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Parameter extraction of photovoltaic models using an improved teaching-learning-based optimization

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ABSTRACT

Accurate and reliable parameter extraction of photovoltaic (PV) models is urgently desired for the simulation, evaluation, control, and optimization of PV systems. Although many meta-heuristic algorithms have been used to extract the PV parameters, the extracted parameters are usually not very accurate and reliable. To accurately and reliably extract the parameters of different PV models, an improved teaching-learning-based optimization (ITLBO) algorithm is proposed in this paper. The novelty of ITLBO lies primarily in the improved teaching and learning strategies with two improvements: (i) the teacher adopts different teaching strategies according to learner levels in the teacher phase; and (ii) in the learner phase, a new learning strategy is proposed to balance exploration and exploitation. The performance of ITLBO is verified by extracting the parameters of the single diode model, the double diode model, and three PV modules. The experimental results indicate that ITLBO obtains better performance with respect to accuracy and reliability compared to the other algorithms.

1. Introduction

In recent years, because of environmental pollution, climate change, global warming, and fuel exhaustion, the use of alternative renewable energy sources, such as wind, wave, nuclear, tidal, geothermal, biomass, and so on, has received growing attention [1–4]. Due to its wide availability and cleanliness, solar energy is considered as one of the most promising renewable energy resources [5]. The main application of solar energy is photovoltaic (PV) power generation [6]. Because solar PV systems are able to directly convert solar energy into electricity, they have been applied worldwide [7,8]. However, using PV systems to generate electricity is an important challenging due to their dependence on weather and environmental factors, particularly temperature and global irradiance [9]. Therefore, to optimize a PV system, an accurate model based on measured current-voltage data is necessary [6,10]. There are several models that are used to represent the relationship between current and voltage. The most widely used are the single diode and double diode models [11]. The accuracy of models parameters is critical to the study of solar PV systems. Therefore, it is very important to use an effective method to extract the parameters of PV models.

Recently, various methods have been devoted to parameter extraction of PV models. These can be mainly categorized into three groups:

- *Analytical methods*: The advantages of these methods are simplicity and rapid computation [12] because they usually solve the problem by analyzing a series of mathematical equations [13]. However, some assumptions need to be made before analyzing, which reduces the accuracy of the solutions [14,15].
- *Deterministic methods*: These methods [16,17] are highly sensitive to the initial guess and are easily trapped in local optimum [18]. Additionally, the deterministic methods have strict requirements on the models, such as differentiability and convexity. However, PV models are often implicit, nonlinear, and multi-modal, leading to poor solutions when employing deterministic methods.
- *Meta-heuristic methods*: To overcome the shortcomings of the first two methods, meta-heuristic methods inspired by natural phenomenon have been serviced as a promising alternative for parameter extraction of PV models. Because these methods do not have strict requirements and are easily implemented, they have recently drawn more attention.

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Nomenclature

I	cell output current (A)
I_{ph}	photo-generated current (A)
I_d, I_{d1}, I_{d2}	diode currents (μA)
V	cell output voltage (V)
V_t	junction thermal voltage (V)
R_s	series resistance (Ω)
R_{sh}	shunt resistance (Ω)
a, a_1, a_2	diode ideal factors
N_s	the number of solar cells in series
N_p	the number of solar cells in parallel
k	Boltzmann constant (J/K)
q	electron charge (C)
T	temperature of junction (K)
N	the number of measured data
P	cell output power (W)
$IAEC$	individual absolute error current (A)
$IAEP$	individual absolute error power (W)
RMSE	root mean square error
Np	population size
NFE	the number of objective function evaluation
Max_NFE	maximal NFE
Best	best RMSE
Worst	worst RMSE
Mean	mean RMSE
Std	standard deviation of RMSE
Time	total running time (s)

Up to now, many meta-heuristic methods have been used to extract the parameters of PV models, such as particle swarm optimization [19,20], simulated annealing algorithm [21], genetic algorithm [22], cuckoo search [13], differential evolution [23,24], bird mating optimizer [25], artificial bee colony (ABC) [26], harmony search-based algorithms [27], artificial bee swarm optimization [28], improved chaotic whale optimization algorithm [29], ant lion optimizer [30], improved JAYA algorithm (IJAYA) [10], bee pollinator flower pollination algorithm [31], and multiple learning backtracking search algorithm (MLBSA) [32]. Although these meta-heuristic methods have obtained satisfactory results, their accuracy and reliability need to be further improved. In addition, there are many algorithmic parameters that need to be set by the users, which may greatly affect the performance of the algorithms.

The teaching-learning-based optimization algorithm (TLBO) [33] is based on the effect of the influence of a teacher on the output of learners in a class. The TLBO is a simple and efficient optimization algorithm, yet only has one algorithmic parameter (i.e., the population size). Recently, several TLBO variants have been used to extract the parameters of PV models, such as TLBO with learning experience (LETLBO) [34], generalized oppositional TLBO (GOTLBO) [35], self-adaptive TLBO (SATLBO) [36], and TLBO artificial bee colony (TLABC) [18]. However, these TLBO variants also suffer from the drawbacks of insufficient accuracy and low reliability, especially for the double diode model.

Based on these considerations, in this paper, an improved TLBO algorithm, namely ITLBO, is proposed to accurately and reliably extract the parameters of different PV models. In ITLBO, two improvements are proposed to overcome the drawbacks of the original TLBO. First, in the teacher phase, the teacher uses different teaching strategies to teach learners according to the learners levels (fitness values), rather than just adopting a teaching strategy like the original TLBO, which will guide all learners to a promising area. Secondly, in the learner phase, we put forward to a new learning strategy where the learners are divided into two groups (i.e., better and worse learners) according to their levels. Better learners are fully utilized to their own exploitation capacity, while worse learners are used to improve global search ability and enhance the diversity of the population. Thus, exploration and exploitation are well balanced. To validate the performance of ITLBO, the algorithm was used to extract the parameters of different PV models, i.e., the single diode model, the double diode model, and the PV modules. The results demonstrate that our approach is able to exactly and reliably extract the parameters of different PV models as well as provide highly competitive results compared with other methods.

The main contributions of this paper are as follows:

- An improved TLBO algorithm, ITLBO, is proposed. In ITLBO, two improved strategies are implemented in the teacher phase and the learner phase.
- The performance of the ITLBO algorithm has been extensively investigated by applying it to the parameter extraction problems of different PV models.
- By comparing with other state-of-the-art algorithms, the accuracy and reliability of ITLBO are demonstrated. Thus, ITLBO can be an effective alternative to parameter extraction of PV models.

The rest of this paper is structured as follows. Section 2 states different PV models and the objective function. The original TLBO algorithm is briefly described in Section 3. Section 4 presents the proposed ITLBO algorithm in detail. Section 5 analyzes the results. Finally, Section 6 concludes the paper.

2. Formulation of PV models

As mentioned, there are two widely used models that are capable of explaining the *I-V* characteristics of PV systems. In this section, the single diode model, the double diode model, the PV module, and the objective function are described.

2.1. Single diode model

As shown in Fig. 1, the single diode model of the output current can be formulated as follows [37,38]:

$$I = I_{ph} - I_d\left[\exp\left(\frac{V + IR_s}{aV_t}\right) - 1\right] - \frac{V + IR_s}{R_{sh}}, \tag{1}$$

where I denotes the cell output current; V represents the cell output voltage; I_{ph} is the photo-generated current; I_d is the diode current; R_s is the series resistance; a is the diode ideal factor; R_{sh} is the shunt resistance; and V_t is the junction thermal voltage defined as:

$$V_t = \frac{k\cdot T}{q}, \tag{2}$$

where k is the Boltzmann constant ($1.3806503 \times 10^{-23}$ J/K); q is the electron charge ($1.60217646 \times 10^{-19}$ C), and T indicates the temperature of junction in Kelvin.

For the single diode model, there are five unknown parameters (I_{ph},

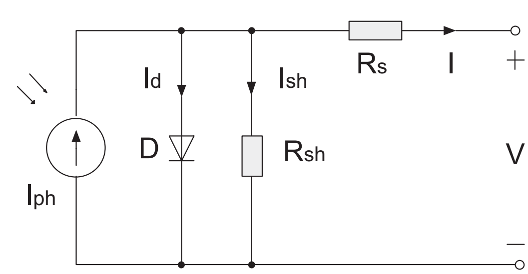

Fig. 1. Equivalent circuit of the single diode model.

I_d, R_s, R_{sh}, a) that need to be extracted.

2.2. Double diode model

For the double diode model, there are two diodes in parallel in the equivalent circuit (Fig. 2). Its relationship of current and voltage can be described as follows:

$$I = I_{ph} - I_{d1}\left[\exp\left(\frac{V + IR_s}{a_1 V_t}\right) - 1\right] - I_{d2}\left[\exp\left(\frac{V + IR_s}{a_2 V_t}\right) - 1\right] - \frac{V + IR_s}{R_{sh}}, \tag{3}$$

where I_{d1} and I_{d2} indicate the currents of the first and second diodes, respectively. Both a_1 and a_2 are the first and second ideal factors of the diodes.

