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Parameter estimation of photovoltaic models with memetic adaptive differential evolution

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ABSTRACT

Parameter estimation of photovoltaic (PV) models plays an important role in the simulation, evaluation, and control of PV systems. In the past decade, although many meta-heuristic methods have been devoted to parameter estimation of PV models and achieved satisfactory results, they may suffer from consuming large computational resources to get promising performance. In order to fast and accurately estimate the parameters of PV models, in this paper, a memetic adaptive differential evolution, namely MADE, is developed. The proposed MADE can be featured as: (i) the success-history based adaptive differential evolution is used for the global search; (ii) the Nelder-Mead simplex method is employed for the local search to refine the solution; and (iii) the ranking-based elimination strategy is proposed to maintain the promising solutions in the external archive. To verify the performance of our approach, it is applied to estimate the unknown parameters of different PV models, *i.e.,* the single diode model, the double diode model, and the PV module. Experimental results obtained by MADE are compared with several state-of-the-art methods reported in the literature. Comparison analysis demonstrates that the proposed MADE exhibits remarkable performance on accuracy and reliability. It also consumes less computational resources than other compared methods.

1. Introduction

Owing to energy crisis, environmental pollution, and climate change caused by the use of fossil energy, demand for alternative renewable energy has increased significantly (Muhsen et al., 2015; Ayala et al., 2015; Bait and Si-Ameur, 2017). Among various alternative renewable sources, solar energy has gained widespread attention (Mcwilliams, 2014; Yu et al., 2017c), due to its renewability, safety, and cleanliness. Nowadays, photovoltaic (PV) systems play an important role in electric power systems, because it can directly convert solar energy into electrical energy (Jordehi, 2018). For PV system optimization, the choice of PV model is crucial (Chin et al., 2015; Muhsen et al., 2016). Several PV models have been developed to describe the current-voltage (*I-V*) characteristics in solar cell (Ishaque and Salam, 2011). Among differential PV models, the single diode model and the double diode model are widely used in practice (Alhajri et al., 2012). However, regardless of the used model, the model parameters need to be accurately estimated, because it is important to the simulation, evaluation, and control of PV systems. Therefore, it is essential to develop an effective approach to estimate the unknown parameters of PV models.

There are different methods that have been proposed to solve the parameter estimation problems of PV models, which are mainly divided into three categories: analytical methods, deterministic methods, and meta-heuristic methods. Analytical methods usually estimate parameters by analyzing a series of mathematical equations (Ma et al., 2013). Although it is simple to implement and can get the solution quickly, it needs to make certain assumptions, which may result in the solution not necessarily accurate. For the deterministic methods, such as Newton-Raphson method (Easwarakhanthan et al., 1986), Lambert W-functions (Ortiz-Conde et al., 2006), and iterative method (Tong et al., 2015), their performance is sensitive to the initial guess. Most importantly, the deterministic methods have strict requirements on the objective function, which needs to be continuous, differentiable, and convex. For the meta-heuristic methods, they are derivative-free optimization methods, which overcome the shortcomings of the first two methods. Recently, some meta-heuristic methods have also been used for parameter estimation of PV models, such as genetic algorithm (GA)

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(Jervase et al., 2001; Zagrouba et al., 2010), differential evolution (DE) (Costa et al., 2010; Jiang et al., 2013; Ishaque and Salam, 2011), particle swarm optimization (PSO) (Ye et al., 2009; Khanna et al., 2015), cuckoo search (CS) (Ma et al., 2013), artificial bee colony (ABC) (Oliva et al., 2014), ant lion optimizer (ALO) (Wu et al., 2017), bee pollinator flower pollination algorithm (BPFPA) (Ram et al., 2017), chaotic whale optimization (CWOA) (Oliva et al., 2017), bird mating optimizer (BMO) (Askarzadeh and Rezazadeh, 2013), hybrid flower pollination algorithm (GOFPANM) (Xu and Wang, 2017), generalized oppositional teaching learning based optimization (GOTLBO) (Chen et al., 2016), repaired adaptive differential evolution (Rcr-IJADE) (Gong and Cai, 2013), improved JAYA optimization algorithm (IJAYA) (Yu et al., 2017a), self-adaptive teaching-learning-based optimization (SATLBO) (Yu et al., 2017b), and teaching-learning-based artificial bee colony (TLABC) (Chen et al., 2018). However, although the above meta-heuristic methods yield satisfactory results, they often consume large amounts of computational resources to obtain promising results. For example, IJAYA, SATLBO, and TLABC require 50,000 function evaluations. In fact, using less computational resources to accurately and reliably estimate the parameters of PV models is meaningful, because it can accelerate the performance evaluation, abnormality detection, or field-installed PV modules of solar cells in the manufacturing process.

