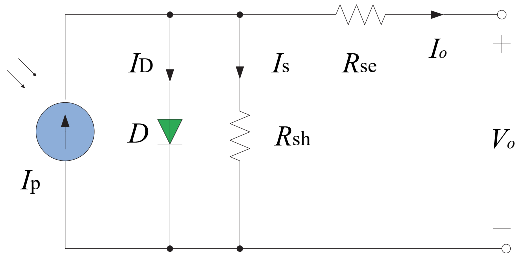

Figure 1 The equivalent circuit diagram of the single diode model

$$I_o = I_p - I_D\left[\exp\left(\frac{V_o + I_o R_{se}}{aV_t}\right) - 1\right] - \frac{V_o + I_o R_{se}}{R_{sh}} \tag{1}$$

where I_p is the current generated by light; I_D is the diode reverse saturation current; R_{se} is the series resistance; R_{se} is the shunt resistance; a is the diode ideal factor; and $V_t = kT/q$ is the thermal voltage, where k is the Boltzmann constant ($1.3806503 \times 10^{-23}$ J/K), T is the temperature at Kelvin units, and q is the electron charge ($1.60217646 \times 10^{-19}$ C). From Eq. (1), there are five unknown parameters I_p, I_D, R_{se}, R_{sh} and a in the single diode model.

2.2. Double Diode Model

Considering the effect of the composite current loss in the depletion region, based on the single diode model, another commonly used model, i.e., the double diode model, is proposed, and its equivalent circuit model is shown in Fig. 2. As can be seen from the figure, relative to the single diode model, this model has one more diode, and its output current I_o can be calculated by Eq. (2):

$$I_o = I_p - I_{D1}\left[\exp\left(\frac{V_o + I_o R_{se}}{a_1 V_t}\right) - 1\right] - I_{D2}\left[\exp\left(\frac{V_o + I_o R_{se}}{a_2 V_t}\right) - 1\right] - \frac{V_o + I_o R_{se}}{R_{sh}} \tag{2}$$

where I_{D1} and I_{D2} are the reverse saturation currents of the two diodes in this model, respectively; a_1 and a_2 are the ideal factors of the two diodes $D1$ and $D2$, respectively. According to Eq. (2), there are seven unknown parameters I_p, I_{D1}, I_{D2}, R_{se}, R_{sh}, a_1 *and* a_2 to be extracted in the double diode model.

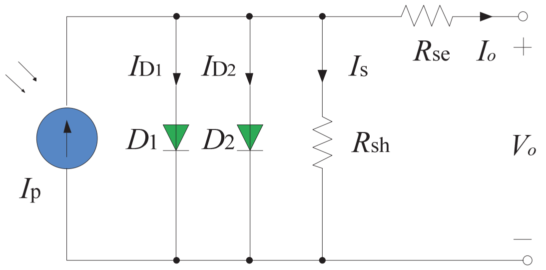

Figure 2 The equivalent circuit diagram of the double diode model

2.3 PV Panel Model

Generally speaking, the voltage provided by a single diode model is limited, and it often fails to meet the practical needs. To solve this problem, it is usually necessary to connect several single diode models in series or parallel to form a battery panel, which is the PV panel model. Its equivalent circuit model is shown in Fig. 3, and its output current I_o can be calculated by Eq. (3).

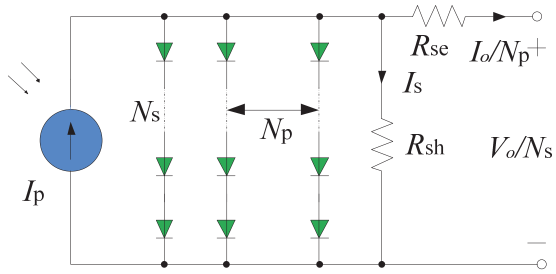

Figure 3 The equivalent circuit diagram of the PV panel model

$$I = I_p N_p - I_D N_p \left[\exp\left(\frac{V_o N_p + I_o R_{se} N_s}{a N_s N_p V_t} \right) - 1 \right] - \frac{V_o N_p + I_o R_{se} N_s}{R_{sh} N_s} \tag{3}$$

where N_p and N_s are the number of parallel and series connections, respectively. From Eq. (3), there are five unknown parameters I_p, I_D, R_{se}, R_{sh} and a to be extracted in the PV panel model.

2.4 Objective function

For the PV model parameter extraction problem, the common treatment is to extract these unknown parameters first, and then minimize the error between the current obtained from the experimental simulation and the actual measured current data through these extracted parameters. However, it is very difficult to solve each parameter of the PV model directly, like the way dealt with in many pieces of literature [6]; this paper also adopts transforming the parameter extraction problem into a nonlinear optimization problem and using the Root Mean Square Error (*RMSE*) as the objective function. The optimization objective is expressed as follows:

$$\text{minimize} \quad RMSE(x) = \sqrt{\frac{1}{N} \sum_{i=1}^{N} f^2 (V_i, I_i, x)} \tag{4}$$

where x is the vector containing the unknown parameters to be extracted; N is the number of actual measured I-V data sets; and $f = (I - \tilde{I})$ is the error function, i.e., the error between the experimental simulated current $\tilde{I}_0$ and the actualmeasured current I_o. From Eq. (4), it can be seen that the use of the *RMSE* as the objective function transforms the PV parameter extraction problem into an optimization problem that seeks for the minimum value. In other words, the smaller the value of the *RMSE* is, the more accurate the extracted parameters are.