In the double diode model, there are seven unknown parameters (I_{ph}, I_{d1}, I_{d2}, R_s, R_{sh}, a_1, a_2) to be extracted.

2.3. PV module

The equivalent circuit of the PV module is shown in Fig. 3. It can be seen that the PV module combines several diodes connected in series or in parallel, and the output current can be expressed as [29]:

$$I = I_{ph}N_p - I_d N_p\left[\exp\left(\frac{V + IR_s N_s/N_p}{aN_s V_t}\right) - 1\right] - \frac{V + IR_s N_s/N_p}{R_{sh}N_s/N_p}, \tag{4}$$

where N_s and N_p represent the number of solar cells connected in series or in parallel, respectively. Because the PV modules used in the experiments are all in series, N_p is set to 1. Thus, Eq. (4) can be represented as follows:

$$I = I_{ph} - I_d\left[\exp\left(\frac{V + IR_s N_s}{aN_s V_t}\right) - 1\right] - \frac{V + IR_s N_s}{R_{sh}N_s}. \tag{5}$$

For the PV module, five unknown parameters need to be extracted, including I_{ph}, I_d, R_s, R_{sh}, and a.

2.4. Objective function

For the parameter extraction problem of PV models, the main target is to extract a set of parameters that minimize the error between the measured and simulated current data. The absolute error between measured and simulated current is defined as individual absolute error current (IAEC), which is formulated as follows:

- For the single diode model:

$$IAEC = \left|I_{ph} - I_d\left[\exp\left(\frac{V + IR_s}{aV_t}\right) - 1\right] - \frac{V + IR_s}{R_{sh}} - I\right|. \tag{6}$$

- For the double diode model:

$$IAEC = \left|I_{ph} - I_{d1}\left[\exp\left(\frac{V + IR_s}{a_1 V_t}\right) - 1\right] - I_{d2}\left[\exp\left(\frac{V + IR_s}{a_2 V_t}\right) - 1\right] - \frac{V + IR_s}{R_{sh}} - I\right|. \tag{7}$$

- For the PV module:

$$IAEC = \left|I_{ph} - I_d\left[\exp\left(\frac{V + IR_s N_s}{aN_s V_t}\right) - 1\right] - \frac{V + IR_s N_s}{R_{sh}N_s} - I\right|. \tag{8}$$

In order to quantify the overall error between the measured and simulated current, the root mean square error (RMSE) is used as the objective function:

$$\text{RMSE} = f(\mathbf{x}) = \sqrt{\frac{1}{N}\sum_{i=1}^{N} IAEC^2}, \tag{9}$$

where N is the number of measured current data, and $\mathbf{x}$ is the decision vector containing the unknown parameters to be extracted. It is clear that the smaller the RMSE, the more accurate the extracted parameters.

3. TLBO

TLBO, as a simple and efficient optimization method, was proposed by Rao et al. [33]. The main idea comes from the influence of a teacher on the output of learners in a class. It is a population-based optimization algorithm for nonlinear optimization problems. TLBO mainly consists of two phases: the teacher phase and the learner phase. In the teacher phase, teacher shares her/his knowledge with the learners. In the learner phase, learners also learn from each other.

3.1. Teacher phase

For a class consisting of one teacher and $Np - 1$ learners ($\mathbf{x}_i$, $i = 1, \cdots, Np$), the best learner of the class is usually regarded as the teacher ($\mathbf{x}_{\text{teacher}}$), which disseminates the knowledge to the learners so as to improve the mean value of the class. The mean value ($\mathbf{x}_{\text{mean}}$) of the class is defined as:

$$\mathbf{x}_{\text{mean}} = \frac{1}{Np}\sum_{i=1}^{Np}\mathbf{x}_i. \tag{10}$$

In the teaching process, each learner is updated as follows:

$$\mathbf{x}_{i,new} = \mathbf{x}_i + rand\cdot(\mathbf{x}_{\text{teacher}} - T_F\cdot\mathbf{x}_{\text{mean}}), \tag{11}$$

where $\mathbf{x}_{i,new}$ is the i-th updated learner; $rand$ is a random number in the range $[0, 1]$; and T_F is the teaching factor with its value set to either 1 or 2.

After each iteration, all $\mathbf{x}_{i,new}$ are evaluated based on the objective function. If $\mathbf{x}_{i,new}$ is better than $\mathbf{x}_i$, then$\mathbf{x}_i$ is replaced with $\mathbf{x}_{i,new}$; otherwise, $\mathbf{x}_i$ is unchanged.

3.2. Learner phase

In the learner phase, a learner randomly chooses another learner to interact for improving her/his knowledge by some ways, such as discussions, formal communications. The learning process is formulated as follows:

$$\mathbf{x}_{i,new} = \begin{cases}\mathbf{x}_i + rand\cdot(\mathbf{x}_i - \mathbf{x}_j), & \text{if } f(\mathbf{x}_i) < f(\mathbf{x}_j)\\ \mathbf{x}_i + rand\cdot(\mathbf{x}_j - \mathbf{x}_i), & \text{otherwise}\end{cases}, \tag{12}$$

where $\mathbf{x}_j$ is the j-th learner different from $\mathbf{x}_i$, $f(\mathbf{x})$ is the objective function value of $\mathbf{x}$. If $\mathbf{x}_{i,new}$ is better than $\mathbf{x}_i$, then accept $\mathbf{x}_{i,new}$.

4. Our approach: ITLBO

As described above, both the teacher phase and the learner phase are

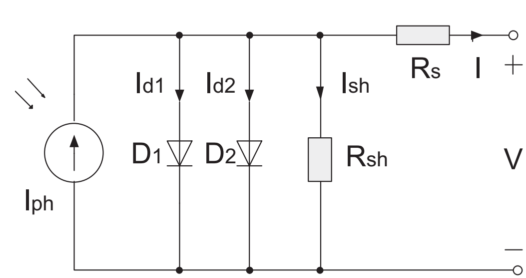

Fig. 2. Equivalent circuit of the double diode model.

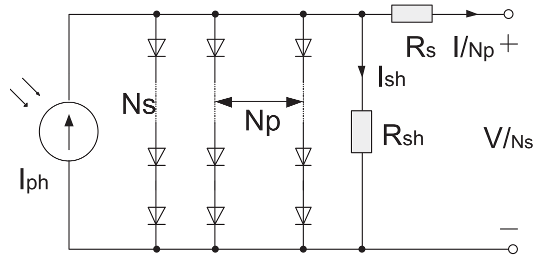

Fig. 3. Equivalent circuit of the PV module.

used in TLBO to find the optimal solution. In the teacher phase, the teacher tries to make all learners learn from her/him to improve $\mathbf{x}_{mean}$. Nevertheless, the improvement of each learner depends on their own learning ability to some extent [39]. Additionally, in the learner phase, a learner $\mathbf{x}_i$ just randomly selects another learner $\mathbf{x}_j$ to exchange information, which may result in limited learning ability and poor global search ability [36]. In order to improve the performance of TLBO, we propose an improved TLBO (ITLBO) algorithm in the subsequent subsections.

4.1. Improved teacher phase

In the teacher phase of the original TLBO, all learners will be guided by the teacher $\mathbf{x}_{\text{teacher}}$ and $\mathbf{x}_{\text{mean}}$ as shown in Eq. (11). In fact, in a class, different learners have different learning levels. Thus, different teaching strategies should be used for different learners to obtain higher scores. Based on this consideration, we divide the learners of a class into two groups. If $f(\mathbf{x}_i) < f(\mathbf{x}_{\text{mean}})$, the learners have better learning levels. Otherwise, the learners have worse learning levels. For the worse learners, the original teaching strategy shown in Eq. (11) is used. However, for the better learners, we propose a new teaching strategy, where the better learners are guided by the teacher $\mathbf{x}_{\text{teacher}}$ and themselves $\mathbf{x}_i$. In addition, in order to avoid trapping into the local optima, two different learners randomly selected are also used to guide the better learners. The improved teacher process is given as:

$$\mathbf{x}_{i,new} = \begin{cases} \mathbf{x}_i + rand\cdot(\mathbf{x}_{\text{teacher}} - \mathbf{x}_i) + rand\cdot(\mathbf{x}_{r_1} - \mathbf{x}_{r_2}), & \text{iff}\,(\mathbf{x}_i) < f(\mathbf{x}_{\text{mean}}) \\ \mathbf{x}_i + rand\cdot(\mathbf{x}_{\text{teacher}} - T_F\cdot\mathbf{x}_{\text{mean}}), & \text{otherwise} \end{cases}, \tag{13}$$

where r_1, r_2 are random integers in $\{1, Np\}$, and $r_1 \neq r_2 \neq i$.