To reduce the computational resources yet maintain the accuracy, in this paper, we develop a memetic adaptive DE method, referred to as MADE. In MADE, the success-history based adaptive DE (SHADE) presented in Tanabe and Fukunaga (2013) is used for the global search. SHADE is selected due to its promising results obtained in the benchmark problems (Piotrowski and Napiorkowski, 2018). Secondly, the Nelder-Mead simplex method (NMM) is employed for the local search to refine the solution. Thirdly, the ranking-based elimination strategy is proposed to maintain more promising solutions in the external archive. To evaluate the performance of our approach, it is used to estimate the parameters of the single diode model, the double diode model, and three PV modules. MADE is compared with several state-of-the-art methods. Experimental results indicate that MADE is able to provide highly competitive results with less computational resources for different PV models.

The main contributions of this paper are as follows:

- A memetic adaptive differential evolution, which combines SHADE with the Nelder-Mead simplex method, is proposed to estimate parameters of PV models faster and more accurately.
- The ranking-based elimination strategy is proposed to eliminate individuals from external archive rather than randomly eliminating, which can further accelerate the convergence speed.
- The performance of MADE has been extensively investigated on the parameter estimation problems of different PV models.

The remainder of this paper is organized as follows. Section 2 describes different PV models and the objective function. In Section 3, the proposed memetic adaptive DE is elaborated. The results are analyzed for different PV models in Section 4. Finally, Section 5 concludes the paper.

2. PV models and objective function

In the literature, there exist several PV models that have been introduced to describe the *I-V* characteristics of the solar cells and PV modules. In this section, the most commonly used PV models in practice, including the single diode model, the double diode model, and the PV module, are briefly described. Additionally, the objective function used in this work is also defined.

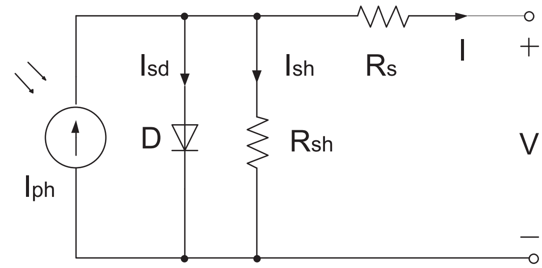

Fig. 1. Equivalent circuit of the single diode model.

2.1. Solar cell models

2.1.1. Single diode model

The equivalent circuit of the single diode model is shown in Fig. 1. In this model, there are a current source in parallel with a diode, a shunt resistor to express the leakage current, and a series resistor to represent the losses of load current. The output current of the solar cell can be formulated as follows:

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

where I represents the cell output current; V is the cell output voltage; I_{ph} is the total current generated by the solar cell; I_{sd} is the diode current; R_s is the series resistance; n 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 $k = 1.3806503 \times 10^{-23}$ J/K is the Boltzmann constant; $q = 1.60217646 \times 10^{-19}$ C is the electron charge, and T represents the temperature of junction in Kelvin.

From Eq. (1), it can be seen that the single diode model has five unknown parameters to be estimated, including I_{ph}, I_{sd}, R_s, R_{sh}, and n.

2.1.2. Double diode model

The equivalent circuit of the double diode model is given in Fig. 2, and the *I-V* characteristics relationship are described as follows:

$$I = I_{ph} - I_{sd1}\left[\exp\left(\frac{V + IR_s}{n_1 V_t}\right) - 1\right] - I_{sd2}\left[\exp\left(\frac{V + IR_s}{n_2 V_t}\right) - 1\right] - \frac{V + IR_s}{R_{sh}} \tag{3}$$

where I_{sd1} and I_{sd2} represent the currents of the first and second diodes, respectively. Both n_1 and n_2 are ideal factors of the diodes.

From the Eq. (3), there are seven unknown parameters that need to be estimated, including I_{ph}, I_{sd1}, I_{sd2}, R_s, R_{sh}, n_1, and n_2.