3 TEACHING-LEARNING-BASED OPTIMIZATION

As a simple and effective heuristic algorithm, the main idea of TLBO comes from the teachers influence on the output of the class learners. It is commonly used to solve nonlinear optimization problems. TLBO solves through two main phases: the teacher phase and the learner phase. In the teacher phase, the teacher shares his/her knowledge to the learners to improve the performance of the whole class. In the learner phase, learners learn from each other through discussions and exchanges to improve their performance.

3.1 Teacher Phase

In TLBO, the teaching and learning process of a class is simulated. In general, a class consists of *NP* learners (x_i, i = 1, …, *NP*), where one of the learners with the best learning level is taken as the teacher (x_{teacher}) and the rest are all learners. In the teacher phase, the teacher improves the average performance of the whole class by sharing his/her knowledge to the learners (x_{mean}). In the teacher phase, each learner updates his/her level through Eq. (5):

$$x_{i,\text{ new}} = x_i + rand \cdot \left(x_{\text{teacher}} - T_F \cdot x_{\text{mean}} \right) \tag{5}$$

where *rand* is a random number between 0 and 1; T_F is the teaching scaling factor, which takes the value of 1 or 2; and x_{mean} is the class grade average, which is calculated as follows:

$$x_{\text{mean}} = \frac{1}{NP} \sum_{i=1}^{NP} x_i \tag{6}$$

After all learners are updated, all updated learners are evaluated by the objective function, and if $RMSE(x_{i,\text{ new}})$ is less than $RMSE(x_i)$, x_i is replaced with $x_{i,\text{ new}}$; otherwise, x_i is retained.

3.2 Learner Phase

In the learner phase, a learner chooses another learner to interact in some way (e.g., discussion, communication) to improve his/her knowledge. The formula for the learning process is as follows:

$$x_{i,\text{new}} = \begin{cases} x_i + rand \cdot \left(x_i - x_j \right), & \text{if } RMSE\left(x_i \right) < RMSE\left(x_j \right) \\ x_i + rand \cdot \left(x_j - x_i \right), & \text{otherwise} \end{cases} \tag{7}$$

where x_j is the *j-th* learner and is different from i.

4 PROPOSED TEACHING-LEARNING-BASED OPTIMIZATION

There are three main shortcomings of the standard TLBO algorithm. Firstly, it requires two phases in solving the problem, which results in consuming 2*NP* of computational resources at the end of one generation of loops. If an effective way can be designed to allow learners to adaptively select the teacher or learner phase according to their level, so that only *NP* of computational resources are consumed at the end of one generation of the cycle, this will greatly save computational resources. Secondly, when making assessment selection, if the updated learners are better than before, it means that the update is successful and these successful learning experiences are not retained and utilized. In addition, in the learner phase, the learner only randomly selects another learner, which leads to under-utilization of information from other learners in the class. To this end, adaptive selection probability, reusing successful learning experience, and improved two phases are proposed. Further, an improved TLBO algorithm, namely self-adaptive teaching-learning-based optimization with reusing successful learning experience (RSTLBO) is developed.

4.1 Adaptive Selection of the Teacher or Learner Phase

In order to enable learners to choose an adapted teacher or learner phase according to their learning level, this paper proposes a probabilistic selection based on the ranking of learners learning level, where learners adaptively choose the appropriate phase through probabilistic selection. First, the objective function values of all learners are calculated and then sorted according to the objective function values in ascending order as shown in Eq. (8):

$$SI = sort\left(RMSE,\ `ascend`\right) \tag{8}$$

where SI is a vector storing the index number corresponding to each learner after sorting. The index number is used to calculate the actual ranking R of each learner in the class as follow:

$$R\left(SI\left(i\right)\right) = NP - i \tag{9}$$

Secondly, the assignment of the selection probability value P is performed by basing the actual ranking of each learner as in Eq. (10):

$$P\left(SI\left(i\right)\right) = \left[\frac{R\left(SI\left(i\right)\right)}{NP}\right]^2 \tag{10}$$

From Eq. (10), it can be seen that the better the learning level of the learner, the greater the assigned selection probability, and vice versa. Finally, the corresponding teacher or learner phase is adaptively selected according to the learners selection probability, and the adaptive selection process is shown in Algorithm 1:

Algorithm 1:Adaptive selection of the teacher or learner phase

```
1: Sorting based on learner objective function values shown as Eq. (8);
2: Calculating the ranking probability of each learner according to Eqs. (9) and (10);
3: for i=1 to NPdo
4: if rand < P(SI(i)) then
5: Select the teacher phase;
6: else
7: Select the learner phase;
8:end if
9: end for
```

From Algorithm 1, it can be seen that a learner with a high P will have a high probability of choosing the teacher phase to bring himself/herself closer to x_{teacher} quickly, thus improving the exploitation ability and speeding up the convergence of the algorithm; for a learner with a low selection probability, it is highly probable that he/she will choose the learner phase in order to improve the exploration ability of the algorithm.

4.2 Reusing successful learning experience

In order to fully utilize learners successful learning experiences, this paper proposes a strategy to reuse successful learning experiences. When a learner makes an update choice, if the learners learning level after the update is better than the learning level before the update, which indicates that this learning is successful, then the successful experience of this learning will be stored in a set S so that the learner can learn from it in the next generation cycle. The successful learning experience of the learner is saved as in Eq. (11):

$$S = \begin{cases} \left[S,\ \left(x_{i,\text{ new}} - x_i\right)\right], & \text{if } x_{i,\text{ new}} \text{ is better than } x_i \\ S, & \text{otherwise} \end{cases} \tag{11}$$

where the initial value of the set S is the empty set with the same size as the population size.