4.2. Improved learner phase

As previously explained, selecting only one learner to exchange information in the learner phase may suffer from the poor global search ability and the limited learning ability. To overcome these drawbacks, a new learning strategy is proposed as follows:

$$\mathbf{x}_{i,new} = \begin{cases} \mathbf{x}_i + rand\cdot(\mathbf{x}_j - \mathbf{x}_k), & \text{iff}\,(\mathbf{x}_i) < f(\mathbf{x}_{\text{mean}}) \\ \mathbf{x}_i + rand\cdot(\mathbf{x}_{r_3} - \mathbf{x}_{r_4}) + rand\cdot(\mathbf{x}_{r_5} - \mathbf{x}_{r_6}), & \text{otherwise} \end{cases}, \tag{14}$$

where j, k, r_3, r_4, r_5, r_6 are random integers in $\{1, Np\}$, and $j \neq k \neq i$, $r_3 \neq r_4 \neq r_5 \neq r_6 \neq i$. The better learners (i.e., $f(\mathbf{x}_i) < f(\mathbf{x}_{\text{mean}})$) learn from the other two learners $\mathbf{x}_j$ and $\mathbf{x}_k$, satisfying $f(\mathbf{x}_j) < f(\mathbf{x}_k)$. This is to ensure that $\mathbf{x}_i$ can pursue a better search direction, and thus it can improve learning ability.

The worse learners learn from the experience of four distinct learners. This learning strategy improves global search ability and enhances the diversity of the population.

Different from the original learner phase, in ITLBO, the learning strategy can make a good tradeoff between exploitation and exploration. The reason is that the better learners make full use of their exploitation ability, while the worse learners improve population diversity and exploration ability.

Algorithm 1. The pseudo-code of ITLBO

Input: Control parameters: Np, Max_NFE
Output: The optimal solution
Set $NFE = 0$;
Initialize the population randomly ;
while $NFE < Max\_NFE$ **do**
  Calculate $\mathbf{x}_{\text{mean}}$ and evaluate its objective function value;
  $NFE = NFE + 1$;
  // Teacher Phase;
  for $i = 1$ *to* Np **do**
    Calculate $\mathbf{x}_{i,new}$ with Equation (13);
    if $f(\mathbf{x}_{i,new}) < f(\mathbf{x}_i)$ **then**
      $\mathbf{x}_i = \mathbf{x}_{i,new}$;
  $NFE = NFE + Np$;
  // Learner Phase;
  for $i = 1$ *to* NP **do**
    Calculate $\mathbf{x}_{i,new}$ with Equation (14);
    if $f(\mathbf{x}_{i,new}) < f(\mathbf{x}_i)$ **then**
      $\mathbf{x}_i = \mathbf{x}_{i,new}$;
  $NFE = NFE + Np$;

4.3. Process of ITLBO

The pseudo-code of ITLBO is shown in Algorithm 1, where *Np* is the population size (i.e., the number of members of a class), *NFE* is the number of objective function evaluation, and *Max_NFE* is the maximal *NFE*. From Algorithm 1, we can see that the proposed ITLBO algorithm is also very simple. It does not increase the complexity of the original TLBO algorithm. In addition, there are no new parameters introduced in ITLBO. Fig. 4 describes the flow chart of the ITLBO, where the improved teacher and learner phase are applied to find the optimal solution.

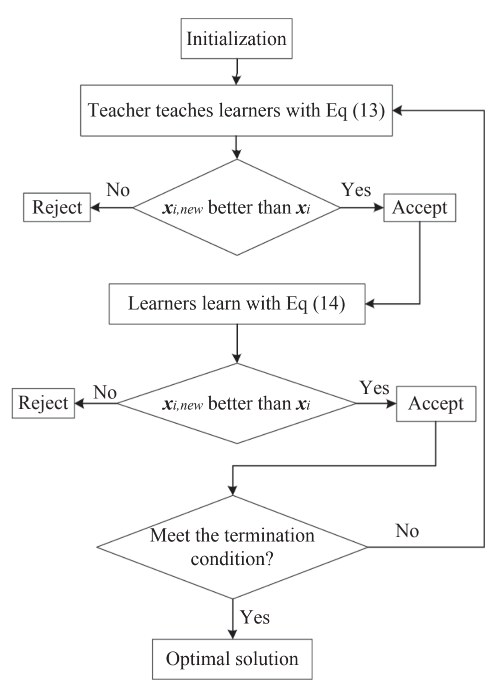

Fig. 4. Flow chart of the ITLBO.

Table 1
The search range of each parameter.

Parameter	single/double diode		Photowatt-PWP-201		STM6-40/36		STP6-120/36	
	LB	UB	LB	UB	LB	UB	LB	UB
I_{ph} (A)	0	1	0	2	0	2	0	8
I_d, I_{d1}, I_{d2} (μA)	0	1	0	50	0	50	0	50
R_s (Ω)	0	0.5	0	2	0	0.36	0	0.36
R_{sh} (Ω)	0	100	0	2000	0	1000	0	1500
a, a_1, a_2	1	2	1	50	1	60	1	50

5. Results and analysis

To verify the performance of ITLBO, the algorithm is applied to extract the parameters of different PV models that contain the single diode model, double diode model, and PV module models.

- For the single and double diode models, the current-voltage data was obtained from [16], which is measured on a 57 mm diameter commercial silicon R.T.C. France solar cell under 1000 W/m^2 at 33 °C.
- For the PV module, three different modules are used: poly-crystalline Photowatt-PWP201, mono-crystalline STM6-40/36, and poly-crystalline STP6-120/36. The Photowatt-PWP201 consists of 36 cells connected in series and is measured under 1000 W/m^2 at 45 °C [16]. The STM6-40/36 and STP6-120/36 both have 36 cells connected in series and are measured at 51 °C and 55 °C, respectively. The current-voltage data of the two modules was obtained from [40,41].

For fair comparison, the search range of each parameter is given in Table 1, which is the same as used in other literature [10,18,32,41].

Additionally, ITLBO was compared with seven well-established algorithms: IJAYA [10], MLBSA [32], TLBO [33], SATLBO [36], LETLBO [34], GOTLBO [35], and TLABC [18]. The parameter settings of the compared algorithms are given in Table 2. The *Max_NFE* was set to 50, 000 for the compared algorithms. All algorithms were implemented in Matlab 2016b and each algorithm executed 30 independent runs. All comparative experiments were executed on a desktop PC with an Intel Core i5-4590 M processor @ 3.30 GHz, 8 GB RAM, under the Windows 7 64-bit OS.

5.1. Results on the single diode model

For the single diode model, ITLBO was compared with IJAYA [10], MLBSA [32], TLBO [33], SATLBO [36], LETLBO [34], GOTLBO [35], and TLABC [18] with respect to the RMSE values. The extracted parameters and the corresponding RSME values are reported in Table 3, where the best RMSE values have been highlighted in **boldface**. Note that, in Table 3, the best results are reported for each algorithm among different runs. The statistical results are given in Section 5.4.

From Table 3, it can be observed that ITLBO, TLABC, SATLBO, and MLBSA obtained the best RMSE value (9.8602E−04). LETLBO and IJAYA provided the second best result (9.8603E−04), followed by GOTLBO and TLBO. Although the second best RMSE value is close to the best RMSE value, it is meaningful for any reduction in the objective function. Because accurate parameter values were unavailable, the smaller the objective function value, the more accurate the extracted parameters.

In addition, the extracted parameters of ITLBO were used to plot the *I-V* and *P-V* curves, which are shown in Fig. 5. It is clear that the measured and simulated data obtained by ITLBO are highly consistent for both the *I-V* and *P-V* curves. Note that some data points are negative in Fig. 5, where the negative sign indicates that the current or voltage direction is opposite to the specified direction, more specifically, a reverse current or voltage.

Table 2
Parameter settings of different algorithms.

Algorithm	Parameter setting
IJAYA [10]	$Np = 20$
MLBSA [32]	$Np = 50$
TLBO [33]	$Np = 50$
SATLBO [36]	$Np = 40$
LETLBO [34]	$Np = 50$
GOTLBO [35]	$Np = 50$, jumping rate $J_r = 0.3$
TLABC [18]	$Np = 50$, $limit = 200$, scale factor $F = rand(0, 1)$
ITLBO	$Np = 50$

Table 3
Comparison of ITLBO with other algorithms on the single diode model.

Algorithm	I_{ph} (A)	I_d (μA)	R_s (Ω)	R_{sh} (Ω)	a	RMSE
IJAYA	0.7608	0.3281	0.0364	53.7595	1.4811	9.8603E−04
MLBSA	0.7608	0.3230	0.0364	53.7185	1.4812	**9.8602E−04**
TLBO	0.7607	0.3294	0.0363	54.3015	1.4831	9.8733E−04
SATLBO	0.7608	0.3232	0.0364	53.7256	1.4812	**9.8602E−04**
LETLBO	0.7608	0.3222	0.0364	53.6655	1.4809	9.8603E−04
GOTLBO	0.7608	0.3226	0.0364	53.3388	1.4811	9.8658E−04
TLABC	0.7608	0.3230	0.0364	53.7164	1.4812	**9.8602E−04**
ITLBO	0.7608	0.3230	0.0364	53.7185	1.4812	**9.8602E−04**

5.2. Results on the double diode model

For the double diode model, there are seven unknown parameters that increase the difficulty of the parameter extraction using the optimization algorithm. ITLBO is also compared with the seven algorithms mentioned in Table 2. The extracted parameters and the RMSE values of the compared algorithms are shown in Table 4. From the RMSE values, we can observe that the proposed ITLBO algorithm provided the best result among the eight algorithms.