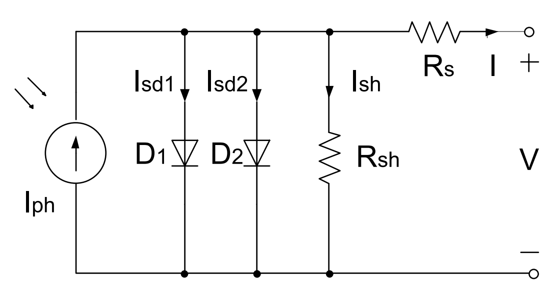

Fig. 2. Equivalent circuit of the double diode model.

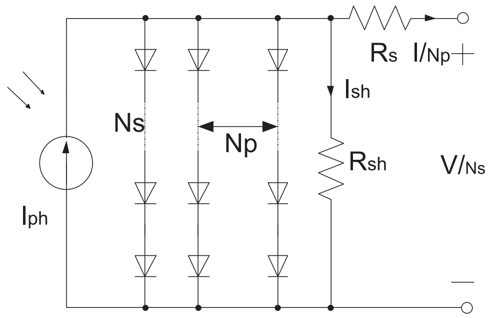

Fig. 3. Equivalent circuit of the PV module.

2.2. PV module

The PV module is a combination of several solar cells connected in series or in parallel (Yu et al., 2017c,a). Its equivalent circuit is described in Fig. 3, and the output current of the PV module is formulated as follows (Gao et al., 2018):

$$I = I_{ph}N_p - I_{sd}N_p\left[\exp\left(\frac{V + IR_sN_s/N_p}{nN_sV_t}\right) - 1\right] - \frac{V + IR_sN_s/N_p}{R_{sh}N_s/N_p} \tag{4}$$

where N_s and N_p denote the number of solar cells connected in series or in parallel, respectively. Since the PV module models used in the experiments are all in series, Eq. (4) can be simplified as follows (Oliva et al., 2017).

$$I = I_{ph} - I_{sd}\left[\exp\left(\frac{V + IR_sN_s}{nN_sV_t}\right) - 1\right] - \frac{V + IR_sN_s}{R_{sh}N_s} \tag{5}$$

Similar to the single diode model, the PV module also has five unknown parameters to be estimated, including I_{ph}, I_{sd}, R_s, R_{sh}, and n.

2.3. Objective function

In this work, the parameter estimation problem of PV models is formulated as an optimization problem. The root mean square error (RMSE) is used as the objective function:

$$\text{minimize} \quad \text{RMSE}(\mathbf{x}) = \sqrt{\frac{1}{N}\sum_{k=1}^{N} f(V, I, \mathbf{x})^2} \tag{6}$$

where N denotes the total number of experimental data, while $\mathbf{x}$ is a vector containing the parameters to be estimated. From Eq. (6), it is obvious that the smaller the value of RMSE, the more accurate the estimated parameters.

For the single diode model:

$$f(V, I, \mathbf{x}) = I_{ph} - I_{sd}\left[\exp\left(\frac{V + IR_s}{nV_t}\right) - 1\right] - \frac{V + IR_s}{R_{sh}} - I \tag{7}$$

$$\mathbf{x} = \{I_{ph}, I_{sd}, R_s, R_{sh}, n\} \tag{8}$$

For the double diode model:

$$f(V, I, \mathbf{x}) = I_{ph} - I_{sd1}\left[\exp\left(\frac{V + IR_s}{n_1V_t}\right) - 1\right] - I_{sd2}\left[\exp\left(\frac{V + IR_s}{n_2V_t}\right) - 1\right] - \frac{V + IR_s}{R_{sh}} - I \tag{9}$$

$$\mathbf{x} = \{I_{ph}, I_{sd1}, I_{sd2}, R_s, R_{sh}, n_1, n_2\} \tag{10}$$

For the PV module:

$$f(V, I, \mathbf{x}) = I_{ph} - I_{sd}\left[\exp\left(\frac{V + IR_sN_s}{nN_sV_t}\right) - 1\right] - \frac{V + IR_sN_s}{R_{sh}N_s} - I \tag{11}$$

$$\mathbf{x} = \{I_{ph}, I_{sd}, R_s, R_{sh}, n\} \tag{12}$$

3. Our approach: memetic adaptive differential evolution

As mentioned in Section 1, there are a lot of meta-heuristic methods for parameter estimation of PV models, however, the combination of advanced DE with the local search method to extract parameters of PV models is scarce. In addition, to obtain promising results, the meta-heuristic methods usually require large computational resources. Among various DE variants, SHADE (Tanabe and Fukunaga, 2013) obtained very promising results (Gong et al., 2018). In addition, the Nelder-Mead simplex method is a widely used local search method for function minimization (Olsson and Nelson, 1975). Based on the above considerations, to fast and accurately extract the parameters of different PV models, in this section, we propose a memetic adaptive differential evolution (MADE) method.