4.3 Improved Teacher and Learner Phases

Based on the reusing successful learning experience proposed above, an improved teacher phase and learner phase are developed. In the improved teacher phase, the learner learns from the knowledge imparted by the teacher on the one hand, and draws on the past successful learning experiences of other learners on the other hand, with the updating formula as in Eq. (12):

$$x_{i,\text{ new}} = x_i + rand \cdot \left(x_{\text{teacher}} - T_F \cdot x_{\text{mean}}\right) + rand \cdot \mathrm{S}\left(ind\right) \tag{12}$$

where ind = *randi*(length(S)) is a random integer, i.e., a successful learning experience is randomly selected for learning.

In the standard TLBO, learners are only randomly selected to learn from one learner during the learner phase, which leads to under-utilization of information from other learners. To address this problem, an improved learner phase is proposed as shown in Eq. (13):

Algorithm 2: Pseudo code of RSTLBO

```
Input: Control parameters: M_NFE, NP
 1: Set g = 1, G_m = M_NFE/NP, S = [], k = 1;
 2: Initialize all learners in class randomly;
 3: Evaluate the objective function values of learners;
 4: while g < G_m do
 5:     Calculate the ranked selection probability P for each learner
        based on Eq. (8) and Eq. (10);
 6:     for i =1 to NP do
 7:         if rand < P(SI(i)) then // Select the teacher phase
 8:             if g = 1 then
 9:                 Use Eq.(5) to calculate x_{i,new};
10:             else
11:                 Use Eq.(12) to calculate x_{i,new};
12:             end if
13:         else                // Select the learner phase
14:             if g == 1 then
15:                 Use Eq.(7) to calculate x_{i,new};
16:             else
17:                 Use Eq.(13) to calculate x_{i,new};
18:             end if
19:         end if
20:     end for
21:     for i =1 to NP do
22:         if RMSE(x_{i,new}) < RMSE(x_i) then
23:             S(k,:) = x_{i,new} − x_i;
24:             x_i = x_{i,new};
25:             k = k + 1;
26:         end if
27:         if k > NP then
28:             k = 1;
29:         end if
30:     end for
31:     g = g + 1;
32: end while
33: Output: The extracted optimal PV parameters
```

$$x_{i,\text{ new}} = x_{r1} + rand \cdot \left(x_{r2} - x_{r3}\right) + rand \cdot S\left(ind\right) \tag{13}$$

where r_1, r_2, r_3 are three random integers selected inside the set $\{1, \ldots, NP\}$ and different from i.

From Eq. (13), it can be seen that in the improved learner phase, the information in the population is fully utilized by randomly selecting three learners and drawing on past successful learning experiences to enhance the exploration capability of the algorithm and improve the population diversity.

4.4 Framework of RSTLBO

Based on the above points of improvement, an improved TLBO algorithm, RSTLBO, is proposed in this paper. The pseudo code of RSTLBO framework is shown in Algorithm 2, where *M_NFE* represents the maximum number of function evaluations and G_m is the maximum number of iterations. In addition, k and g are counters on the number of iterations and the size of S, respectively. The main flow of the whole algorithm is as follows:

1) Set initialization variables such as g, G_m, k, etc.
2) Randomly initialize the entire class of learners and calculate their objective function values as in lines 2 - 3.
3) Next, the algorithm enters the main loop, which first proceeds to calculate the ranked selection probabilities, followed by two main components. The first one is to update the learners by adaptively choosing the teacher or learner phase from the obtained ranked selection probabilities shown as lines 7 - 20. It is worth mentioning that in updating the learners, the improved teacher and learner phases proposed in this paper are used, where the developed reusing successful learning experience is taken into account. The second is to evaluate the updated learners and update the successful learning experience set S (lines 21 - 30). It is worth mentioning that when k is larger than NP, the successful learning experiences in S are replaced according to the first-come-first-out principle.

As can be seen from Algorithm 2, the proposed RSTLBO not only has a simple structure that is easy to implement, but also does not introduce additional parameters of the algorithm except a population size NP that is necessary for all algorithms. In addition, to further clearly illustrate the search process of RSTLBO, its flowchart is given in Fig. 4.

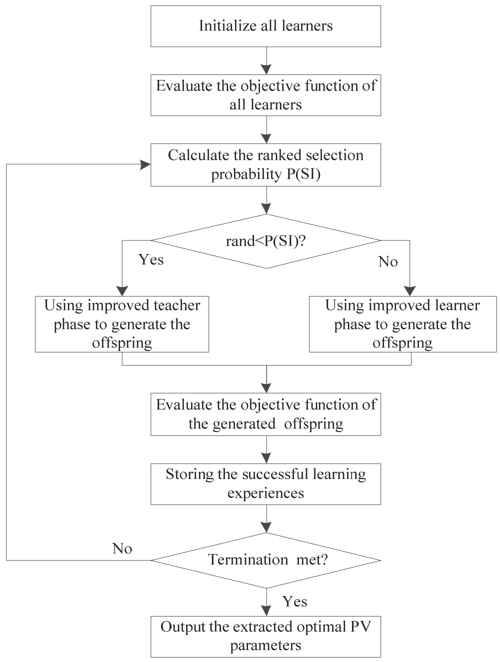

Figure 4 The flowchart of the proposed RSTLBO

5 EXPERIMENTAL RESULTS AND ANALYSIS
5.1 Experimental Setup

For both single and double diode models, the datasets are used from the R.T.C. France solar cell [8], which was measured on a 57 mm diameter R.T.C France commercial solar cell. For the PV panel model, two datasets, single-crystalline STM6-40/36 and multi-crystalline STP6-120/36, are used in this paper, and the I-V data for both models are taken from the literature [6]. The ranges of unknown parameter values for these models are shown in Tab. 1.