To validate the accuracy of the extracted ITLBO parameters, they were used to reconstruct the *I-V* and *P-V* characteristics shown as Fig. 6. Further, the IAEC and IAEP[1] are reported in Table 5. From Fig. 6 and Table 5, it is easy to see that the measured and simulated data have a good coincidence, and the maximal IAEC and IAEP are less than 2.0E−03.

5.3. Results on the PV modules

In Section 5.1 and 5.2, the single and double diode models were used to evaluate the performance of ITLBO. In this subsection, three widely used PV modules (i.e., Photowatt-PWP201, STM6-40/36, and

[1] Absolute error between measured and simulated power is calculated as $|P_{measured} - P_{simulated}|$.

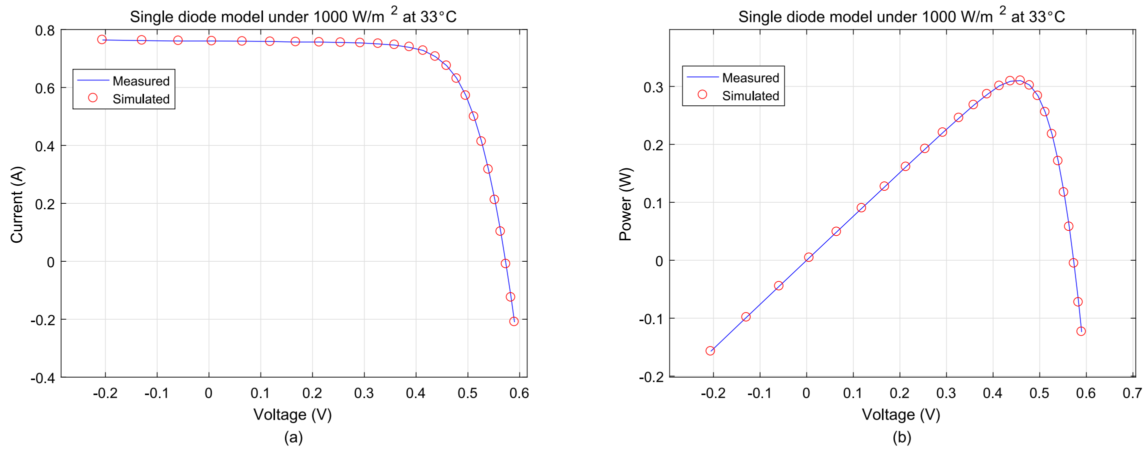

Fig. 5. Comparison between the measured and simulated data obtained by ITLBO for the single diode model: (a) *I-V* characteristic, (b) *P-V* characteristic.

Table 4
Comparison of ITLBO with other algorithms on the double diode model.

Algorithm	I_{ph} (A)	I_{d1} (μA)	R_s (Ω)	R_{sh} (Ω)	a_1	I_{d2} (μA)	a_2	RMSE
IJAYA	0.7601	0.0050	0.0376	77.8519	1.2186	0.7509	1.6247	9.8293E−04
MLBSA	0.7608	0.2273	0.0367	55.4612	1.4515	0.7384	2.0000	9.8249E−04
TLBO	0.7610	0.2947	0.0366	53.1210	1.4730	0.1373	1.9938	1.0069E−03
SATLBO	0.7608	0.2509	0.0366	55.1170	1.4598	0.5454	1.9994	9.8280E−04
LETLBO	0.7608	0.1137	0.0364	54.0688	1.9284	0.3032	1.4760	9.8571E−04
GOTLBO	0.7608	0.2717	0.0366	53.6187	1.4668	0.2595	1.9161	9.9544E−04
TLABC	0.7608	0.4239	0.0367	54.6680	1.9075	0.2401	1.4567	9.8415E−04
ITLBO	0.7608	0.2260	0.0367	55.4854	1.4510	0.7493	2.0000	**9.8248E−04**

The boldface number means the best result obtained among the compared algorithms.

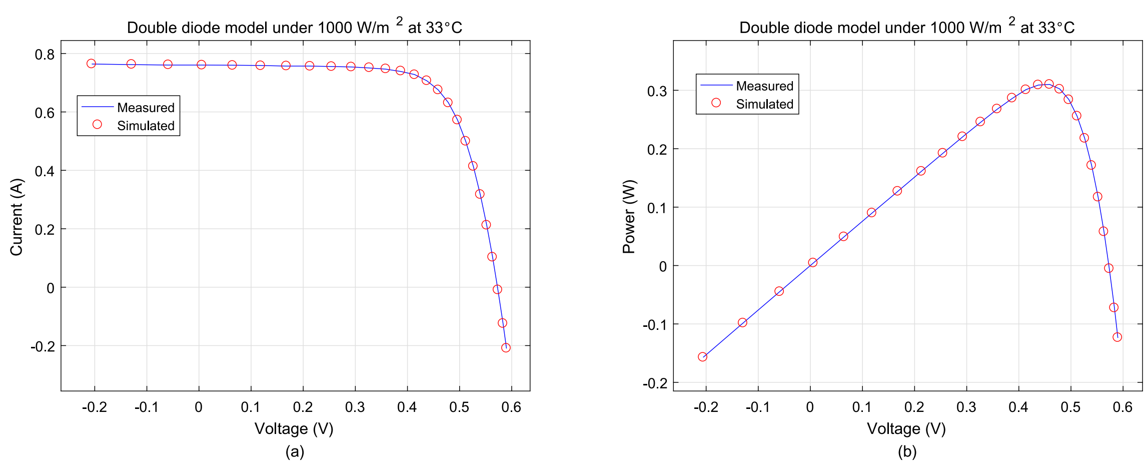

Fig. 6. Comparison between the measured and simulated data obtained by ITLBO for the double diode model: (a) *I-V* characteristic, (b) *P-V* characteristic.

STP6-120/36) are selected to further verify the effectiveness of our approach. The results for the three PV modules are respectively reported in Tables 6–8. From the results, we can see that the eight algorithms yielded very similar RMSE values for the three PV modules. Therefore, we can say that proposed ITLBO algorithm is effective and consistently provides highly competitive RMSE values compared with other methods.

Additionally, in order to indicate the accuracy of the extracted ITLBO parameters, the results of IAEC and IAEP between the measured and simulated data are tabulated in Tables 9–11. The characteristics of *I-V* and *P-V* are also respectively shown in Figs. 7–9 for Photowatt-PWP201, STM6-40/36, and STP6-120/36. According to the results, it can be seen that the simulated data of ITLBO agree well with the measured data for the three modules.

5.4. Statistical results of the compared algorithms

In the above subsections, the best results of each algorithm over different runs are reported. Since the eight algorithms are stochastic methods, it is very important to evaluate the overall performance of these algorithms with respect to the statistical results. Based on this consideration, the best, worst, mean, standard deviation of RMSE values, and the total run time for the eight algorithms are shown in Table 12.

From Table 12, it can be observed that:

- For the best RMSE values, only ITLBO obtains the best RMSE values for all models. MLBSA, SATLBO, GOTLBO, and TLABC can provide the best RMSE values for four models, except the double diode model. LETLBO gets the best RMSE values for the three PV modules.

Table 5
Simulated results of ITLBO for the double diode model.