3.1. SHADE

Since the basic DE algorithm was proposed by Storn and Price (Storn and Price, 1997), several advanced variants have been presented. SHADE (Tanabe and Fukunaga, 2013) is one of the most successful DE variants, which uses a history based parameter adaptation scheme. In this section, the SHADE algorithm will be briefly described.

In SHADE, it employs a historical memory with H entries, which consists of M_{CR}, M_F to adapt the parameters CR and F of DE. Initially, all of $M_{CR,i}$, $M_{F,i}$ ($i = 1, 2, \ldots, H$) are set to be 0.5.

At each generation, for each individual $\mathbf{x}_i$, the CR_i and F_i are independently generated as:

$$CR_i = randn_i(M_{CR,r_i}, 0.1) \tag{13}$$

$$F_i = randc_i(M_{F,r_i}, 0.1) \tag{14}$$

where r_i is a random integer between 1 and H;$randn$ and $randc$ represent the Gaussian and the Cauchy distribution, respectively.

After each generation, the M_{CR} and M_F are updated:

$$M_{CR,k} = \begin{cases} mean_{WA}(S_{CR}) & if\ S_{CR} \neq \varnothing \\ M_{CR,k} & otherwise \end{cases} \tag{15}$$

$$M_{F,k} = \begin{cases} mean_{WL}(S_F) & if\ S_F \neq \varnothing \\ M_{F,k} & otherwise \end{cases} \tag{16}$$

where k represents an index that determines the position in the memory to be updated, k is initialized to 1. As long as a new element is added to the history, k is incremented by 1. If $k > H$, then k is reset to 1. S_{CR} and S_F store the successful CR_i and F_i in the previous generation, respectively. A detailed description of the weighted mean $mean_{WA}(S_{CR})$ and the weighted Lehmer mean $mean_{WL}(S_F)$ can be found in Tanabe and Fukunaga (2013).

3.2. Nelder-Mead simplex method

The Nelder-Mead simplex method (NMM) is a direct search method for function minimization (Olsson and Nelson, 1975). Because the method does not require any derivatives, it has been widely applied in various fields (Rahami et al., 2011).

This method uses five possible operations, including sort, reflection, expansion, contraction, and shrink. Through these five operations, NMM can quickly find a local optimum near the initial solution. However, this method relies heavily on the initial guess. If the initial guess is poor, it may not find any promising solution at all.

3.3. Ranking-based elimination strategy

In JADE (Zhang and Sanderson, 2009), a new mutation strategy, namely DE/current-to-*p*best with an external archive ($\mathbb{A}$), is presented. The archive $\mathbb{A}$ stores the inferior solutions. A mutation vector $\mathbf{v}_i$ is generated as follow:

$$\mathbf{v}_i = \mathbf{x}_i + F_i\cdot(\mathbf{x}_{pbest} - \mathbf{x}_i) + F_i\cdot(\mathbf{x}_{r_1} - \mathbf{x}_{r_2}) \tag{17}$$

where $\mathbf{x}_{pbest}$ is randomly chosen from the top $100p\%$ individuals. $\mathbf{x}_i$, $\mathbf{x}_{pbest}$, and $\mathbf{x}_{r_1}$ are selected from the current population ($\mathbb{P}$), while $\mathbf{x}_{r_2}$ is randomly chosen from the union of $\mathbb{P} \cup \mathbb{A}$.

Due to its capable of improving the diversity of the population (Zhang and Sanderson, 2009), the external archive is inherited by SHADE. Initially, the archive is empty. Once there is a new inferior solution, the archive will be updated. If the archive size exceeds the population size (*NP*), some solutions will be randomly discarded from the archive to ensure that the archive size is fixed to *NP*. However, this random elimination mechanism may slow down its convergence speed. To address this issue, in this work, the ranking-based elimination strategy is proposed.

For the ranking-based elimination strategy, the solutions in the archive are ranked from the best to the worst based on their objective function values. Then, the worst inferior solution will be replaced when a new inferior solution ($\mathbf{x}_{new}$) inserts into the archive. In this way, the better solution in the archive will have more chance to be chosen as $\mathbf{x}_{r_2}$, which may speed up its convergence.