Table 1 Range of unknown parameter values for different PV models

Parameter	R.T.C. solar cell		STM6-40/36		STP6-120/36	
	LB	UB	LB	UB	LB	UB
I_p / A	0	1	0	2	0	8
I_D, I_{D1}, I_{D2} / μA	0	1	0	50	0	50
R_{se} / Ω	0	0.5	0	0.36	0	0.36
R_{sh} / Ω	0	100	0	1000	0	1500
a, a_1, a_2	1	2	1	60	1	50

In addition, in order to validate the performance of RSTLBO, some representative PV parameter extraction methods are selected for comparison in this paper. These optimization methods are penalty-based differential evolution (P-DE) [17], standard teaching-learning-based optimization (TLBO) [27], generalized oppositional teaching- learning-based optimization (GOTLBO)[30], self-adaptive teaching-learning-based optimization (SATLBO) [31], hybrid teaching-learning-based artificial bee colony optimization (TLABC) [32], improved teaching-learning-based optimization (ITLBO) [6], and their algorithm parameter settings are shown in Tab. 2. These algorithms were implemented using Matlab software programming. For fair comparison, the maximum number of function evaluations, *M_NFE*, is set to 30,000 for all the compared algorithms. All the experimental results are obtained by running the algorithms independently for 30 times under Windows 7 64 bit operating system with i5-4590M processor @ 3.30 GHz and 8GB RAM.

Table 2 Parameter settings for different algorithms

Algorithm	Parameter setting
P-DE	NP = 70, F = 0.8, CR = 1.0
TLBO	NP = 50
GOTLBO	NP = 50, Jr = 0.3
SATLBO	NP = 40
TLABC	NP = 50, limit = 200, F = *rand*
ITLBO	NP = 50
RSTLBO	NP = 50

5.2 Single Diode Model Results

The experimental results of RSTLBO and other optimization algorithms on the single diode model are shown in Tab. 3. As can be seen from Tab. 3, the selected optimization algorithms all achieved the same *RMSE* value (9.8602E-04). Accordingly it is difficult to state which algorithm is better; for this reason, the statistical results of 30 independent runs are given in Tab. 4, which include the minimum (Min), maximum (Max), mean (Mean), standard deviation (Std) of the *RMSE*, and the CPU computation time (CPU time) for one independent run.

Table 3 Comparison of results of different parameter extraction methods on the single diode model

Algorithm	I_p / A	I_D / μA	R_{se} / Ω	R_{sh} / Ω	a	*RMSE*
P-DE	0.7608	0.3230	0.0364	53.7185	1.4812	9.8602E–04
TLBO	0.7608	0.3230	0.0364	53.7185	1.4812	9.8602E–04
GOTLBO	0.7608	0.3230	0.0364	53.7185	1.4812	9.8602E–04
SATLBO	0.7608	0.0000	0.0364	53.7185	1.4812	9.8602E–04
TLABC	0.7608	0.3230	0.0364	53.7185	1.4812	9.8602E–04
ITLBO	0.7608	0.3230	0.0364	53.7185	1.4812	9.8602E–04
RSTLBO	0.7608	0.3230	0.0364	53.7185	1.4812	9.8602E–04

Table 4 Comparison of statistical results of the single diode model

Algorithm	*RMSE*				CPU time / s
	Min	Max	Mean	Std	
P-DE	9.8602E–04	3.7379E–03	1.7788E–03	1.23E–03	0.19
TLBO	9.8602E–04	1.2391E–03	1.0186E–03	6.05E–05	0.24
GOTLBO	9.8602E–04	1.2794E–03	1.0144E–03	6.78E–05	0.37
SATLBO	9.8602E–04	9.8602E–04	9.8602E–04	8.59E–17	0.26
TLABC	9.8602E–04	1.4449E–03	1.0369E–03	9.60E–05	0.85
ITLBO	9.8602E–04	9.8602E–04	9.8602E–04	2.78E–17	0.28
RSTLBO	9.8602E–04	9.8602E–04	9.8602E–04	3.04E–17	0.26

From the statistical results in Tab. 4, it is clear that SATLBO, ITLBO and RSTLBO have a significant advantage over several other optimization algorithms in terms of the three evaluation metrics, Max, Mean and Std, which indicates that these three algorithms have better stability and reliability.