Item	V (V)	$I_{measured}$ (A)	$I_{simulated}$ (A)	IAEC (A)	$P_{measured}$ (W)	$P_{simulated}$ (W)	IAEP (W)
1	−0.2057	0.764	0.76398342	**0.00001658**	−0.1571548	−0.15715139	0.00000341
2	−0.1291	0.762	0.76260370	0.00060370	−0.0983742	−0.09845214	0.00007794
3	−0.0588	0.7605	0.76133714	0.00083714	−0.0447174	−0.04476662	0.00004922
4	0.0057	0.7605	0.76017400	0.00032600	0.00433485	0.00433299	**0.00000186**
5	0.0646	0.76	0.75910827	0.00089173	0.049096	0.04903839	0.00005761
6	0.1185	0.759	0.75812202	0.00087798	0.0899415	0.08983746	0.00010404
7	0.1678	0.757	0.75718848	0.00018848	0.1270246	0.12705623	0.00003163
8	0.2132	0.757	0.75624423	0.00075577	0.1613924	0.16123127	0.00016113
9	0.2545	0.7555	0.75517766	0.00032234	0.19227475	0.19219271	0.00008204
10	0.2924	0.754	0.75372286	0.00027714	0.2204696	0.22038856	0.00008104
11	0.3269	0.7505	0.75139611	0.00089611	0.24533845	0.24563139	0.00029294
12	0.3585	0.7465	0.74729616	0.00079616	0.26762025	0.26790568	0.00028543
13	0.3873	0.7385	0.73999138	<u>0.00149138</u>	0.28602105	0.28659866	0.00057761
14	0.4137	0.728	0.72726488	0.00073512	0.3011736	0.30086948	0.00030412
15	0.4373	0.7065	0.70683581	0.00033581	0.30895245	0.30909930	0.00014685
16	0.459	0.6755	0.67523011	0.00026989	0.3100545	0.30993062	0.00012388
17	0.4784	0.632	0.63088763	0.00111237	0.3023488	0.30181664	0.00053216
18	0.496	0.573	0.57214027	0.00085973	0.284208	0.28378157	0.00042643
19	0.5119	0.499	0.49957059	0.00057059	0.2554381	0.25573018	0.00029208
20	0.5265	0.413	0.41355632	0.00055632	0.2174445	0.21773740	0.00029290
21	0.5398	0.3165	0.31724207	0.00074207	0.1708467	0.17124727	0.00040057
22	0.5521	0.212	0.21208148	0.00008148	0.1170452	0.11709018	0.00004498
23	0.5633	0.1035	0.10267156	0.00082844	0.05830155	0.05783489	0.00046666
24	0.5736	−0.01	−0.00929723	0.00070277	−0.005736	−0.00533289	0.00040311
25	0.5833	−0.123	−0.12439038	0.00139038	−0.0717459	−0.07255691	<u>0.00081101</u>
26	0.59	−0.21	−0.20914692	0.00085308	−0.1239	−0.12339668	0.00050332
∑	–	–	–	0.01731854	–	–	0.00655394

The boldface number means the best result obtained among the compared algorithms. The underline number indicate the worst value among the results.

Table 6
Comparison of ITLBO with other algorithms on the Photowatt-PWP201 module.

Algorithm	I_{ph} (A)	I_d (μA)	R_s (Ω)	R_{sh} (Ω)	a	RMSE
IJAYA	1.0302	3.4703	1.2016	977.3752	48.6298	**2.4251E−03**
MLBSA	1.0305	3.4823	1.2013	981.9823	48.6428	**2.4251E−03**
TLBO	1.0305	3.4872	1.2011	984.8760	48.6482	**2.4251E−03**
SATLBO	1.0305	3.4827	1.2013	982.4038	48.6433	**2.4251E−03**
LETLBO	1.0305	3.4709	1.2017	981.0293	48.6302	**2.4251E−03**
GOTLBO	1.0305	3.4991	1.2008	989.6889	48.6611	**2.4251E−03**
TLABC	1.0306	3.4715	1.2017	972.9357	48.6313	**2.4251E−03**
ITLBO	1.0305	3.4823	1.2013	981.9823	48.6428	**2.4251E−03**

The boldface number means the best result obtained among the compared algorithms.

Table 7
Comparison of ITLBO with other algorithms on the STM6-40/36 module.

Algorithm	I_{ph} (A)	I_d (μA)	R_s (Ω)	R_{sh} (Ω)	a	RMSE
IJAYA	1.6637	1.8353	0.0040	15.9449	1.5263	1.7548E−03
MLBSA	1.6639	1.7387	0.0043	15.9283	1.5203	**1.7298E−03**
TLBO	1.6638	1.7307	0.0043	15.9955	1.5198	1.7305E−03
SATLBO	1.6639	1.7387	0.0043	15.9283	1.5203	**1.7298E−03**
LETLBO	1.6639	1.7387	0.0043	15.9283	1.5203	**1.7298E−03**
GOTLBO	1.6639	1.7387	0.0043	15.9283	1.5203	**1.7298E−03**
TLABC	1.6639	1.7387	0.0043	15.9283	1.5203	**1.7298E−03**
ITLBO	1.6639	1.7387	0.0043	15.9283	1.5203	**1.7298E−03**

The boldface number means the best result obtained among the compared algorithms.

IJAYA and TLBO are worse than the other compared algorithms.

- With regard to the worst RMSE values, ITLBO still obtains the minimal worst values for four models, except the double diode model.
- In terms of the mean RMSE values, it is clear that ITLBO yields the best performance out of all the other algorithms for all models.
- Considering the standard deviation of the RMSE values, it is capable of reflecting the robustness of the algorithms. It is easy to see that ITLBO gets the smallest standard deviation among the compared algorithms for all PV models.
- In regards to the computational time, GOTLBO, TLBO, LETLBO, SATLBO, and ITLBO take less time than the rest of the algorithms for all models. Additionally, although ITLBO does not spend the least amount of time, it achieves the best results with relatively little time.

Table 8
Comparison of ITLBO with other algorithms on the STP6-120/36 module.

Algorithm	I_{ph} (A)	I_d (μA)	R_s (Ω)	R_{sh} (Ω)	a	RMSE
IJAYA	7.4672	2.2536	0.0046	27.5925	1.2571	1.6731E−02
MLBSA	7.4725	2.3350	0.0046	22.2199	1.2601	**1.6601E−02**
TLBO	7.4782	1.9194	0.0047	13.2688	1.2440	1.6892E−02
SATLBO	7.4725	2.3350	0.0046	22.2199	1.2601	**1.6601E−02**
LETLBO	7.4725	2.3350	0.0046	22.2199	1.2601	**1.6601E−02**
GOTLBO	7.4725	2.3350	0.0046	22.2199	1.2601	**1.6601E−02**
TLABC	7.4725	2.3349	0.0046	22.2117	1.2601	**1.6601E−02**
ITLBO	7.4725	2.3350	0.0046	22.2199	1.2601	**1.6601E−02**

The boldface number means the best result obtained among the compared algorithms.

The Wilcoxon and the Friedman Aligned tests [42], based on the mean RMSE values, were used to clarify the statistical differences of different parameter extraction methods. Note that the tool of the statistical tests used in this paper is the KEEL software [43]. The result of the Wilcoxon test is reported in Table 13, where we can see that the difference of all compared methods is not distinct. However, the proposed ITLBO achieves the best average ranking in the Friedman Aligned test shown in Table 14.

Based on the statistical results, we can conclude that ITLBO is able to achieve superior performance compared with other related algorithms. It is an effective and reliable method for parameter extraction of PV models.

Table 9
Simulated results of ITLBO for Photowatt-PWP201 module.

Item	V (V)	$I_{measured}$ (A)	$I_{simulated}$ (A)	IAEC (A)	$P_{measured}$ (W)	$P_{simulated}$ (W)	IAEP (W)
1	0.1248	1.0315	1.02912209	0.00237791	0.1287312	0.12843444	**0.00029676**
2	1.8093	1.03	1.02738435	0.00261565	1.863579	1.85884651	0.00473249
3	3.3511	1.026	1.02574214	0.00025786	3.4382286	3.43736448	0.00086412
4	4.7622	1.022	1.02410399	0.00210399	4.8669684	4.87698803	0.01001963
5	6.0538	1.018	1.02228341	0.00428341	6.1627684	6.18869931	0.02593091
6	7.2364	1.0155	1.01991740	<u>0.00441740</u>	7.3485642	7.38053027	0.03196607
7	8.3189	1.014	1.01635081	0.00235081	8.4353646	8.45492077	0.01955617
8	9.3097	1.01	1.01049143	0.00049143	9.402797	9.40737207	0.00457507
9	10.2163	1.0035	1.00067876	0.00282124	10.25205705	10.22323442	0.02882263
10	11.0449	0.988	0.98465335	0.00334665	10.9123612	10.87539777	0.03696343
11	11.8018	0.963	0.95969741	0.00330259	11.3651334	11.32615688	0.03897652
12	12.4929	0.9255	0.92304875	0.00245125	11.56217895	11.53155579	0.03062316
13	13.1231	0.8725	0.87258816	0.00008816	11.44990475	11.45106168	0.00115693
14	13.6983	0.8075	0.80731012	0.00018988	11.06137725	11.05877623	0.00260102
15	14.2221	0.7265	0.72795782	0.00145782	10.33235565	10.35308888	0.02073323
16	14.6995	0.6345	0.63646618	0.00196618	9.32683275	9.35573459	0.02890184
17	15.1346	0.5345	0.53569607	0.00119607	8.0894437	8.10754576	0.01810206
18	15.5311	0.4275	0.42881615	0.00131615	6.63954525	6.65998648	0.02044123
19	15.8929	0.3185	0.31866866	0.00016866	5.06188865	5.06456910	0.00268045
20	16.2229	0.2085	0.20785711	0.00064289	3.38247465	3.37204517	0.01042948
21	16.5241	0.101	0.09835421	0.00264579	1.6689341	1.62521481	<u>0.04371929</u>
22	16.7987	−0.008	−0.00816934	0.00016934	−0.1343896	−0.13723426	0.00284466
23	17.0499	−0.111	−0.11096846	**0.00003154**	−1.8925389	−1.89200116	0.00053774
24	17.2793	−0.209	−0.20911762	0.00011762	−3.6113737	−3.61340604	0.00203234
25	17.4885	−0.303	−0.30202238	0.00097762	−5.2990155	−5.28191833	0.01709717
∑	–	–	–	0.04178790	–	–	0.40460441

The boldface number means the best result obtained among the compared algorithms. The underline number indicate the worst value among the results.