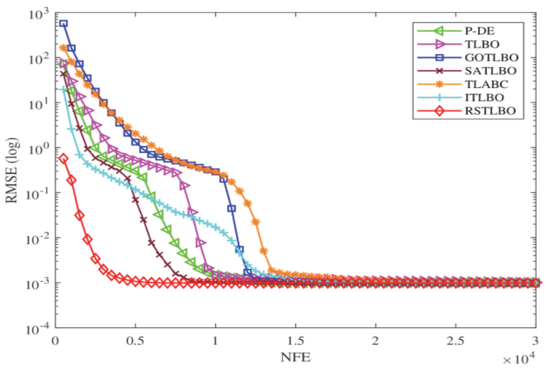

Figure 5 Convergence plots of different algorithms on the single diode model

In terms of CPU computation time, P-DE consumes the least time, followed by TLBO, SATLBO, RSTLBO, ITLBO, GOTLBO, and TLABC. Considering all the evaluation metrics, RSTLBO and SATLBO have the best performance on the single diode model, followed by ITLBO. In addition, in order to further confirm the superiority of the proposed RSTLBO algorithm is superior, Fig. 5 provides the convergence images of the *RMSE* values of different algorithms as the number of function evaluations varies. As can be seen in Fig. 5, RSTLBO converges the fastest, followed by SATLBO and others.

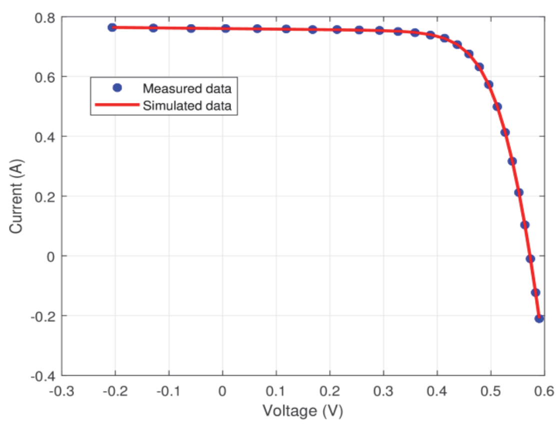

Figure 6 Simulation data fitted to measured data on the single diode model

In addition, the parameter values extracted by RSTLBO are substituted into the objective function to calculate the simulated current values. The fitting plot of the simulated current value with the actual measured current value is given in Fig. 6, from which it is clear that the simulated current calculated by extracting the parameter values through RSTLBO is highly consistent with the actual current, which indirectly indicates the accuracy of the extracted parameters.

5.3 Double Diode Model Results

The results of different optimization algorithms on the double diode model are given in Tab. 5. From Tab. 5, it can be seen that the minimum *RMSE* value (9.8248E–04) is obtained by P-DE, ITLBO and RSTLBO followed by TLBO (9.8280E–04), TLABC (9.8313E–04), SATLBO (9.8368E–04) and GOTLBO (9.8380E–04).

Table 5 Comparison of results of different parameter extraction methods on the double diode model

Algorithm	Ip / A	ID_1 / μA	Rse / Ω	Rsh / Ω	a_1	ID_2 / μA	a_2	*RMSE*
P-DE	0.7608	0.2260	0.0367	55.4854	1.4510	0.7493	2.0000	9.8248E–04
TLBO	0.7608	0.2144	0.0368	55.6168	1.4468	0.7788	1.9783	9.8280E–04
GOTLBO	0.7608	0.3797	0.0366	54.723	1.8963	0.2461	1.4589	9.8380E–04
SATLBO	0.7608	0.2298	0.0367	55.1148	1.4532	0.4842	1.9054	9.8368E–04
TLABC	0.7608	0.2323	0.0367	55.1266	1.4538	0.5575	1.9445	9.8313E–04
ITLBO	0.7608	0.7471	0.0367	55.4796	2.0000	0.2262	1.4511	9.8248E–04
RSTLBO	0.7608	0.7493	0.0367	55.4854	2.0000	0.226	1.4510	9.8248E–04

Table 6 Comparison of statistical results of the double diode model

Algorithm	*RMSE*				CPU time / s
	Min	Max	Mean	Std	
P-DE	9.8248E–04	3.5847E–03	1.8545E–03	1.23E–03	0.23
TLBO	9.8280E–04	2.2461E–03	1.2260E–03	3.49E–04	0.25
GOTLBO	9.8380E–04	1.7850E–03	1.1305E–03	2.15E–04	0.26
SATLBO	9.8368E–04	1.0512E–03	9.9292E–04	1.61E–05	0.27
TLABC	9.8313E–04	2.6652E–03	1.2250E–03	3.84E–04	0.89
ITLBO	9.8248E–04	9.8653E–04	9.8486E–04	1.55E–06	0.29
RSTLBO	9.8248E–04	9.8610E–04	9.8356E–04	1.30E–06	0.28

Although the minimum *RMSE* value obtained by RSTLBO is not much different from that of the other algorithms, any algorithm is relevant for being able to reduce the objective function value due to the impossibility of obtaining a certain exact parameter value. Tab. 6 gives the statistical results of the different algorithms for 30 independent runs on the double diode model. As can be seen from Tab. 6, RSTLBO does not use the least amount of CPU computation time, but it occupies a significant advantage in the three evaluation metrics of Max, Mean, and Std, which suggests that RSTLBO still has a better performance on the double diode model with two more parameters than the single diode model.

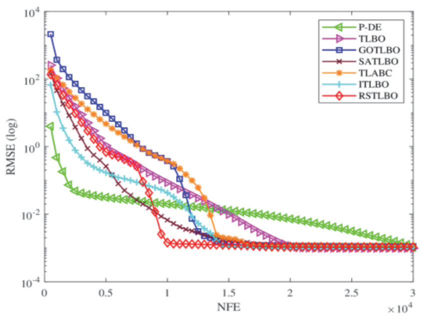

Figure 7 Convergence plots of different algorithms on the double diode model

Next, the convergence curves of the different algorithms on the double diode model and the fitting plots of the simulated currents obtained from the parameters extracted by RSTLBO to the actual measured currents are given in Fig. 7 and Fig. 8, respectively. From Fig. 7, it can be seen that RSTLBO still has the fastest convergence speed on the double diode model, and P-DE has the slowest convergence. From the fitting plot in Fig. 8, the simulated currents obtained from the parameters extracted by RSTLBO are highly consistent with the actual measured currents, which indicates that the parameters extracted by RSTLBO are also very accurate and reliable on the double diode model.

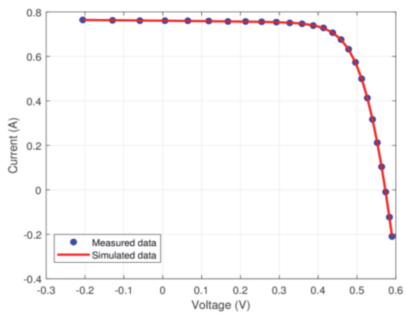

Figure 8 Simulation data fitted to measured data on the double diode model

5.4 PV Panel Model Results

In this paper, two different types of PV panel model datasets are selected, i.e., STM6-40/36 based on mono-crystalline and STP6-120/36 based on poly-crystalline. The experimental results of the different algorithms on these two models are given in Tab. 7 to Tab. 10 and Fig. 9 to Fig. 12, respectively. For the mono-crystalline STM6-40/36 PV panel model, as shown in Tab. 7, P-DE, SATLBO, ITLBO, and RSTLBO achieve the smallest *RMSE* value (1.7298E–03). The statistical results in Tab. 8 show that the proposed RSTLBO in this paper is close to several other methods in terms of CPU computation time, and is better than TLABC. However, for the rest of the evaluation metrics, especially the Std metrics that can reflect the robustness of the algorithms, the RSTLBO shows great competitiveness.

Table 7 Comparison of results of different parameter extraction methods on the mono-crystalline STM6-40/36

Algorithm	I_P / A	I_D / μA	R_{se} / Ω	R_{sh} / Ω	a	$RMSE$
P-DE	1.6639	1.7387	0.0043	15.9283	1.5203	1.7298E–03
TLBO	1.6632	2.1266	0.0037	17.0554	1.5428	1.8214E–03
GOTLBO	1.6631	2.5899	0.003	18.2436	1.5654	1.9756E–03
SATLBO	1.6639	1.7387	0.0043	15.9283	1.5203	1.7298E–03
TLABC	1.6638	1.9253	0.0039	16.2947	1.5316	1.7485E–03
ITLBO	1.6639	1.7387	0.0043	15.9283	1.5203	1.7298E–03
RSTLBO	1.6639	1.7387	0.0043	15.9283	1.5203	1.7298E–03

Table 8 Comparison of statistical results of the mono-crystalline STM6-40/36

Algorithm	$RMSE$				CPU time / s
	Min	Max	Mean	Std	
P-DE	1.7298E–03	1.6988E–01	1.8633E–02	3.63E–02	0.19
TLBO	1.8214E–03	3.4801E–02	8.4570E–03	8.55E–03	0.23
GOTLBO	1.9756E–03	8.3619E–02	1.0264E–02	1.76E–02	0.24
SATLBO	1.7298E–03	4.4103E–03	1.9610E–03	5.09E–04	0.25
TLABC	1.7485E–03	3.0626E–03	2.4859E–03	3.80E–04	0.84
ITLBO	1.7298E–03	1.7345E–03	1.7300E–03	8.55E–07	0.27
RSTLBO	1.7298E–03	1.7298E–03	1.7298E–03	1.33E–12	0.26

In addition, the convergence plot in Fig. 9 shows that RSTLBO obviously converges faster than P-DE, TLBO, GOTLBO, TLABC, ITLBO, etc., and has a comparable convergence speed with SATLBO. The fitting curves in Fig. 10 show that the simulated currents obtained from the parameters extracted by RSTLBO have a good fit with the actual measured currents.

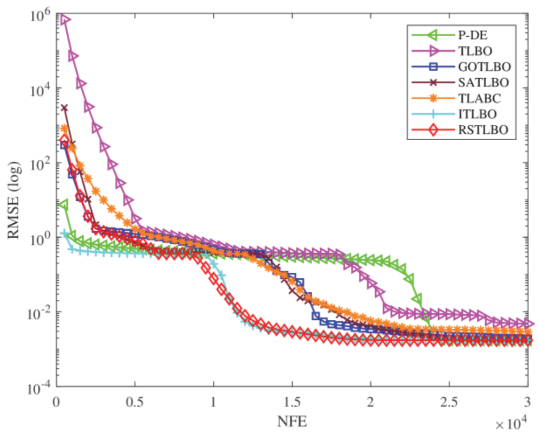

Figure 9 Convergence plots of different algorithms on the mono-crystalline STM6-40/36