Table 10
Simulated results of ITLBO for STM6-40/36 module.

Item	V (V)	$I_{measured}$ (A)	$I_{simulated}$ (A)	IAEC (A)	$P_{measured}$ (W)	$P_{simulated}$ (W)	IAEP (W)
1	0	1.663	1.66345813	0.00045813	0	0	**0**
2	0.118	1.663	1.66325224	0.00025224	0.196234	0.19626376	0.00002976
3	2.237	1.661	1.65955120	0.00144880	3.715657	3.71241603	0.00324097
4	5.434	1.653	1.65391444	0.00091444	8.982402	8.98737109	0.00496909
5	7.26	1.65	1.65056575	0.00056575	11.979	11.98310732	0.00410732
6	9.68	1.645	1.64543044	0.00043044	15.9236	15.92776663	0.00416663
7	11.59	1.64	1.63923405	0.00076595	19.0076	18.99872264	0.00887736
8	12.6	1.636	1.63371510	0.00228490	20.6136	20.58481021	0.02878979
9	13.37	1.629	1.62728848	0.00171152	21.77973	21.75684699	0.02288301
10	14.09	1.619	1.61831518	0.00068482	22.81171	22.80206083	0.00964917
11	14.88	1.597	1.60306738	<u>0.00606738</u>	23.76336	23.85364261	<u>0.09028261</u>
12	15.59	1.581	1.58158500	0.00058500	24.64779	24.65691009	0.00912009
13	16.4	1.542	1.54232745	0.00032745	25.2888	25.29417018	0.00537018
14	16.71	1.524	1.52122497	0.00277503	25.46604	25.41966933	0.04637067
15	16.98	1.5	1.49920572	0.00079428	25.47	25.45651315	0.01348685
16	17.13	1.485	1.48527115	0.00027115	25.43805	25.44269473	0.00464473
17	17.32	1.465	1.46564321	0.00064321	25.3738	25.38494047	0.01114047
18	17.91	1.388	1.38759934	0.00040066	24.85908	24.85190419	0.00717581
19	19.08	1.118	1.11837210	0.00037210	21.33144	21.33853973	0.00709973
20	21.02	0	−0.00002131	**0.00002131**	0	−0.00044803	0.00044803
∑	–	–	–	0.02177457	–	–	0.28185229

The boldface number means the best result obtained among the compared algorithms. The underline number indicate the worst value among the results.

5.5. Influence of different components in ITLBO

In ITLBO, two improved components are presented to enhance the performance of the original TLBO method: (i) improved teacher phase, and (ii) improved learner phase. In this subsection, the influence of the two components is discussed. Two ITLBO variants are developed, i.e., ITLBO-1 only with the improved teacher phase, and ITLBO-2 only with the improved learner phase. The statistical RMSE results of TLBO, ITLBO-1, ITLBO-2, and ITLBO are compared and reported in Table 15. Additionally, the results of the Wilcoxon and Friedman Aligned test are presented in Tables 16 and 17.

From Tables 15–17, it can be observed that:

- The proposed ITLBO method gets the best results for all PV models compared with TLBO, ITLBO-1, and ITLBO-2, which means that the combination of the two improvements is essential to improve the performance of the original TLBO method.
- For the best RMSE values, ITLBO-1 provides better results than ITLBO-2 for all models, which indicates that the improved teacher phase is very beneficial to finding the best solution.
- With respect to the worst, mean, and standard deviation of RMSE values, although the differences between the results of ITLBO-1 and ITLBO-2 are small for the first two models, it is clear that ITLBO-2 obtains better results than ITLBO-1 for the other three models. The reason is that the improved learner phase is able to enhance the

Table 11
Simulated results of ITLBO for STP6-120/36 module.

Item	V (V)	$I_{measured}$ (A)	$I_{simulated}$ (A)	IAEC (A)	$P_{measured}$ (W)	$P_{simulated}$ (W)	IAEP (W)
1	0	7.48	7.47098129	0.00901871	0	0	**0**
2	9.06	7.45	7.45253755	0.00253755	67.497	67.51999023	0.02299023
3	9.74	7.44	7.44671497	0.00671497	72.4656	72.53100378	0.06540378
4	10.32	7.42	7.43909223	0.01909223	76.5744	76.77143185	0.19703185
5	11.17	7.41	7.42026500	0.01026500	82.7697	82.88436008	0.11466008
6	11.81	7.38	7.39587315	0.01587315	87.1578	87.34526186	0.18746186
7	12.36	7.37	7.36326479	0.00673521	91.0932	91.00995282	0.08324718
8	12.74	7.34	7.33148307	0.00851693	93.5116	93.40309430	0.10850570
9	13.16	7.29	7.28412985	0.00587015	95.9364	95.85914884	0.07725116
10	13.59	7.23	7.21776060	0.01223940	98.2557	98.08936657	0.16633343
11	14.17	7.1	7.08813731	0.01186269	100.607	100.43890575	0.16809425
12	14.58	6.97	6.95844905	0.01155095	101.6226	101.45418714	0.16841286
13	14.93	6.83	6.81486011	0.01513989	101.9719	101.74586142	0.22603858
14	15.39	6.58	6.56792937	0.01207063	101.2662	101.08043298	0.18576702
15	15.71	6.36	6.34872743	0.01127257	99.9156	99.73850787	0.17709213
16	16.08	6	6.03749239	0.03749239	96.48	97.08287761	0.60287761
17	16.34	5.75	5.77681380	0.02681380	93.955	94.39313755	0.43813755
18	16.76	5.27	5.27376516	0.00376516	88.3252	88.38830404	0.06310404
19	16.9	5.07	5.08193389	0.01193389	85.683	85.88468272	0.20168272
20	17.1	4.79	4.78583302	0.00416698	81.909	81.83774459	0.07125541
21	17.25	4.56	4.54628941	0.01371059	78.66	78.42349232	0.23650768
22	17.41	4.29	4.27392907	0.01607093	74.6889	74.40910509	0.27979491
23	17.65	3.83	3.83228232	0.00228232	67.5995	67.63978290	0.04028290
24	19.21	0	0.00116434	**0.00116434**	0	0.02236700	0.02236700
∑	–	–	–	0.27616043	–	–	3.90429992

The boldface number means the best result obtained among the compared algorithms. The underline number indicate the worst value among the results.

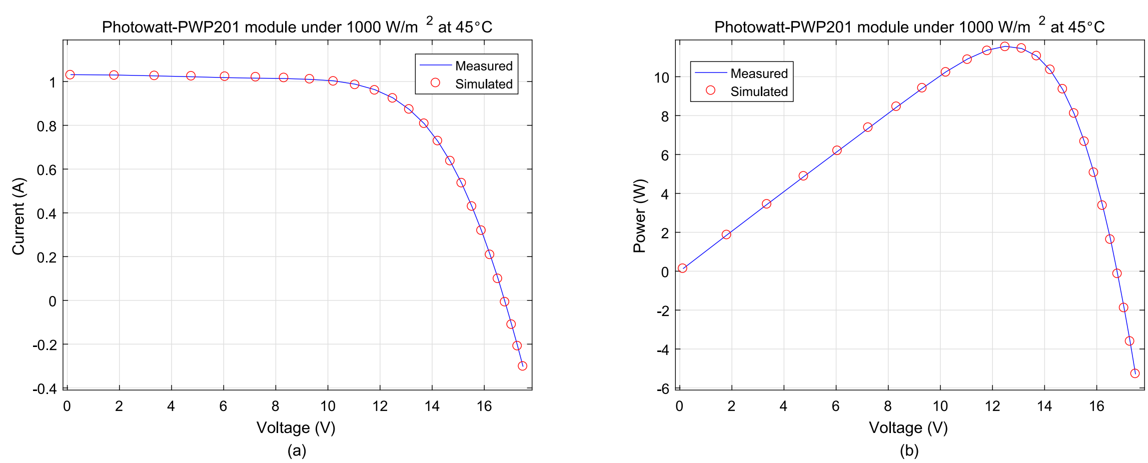

Fig. 7. Comparison between the measured and simulated data obtained by ITLBO for Photowatt-PWP201 module: (a) *I-V* characteristic, (b) *P-V* characteristic.