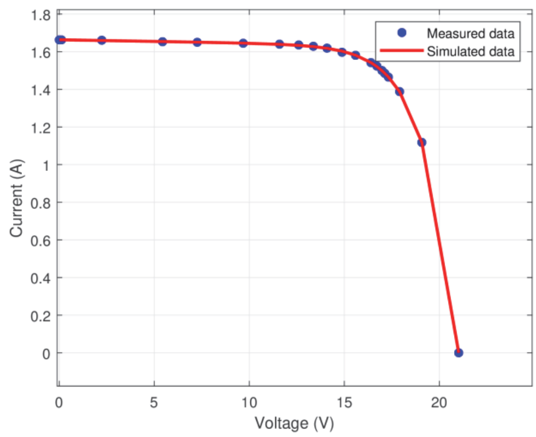

Figure 10 Simulation data fitted to measured data on the mono-crystalline STM6-40/36

For the poly-crystalline STP6-120/36 PV panel model, it can be seen from Tab. 9 that all comparison algorithms are able to obtain the same minimum $RMSE$ value (1.6601E-02), except for GOTLBO (1.6605E-02). And from the statistical results in Tab. 10, like the previous models, RSTLBO achieved the best results in the three evaluation metrics Max, Mean and Std.

Table 9 Comparison of results of different parameter extraction methods on the poly-crystalline STP6-120/36

Algorithm	I_P / A	I_D / μA	R_{se} / Ω	R_{sh} / Ω	a	$RMSE$
P-DE	7.4725	2.335	0.0046	22.2199	1.2601	1.6601E–02
TLBO	7.4725	2.335	0.0046	22.2199	1.2601	1.6601E–02
GOTLBO	7.4731	2.3871	0.0046	22.0657	1.26	1.6605E–02
SATLBO	7.4725	2.335	0.0046	22.2191	1.2601	1.6601E–02
TLABC	7.4725	2.3337	0.0046	22.3323	1.2601	1.6601E–02
ITLBO	7.4725	2.3350	0.0046	22.2199	1.2601	1.6601E–02
RSTLBO	7.4725	2.3350	0.0046	22.2199	1.2601	1.6601E–02

Table 10 Comparison of statistical results of the poly-crystalline STP6-120/36

Algorithm	$RMSE$				CPU time / s
	Min	Max	Mean	Std	
P-DE	1.6601E–02	1.0684E+00	4.1076E–01	4.83E–01	0.19
TLBO	1.6601E–02	3.1140E–01	3.5219E–02	5.30E–02	0.24
GOTLBO	1.6605E–02	6.7994E–01	5.7959E–02	1.24E–01	0.24
SATLBO	1.6601E–02	1.8397E–02	1.6730E–02	3.53E–04	0.26
TLABC	1.6601E–02	3.0053E–02	1.9785E–02	3.15E–03	0.86
ITLBO	1.6601E–02	1.6903E–02	1.6617E–02	6.12E–05	0.28
RSTLBO	1.6601E–02	1.6601E–02	1.6601E–02	1.56E–16	0.26

In addition, as can be seen from the convergence plot in Fig. 11, on the poly-crystalline STP6-120/36 PV panel model, RSTLBO has the fastest convergence speed compared to several other optimization algorithms, approaching convergence at approximately NFE = 15,000. P-DE does not converge on this model, even after the NFE is consumed. Finally, the parameter values extracted by RSTLBO on this model are also very accurate and reliable, as can be seen from the fitting plot of simulated and measured currents in Fig. 12.

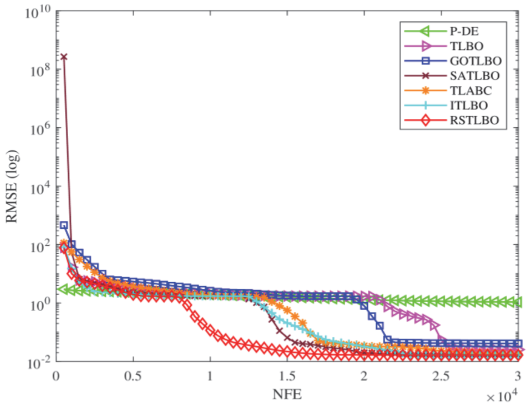

Figure 11 Convergence plots of different algorithms on the poly-crystalline STP6-120/36

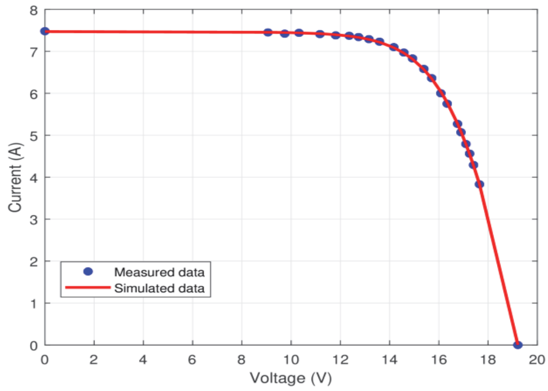

Figure 12 Simulation data fitted to measured data on the poly-crystalline STP6-120/36

Table 11 Statistical results obtained by RSTLBO on different population size for different PV models