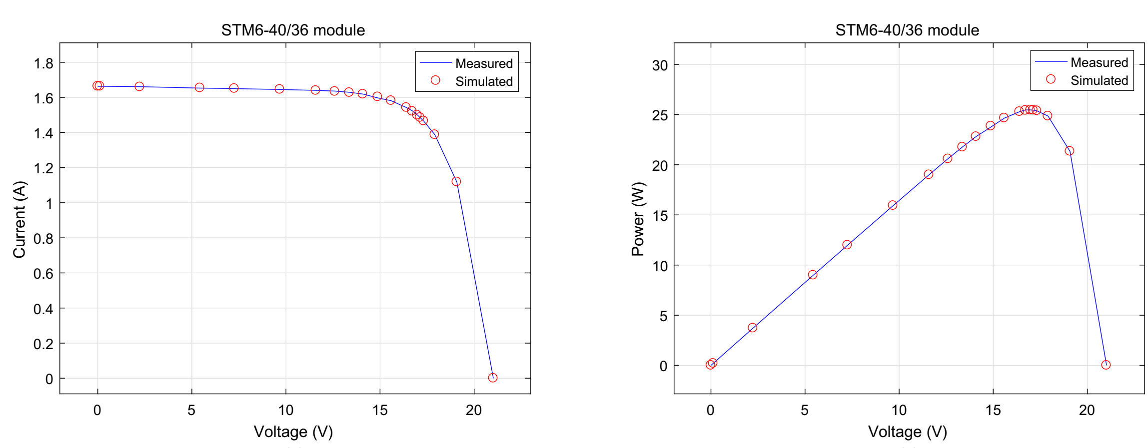

Fig. 8. Comparison between the measured and simulated data obtained by ITLBO for STM6-40/36 module: (a) *I-V* characteristic, (b) *P-V* characteristic.

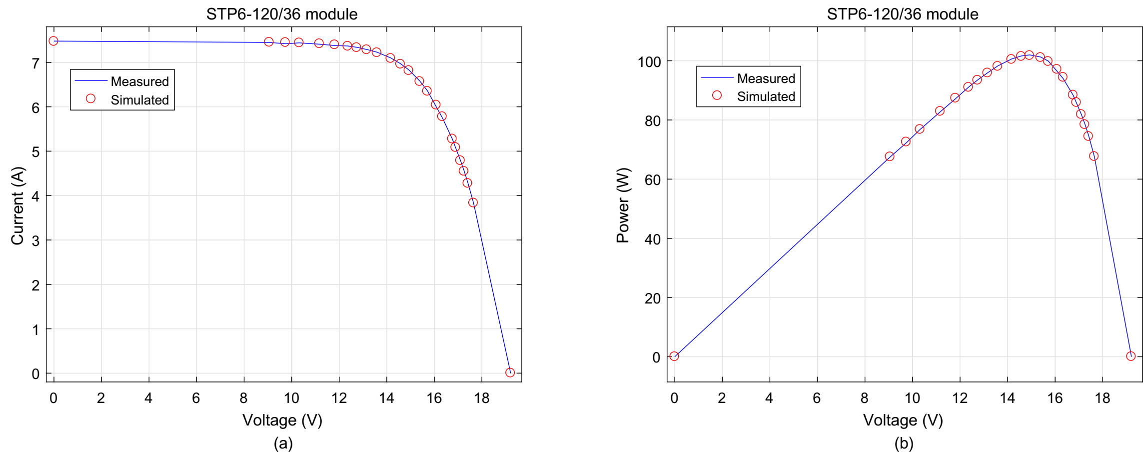

Fig. 9. Comparison between the measured and simulated data obtained by ITLBO for STP6-120/36 module: (a) *I-V* characteristic, (b) *P-V* characteristic.

Table 12
Statistical results of the compared algorithms for different PV models.

Model	Algorithm	RMSE				Time (s)
		Best	Worst	Mean	Std	–
Single diode model	IJAYA	9.8603E−04	1.0622E−03	9.9204E−04	1.40E−05	397.83
	MLBSA	**9.8602E−04**	**9.8602E−04**	**9.8602E−04**	9.15E−12	397.39
	TLBO	9.8722E−04	1.2358E−03	1.0476E−03	6.59E−05	4.15
	SATLBO	**9.8602E−04**	9.9494E−04	9.8780E−04	2.30E−06	4.95
	LETLBO	9.8616E−04	1.0731E−03	1.0118E−03	2.61E−05	4.72
	GOTLBO	**9.8602E−04**	1.4388E−03	1.0289E−03	1.01E−04	**3.94**
	TLABC	**9.8602E−04**	1.0397E−03	9.9852E−04	1.86E−05	27.69
	ITLBO	**9.8602E−04**	**9.8602E−04**	**9.8602E−04**	**2.19E−17**	5.95
Double diode model	IJAYA	9.8293E−04	1.4055E−03	1.0269E−03	9.83E−05	393.60
	MLBSA	9.8249E−04	**9.8798E−04**	9.8518E−04	1.35E−06	401.25
	TLBO	1.0069E−03	1.5206E−03	1.1598E−03	1.56E−04	4.99
	SATLBO	9.8280E−04	1.0470E−03	9.9811E−04	1.95E−05	5.70
	LETLBO	9.8575E−04	1.4119E−03	1.0693E−03	1.20E−04	5.48
	GOTLBO	9.8407E−04	1.4380E−03	1.0453E−03	1.01E−04	**4.50**
	TLABC	9.8415E−04	1.5048E−03	1.0555E−03	1.55E−04	28.01
	ITLBO	**9.8248E−04**	9.8812E−04	**9.8497E−04**	**1.54E−06**	6.60
Photowatt-PWP201	IJAYA	**2.4251E−03**	2.4393E−03	2.4289E−03	3.78E−06	385.56
	MLBSA	**2.4251E−03**	2.4253E−03	**2.4251E−03**	4.34E−08	397.53
	TLBO	**2.4251E−03**	2.5475E−03	2.4383E−03	2.43E−05	4.11
	SATLBO	**2.4251E−03**	2.4291E−03	2.4254E−03	7.41E−07	4.87
	LETLBO	**2.4251E−03**	2.5982E−03	2.4377E−03	3.42E−05	4.68
	GOTLBO	**2.4251E−03**	2.4852E−03	2.4419E−03	1.38E−05	**3.84**
	TLABC	**2.4251E−03**	2.4458E−03	2.4265E−03	4.00E−06	27.69
	ITLBO	**2.4251E−03**	**2.4251E−03**	**2.4251E−03**	**1.27E−17**	5.83
STM6-40/36	IJAYA	1.7548E−03	2.5223E−03	1.9305E−03	1.91E−04	350.14
	MLBSA	**1.7298E−03**	1.7851E−03	1.7382E−03	1.45E−05	366.53
	TLBO	1.7305E−03	2.0593E−02	4.3487E−03	3.45E−03	3.93
	SATLBO	**1.7298E−03**	1.7299E−03	**1.7298E−03**	1.22E−08	4.74
	LETLBO	**1.7298E−03**	1.1358E−01	6.9045E−03	2.03E−02	4.49
	GOTLBO	**1.7298E−03**	1.1244E−02	4.2347E−03	2.68E−03	**3.57**
	TLABC	**1.7298E−03**	6.5053E−03	2.1827E−03	9.22E−04	27.31
	ITLBO	**1.7298E−03**	**1.7298E−03**	**1.7298E−03**	**4.75E−18**	5.55
STP6-120/36	IJAYA	1.6731E−02	1.7304E−02	1.6891E−02	1.12E−04	365.12
	MLBSA	**1.6601E−02**	1.8269E−02	1.6731E−02	3.01E−04	388.09
	TLBO	1.6892E−02	2.1604E−01	3.6690E−02	3.51E−02	4.21
	SATLBO	**1.6601E−02**	**1.6601E−02**	**1.6601E−02**	2.02E−09	4.98
	LETLBO	**1.6601E−02**	1.4131E+00	7.7730E−02	2.55E−01	4.68
	GOTLBO	**1.6601E−02**	1.8099E−01	2.9588E−02	3.05E−02	**3.79**
	TLABC	**1.6601E−02**	2.1497E−02	1.6963E−02	9.47E−04	27.31
	ITLBO	**1.6601E−02**	**1.6601E−02**	**1.6601E−02**	**7.22E−17**	5.79

The boldface number means the best result obtained among the compared algorithms. The underline number indicate the worst value among the results.

Table 13
Results obtained by the Wilcoxon test for algorithm ITLBO.

VS	R^+	R^-	P-value
IJAYA	15.0	0.0	6.25E−2
MLBSA	14.0	1.0	1.25E−1
TLBO	15.0	0.0	6.25E−2
SATLBO	15.0	0.0	6.25E−2
LETLBO	15.0	0.0	6.25E−2
GOTLBO	15.0	0.0	6.25E−2
TLABC	15.0	0.0	6.25E−2

Table 14
Average Rankings of the algorithms (Friedman).

Algorithm	Ranking
ITLBO	**1.2**
IJAYA	4.2
MLBSA	2.2
TLBO	7.4
SATLBO	2.6
LETLBO	7.0
GOTLBO	6.4
TLABC	5.0

The boldface number means the best result obtained among the compared algorithms.