Model	*NP*	*RMSE*			
		Min	Max	Mean	Std
Single diode model	*NP* = 10	9.8945E–04	3.4156E–03	1.6729E–03	6.13E–04
	NP = 20	9.8602E–04	9.8602E–04	9.8602E–04	1.68E–17
	NP = 30	9.8602E–04	9.8602E–04	9.8602E–04	2.34E–17
	NP = 40	9.8602E–04	9.8602E–04	9.8602E–04	2.12E–17
	NP = 50	9.8602E–04	9.8602E–04	9.8602E–04	3.04E–17
	NP = 60	9.8602E–04	9.8602E–04	9.8602E–04	2.54E–17
	NP = 70	9.8602E–04	9.8602E–04	9.8602E–04	4.95E–17
	NP = 80	9.8602E–04	9.8602E–04	9.8602E–04	7.88E–15
	NP = 90	9.8602E–04	9.8602E–04	9.8602E–04	4.65E–12
	NP = 100	9.8602E–04	9.8602E–04	9.8602E–04	2.79E–11
Double diode model	*NP* = 10	1.0505E–03	4.9387E–03	2.2946E–03	1.10E–03
	NP = 20	9.8263E–04	1.0184E–03	9.8641E–04	6.19E–06
	NP = 30	9.8248E–04	9.8602E–04	9.8305E–04	1.20E–06
	NP = 40	9.8248E–04	9.8602E–04	9.8347E–04	1.28E–06
	NP = 50	9.8248E–04	9.8610E–04	9.8356E–04	1.30E–06
	NP = 60	9.8253E–04	1.2083E–03	1.0116E–03	6.61E–05
	NP = 70	9.8321E–04	1.3066E–03	1.0190E–03	9.34E–05
	NP = 80	9.8267E–04	1.5335E–03	1.0726E–03	1.44E–04
	NP = 90	9.8596E–04	1.8378E–03	1.1958E–03	2.92E–04
	NP = 100	9.8595E–04	1.9737E–03	1.2651E–03	2.75E–04
Poly-crystalline STM6-40/36	*NP* = 10	1.9032E–03	8.1496E–02	1.3727E–02	1.98E–02
	NP = 20	1.7298E–03	1.7298E–03	1.7298E–03	3.97E–18
	NP = 30	1.7298E–03	1.7298E–03	1.7298E–03	6.36E–18
	NP = 40	1.7298E–03	1.7298E–03	1.7298E–03	8.02E–18
	NP = 50	1.7298E–03	1.7298E–03	1.7298E–03	1.33E–12
	NP = 60	1.7298E–03	1.7299E–03	1.7298E–03	1.53E–08
	NP = 70	1.7298E–03	2.2718E–03	1.7686E–03	1.13E–04
	NP = 80	1.7298E–03	2.6293E–03	1.8366E–03	2.38E–04
	NP = 90	1.7315E–03	4.0634E–03	2.0382E–03	6.38E–04
	NP = 100	1.7870E–03	3.7813E–03	2.1583E–03	5.12E–04
Mono-crystalline STM6-40/36	*NP* = 10	1.8499E–02	9.2296E–01	1.7213E–01	2.71E–01
	NP = 20	1.6601E–02	1.6601E–02	1.6601E–02	1.02E–16
	NP = 30	1.6601E–02	1.6601E–02	1.6601E–02	7.20E–17
	NP = 40	1.6601E–02	1.6601E–02	1.6601E–02	1.17E–16
	NP = 50	1.6601E–02	1.6601E–02	1.6601E–02	1.56E–16
	NP = 60	1.6601E–02	1.6601E–02	1.6601E–02	7.52E–11
	NP = 70	1.6601E–02	1.6601E–02	1.6601E–02	5.61E–08
	NP = 80	1.6601E–02	1.6654E–02	1.6608E–02	1.18E–05
	NP = 90	1.6601E–02	1.6748E–02	1.6682E–02	3.79E–05
	NP = 100	1.6714E–02	1.7010E–02	1.6789E–02	6.43E–05

5.5 Discussion of Population Size

As described in Section 4.4, the proposed RSTLBO algorithm does not introduce additional algorithmic parameters, except for the population size *NP* that is necessary for all algorithms. To further investigate the performance of RSTLBO, the effect of population size is discussed.The experimental results are shown in Tab. 11, where the population size varies from 10 to 100. The rest of the experimental setup remains the same as in Section 5.1. From this table, it can be seen that

1) The performance of RSTLBO on all PV models drops drastically when the population size achieves a small size, e.g., $NP = 10$, due to the fact that the population size is too small, which leads to insufficient diversity, thus limiting the algorithm's search.
2) For a large population size, e.g., NP is between 60 and 100, and especially in the range of 80 ~ 100, the performance of RSTLBO also decreases dramatically. The possible reason is that a larger population, while maintaining good population diversity, simultaneously reduces the number of loop generations of the algorithm at a fixed number of total evaluations, which leads to a degradation of the algorithm's search performance.
3) Combining the results of all the PV models, the best performance of RSTLBO is obtained when the value of NP is taken in the range of 30 ~ 50.

6 CONCLUSIONS

In conclusion, this paper proposes a self-adaptive teaching-learning based optimization with experience reuse (RSTLBO) to address limitations of standard TLBO and accurately extract PV model parameters. The core novelties of RSTLBO are the adaptive teacher/learner phase selection probability and reusing successful learner experiences to enhance search capability. Experiments demonstrate RSTLBO's superior performance, obtaining highest accuracy across single diode, double diode and PV panel models. Specifically, RSTLBO achieves minimum *RMSE* error, outperforms state-of-the-art methods in statistical results, and exhibits fastest convergence speed. The parametric self-adaptivity and experience reuse offer key improvements over standard TLBO. Overall, RSTLBO provides an effective and reliable approach for extracting PV parameters. It is worth mentioning that for some complex optimization problems such as maximum power point tracking [33] and optimal power flow (OPF) [34], there is still room for further research on the convergence of the RSTLBO.

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