Table 17
Average Rankings of ITLBO and its components (Friedman).

Algorithm	Ranking
ITLBO	**6.6**
TLBO	10
ITLBO-1	14.6
ITLBO-2	10.8

The boldface number means the best result obtained among the compared algorithms.

diversity of the population, and hence improve the robustness of ITLBO.

- The Wilcoxon test result indicates the difference of ITLBO and its components in mean RMSE is not very obvious. However, in terms of comprehensive effects, ITLBO also obtains the best average ranking in the Friedman Aligned test.

Therefore, from this analysis, we can see that removing any improvement cannot get promising results, but combining them together will result in excellent performance for different PV models.

5.6. Discussions

In the previous sections, the superiority of ITLBO has been verified by comparing with seven state-of-the-art methods for parameter extraction of different PV models. Furthermore, the influence of different components in ITLBO has been analyzed. The analysis results show that two improvements are very effective. To further discuss the effectiveness of the ITLBO, we have drawn the convergence curves of ITLBO and TLBO on five PV models as shown in Fig. 10. Although TLBO converges faster than ITLBO in the first four models, ITLBO finds a smaller RMSE value for all models. In other words, ITLBO can jump out of local optimum and search in more feasible area, because the improved teacher phase can help to avoid falling into local optimum and the learner phase effectively balance exploitation and exploration. Meanwhile,

Table 15
Influence of different components in ITLBO for different PV models.

Model	Algorithm	RMSE			
		Best	Worst	Mean	Std
Single diode model	TLBO	9.8722E−04	1.2358E−03	1.0476E−03	6.59E−05
	ITLBO−1	**9.8602E−04**	1.1410E−03	9.9238E−04	2.84E−05
	ITLBO-2	9.8897E−04	1.0968E−03	1.0204E−03	2.79E−05
	ITLBO	**9.8602E−04**	**9.8602E−04**	**9.8602E−04**	**2.19E−17**
Double diode model	TLBO	1.0069E−03	1.5206E−03	1.1598E−03	1.56E−04
	ITLBO-1	9.8365E−04	2.0475E−03	1.1168E−03	2.78E−04
	ITLBO-2	1.0573E−03	2.5044E−03	1.7319E−03	3.34E−04
	ITLBO	**9.8248E−04**	**9.8812E−04**	**9.8497E−04**	**1.54E−06**
Photowatt-PWP201	TLBO	**2.4251E−03**	2.5475E−03	2.4383E−03	2.43E−05
	ITLBO-1	**2.4251E−03**	2.7404E−03	2.4412E−03	6.29E−05
	ITLBO-2	2.4254E−03	2.4555E−03	2.4322E−03	6.98E−06
	ITLBO	**2.4251E−03**	**2.4251E−03**	**2.4251E−03**	**1.27E−17**
STM6-40/36	TLBO	1.7305E−03	2.0593E−02	4.3487E−03	3.45E−03
	ITLBO-1	1.7432E−03	1.0514E−01	1.0653E−02	2.30E−02
	ITLBO-2	3.2797E−03	4.7106E−03	3.8663E−03	4.23E−04
	ITLBO	**1.7298E−03**	**1.7298E−03**	**1.7298E−03**	**4.75E−18**
STP6-120/36	TLBO	1.6892E−02	2.1604E−01	3.6690E−02	3.51E−02
	ITLBO-1	**1.6601E−02**	1.4131E+00	7.2708E−02	2.54E−01
	ITLBO-2	2.3557E−02	3.8255E−02	3.0252E−02	3.94E−03
	ITLBO	**1.6601E−02**	**1.6601E−02**	**1.6601E−02**	**7.22E−17**

The boldface number means the best result obtained among the compared algorithms.

Table 16
The Wilcoxon test for ITLBO and its components.

VS	R^+	R^-	P-value
TLBO	15.0	0.0	6.25E−2
ITLBO-1	15.0	0.0	6.25E−2
ITLBO-2	15.0	0.0	6.25E−2

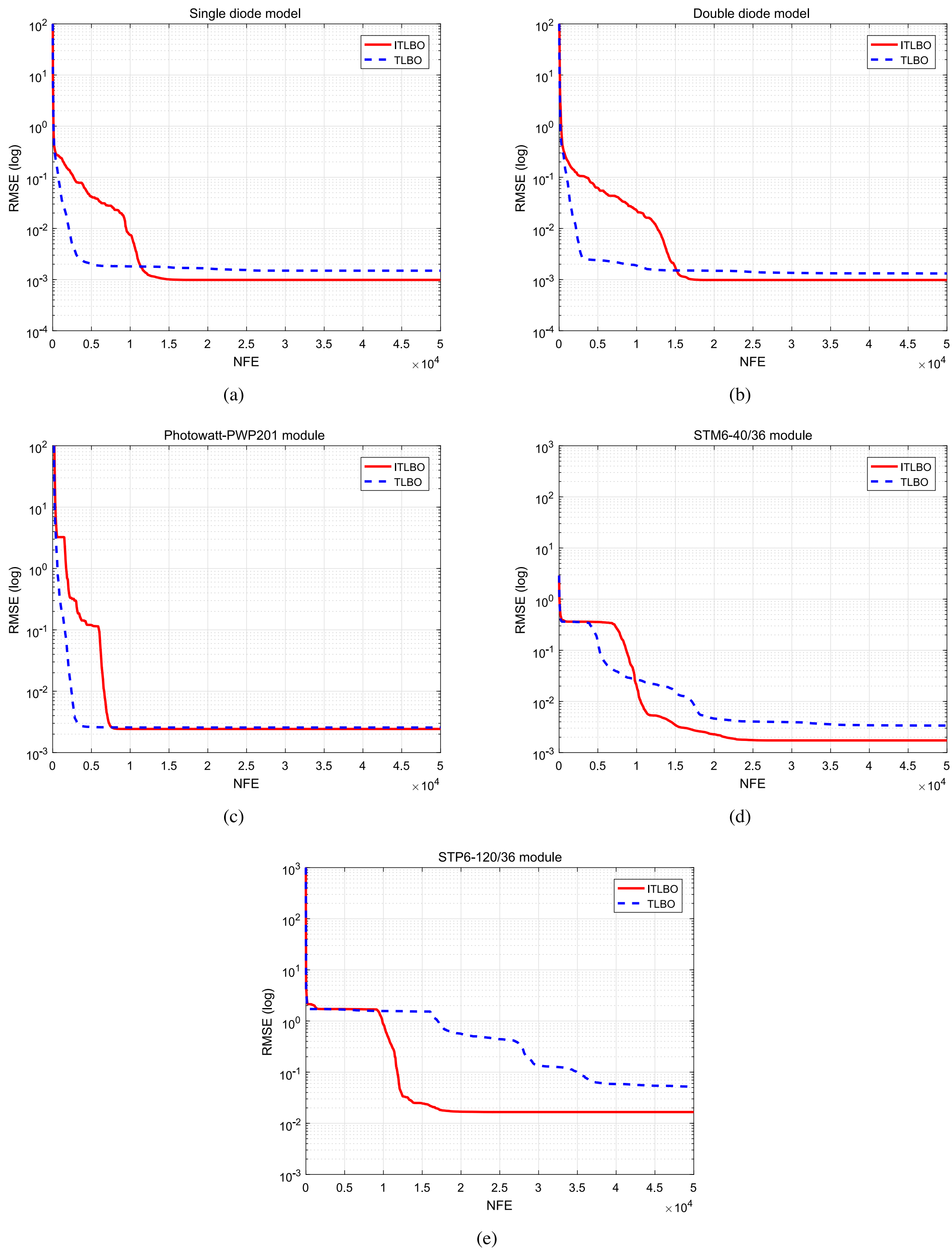

Fig. 10. Convergence curves of ITLBO and TLBO: (a) single diode model (b) double diode model (c) Photowatt-PWP201 module (d) STM6-40/36 module (e) STP6-120/36 module.

since the improved teacher and learner phase increase the number of random individual choices, the improved ITLBO takes more time than TLBO. As far as the overall effect is concerned, the two improvements are very promising for parameter extraction of other complex PV models.

6. Conclusions

In this paper, an improved TLBO, ITLBO, has been proposed to accurately and reliably extract the unknown parameters of different PV models. The innovation of the improved ITLBO lies primarily in the improved teaching and learning strategies, where the teacher uses different teaching ways to guide the learners to improve themselves according to their levels and the exploration and exploitation of the learner phase has been made a good trade-off with a new learning strategy. The performance of ITLBO has been evaluated through the parameter extraction problems of different PV models, namely the single diode model, double diode model, and three PV modules. The results of ITLBO have been compared with other recently proposed well-established algorithms. The results demonstrate that ITLBO is able to provide more accurate and more reliable parameter values. Therefore, it can be an effective and efficient alternative for parameter extraction of other complex PV models.

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