3.4. The proposed MADE

The pseudo-code of MADE is described in Algorithm 1, where NFE is the number of function evaluations, Max_NFE is the maximal NFE, and ϵ is the threshold to control the best individual $\mathbf{x}_{best}$ in the population to be polished or not by NMM. NFE_{NMM} represents the NFE consumed by NMM. From Algorithm 1, the NMM is called when $f(\mathbf{x}_{best}) < \epsilon$. randi$[1, H]$ means that a random integrate number is generated within $[1, H]$, and rand$[2/NP, 0.2]$ indicates a random real number is generated within $[2/NP, 0.2]$.

In MADE, the SHADE, NMM, and ranking-based elimination strategy are combined together: (i) in lines 18–20, the NMM procedure is executed; and (ii) in line 21, the ranking-based elimination strategy is used. It is worth noting that when the NMM procedure is used in MADE, there are three issues should be considered (Chen et al., 2011) as follows:

- *Individuals for refinement*: It defines which individual(s) in the population will undergo the local refinement procedure. In MADE, as shown in line 18 of Algorithm 1, the best individual $\mathbf{x}_{best}$ is selected if its objective function value $f(\mathbf{x}_{best}) < \epsilon$.
- *Intensity of refinement*: It defines the computational resources allocated to the refinement procedure. In this work, if $f(\mathbf{x}_{best}) < 1e-8$ or $NFE_{NMM} > 200 \times D$, the local refinement procedure will be terminated, where D is the dimension of the optimization problem. For the single diode model and the PV module, $D = 5$; for the double diode model, $D = 7$.
- *Refinement procedure*: It means that which local refinement procedure should be chosen to refine the selected individuals. In this work, the NMM method is used due to its simplicity and promising performance for the optimization problems.

Algorithm 1. The pseudo-code of MADE

```
   Input: Control parameters: NP, Max_NFE and ϵ
   Output: The optimal solution
1  Set k = 1, NFE = 0, H = 100, 𝔸 = ∅;
2  All values in M_CR, M_F initialize to 0.5;
3  Initialize the population ℙ randomly;
4  while NFE < Max_NFE do
5      S_CR = ∅, S_F = ∅;
6      for i = 1 to NP do
7          r_i = randi[1, H];
8          Generate CR_i and F_i with Equations (13) and (14), respectively;
9          p_i = rand[2/NP, 0.2];
10         Generate the mutation vector v_i with Equation (17);
11         Generate the trial vector u_i by means of DE's crossover operator;
12         if f(u_i) ≤ f(x_i) then
13             x_i = u_i;
14         if f(u_i) < f(x_i) then
15             x_i → 𝔸;
16             CR_i → S_CR, F_i → S_F;
17     NFE = NFE + NP;
18     if f(x_best) < ϵ then
19         The NMM is called;
20         NFE = NFE + NFE_NMM;
21     Update A with the ranking-based elimination strategy whenever |𝔸| > NP;
22     if S_CR ≠ ∅ and S_F ≠ ∅ then
23         Update M_CR and M_F with Equations (15) and (16), respectively;
24         k = k + 1;
25         if k > H then
26             k = 1;
```

4. Results and analysis

In this section, the performance of MADE is verified for parameter estimation of different PV models. These PV models are the single diode model, the double diode model, and the PV module models. The experimental data of single and double diode models are obtained from Easwarakhanthan et al. (1986), where it is carried out on a 57 mm diameter commercial silicon R.T.C France solar cell at 33 °C. For the PV modules, we select three PV modules, *i.e.,* Photowatt-PWP201 (Easwarakhanthan et al., 1986), STM6-40/36, and STP6-120/36 (Oliva et al., 2017). For the Photowatt-PWP201 module, there are 36 polycrystalline silicon cells connected in series. The STM6-40/36 module and STP6-120/36 module are manufactured by Schutten Solar with 36 monocrystalline cells connected in series. The experimental data of the Photowatt-PWP201 module is obtained from Easwarakhanthan et al. (1986), which is measured at 45 °C. The experimental data of the STM6-40/36 and STP6-120/36 modules are taken from Oliva et al. (2017), measured at 51 °C and 55 °C, respectively. It is worth mentioning that

Table 1
Parameters range for the PV models.

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_{sd}, I_{sd1}, I_{sd2} (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
n, n_1, n_2	1	2	1	50	1	60	1	50

Table 2
Comparison among different algorithms on the single diode model.

Parameter	Algorithm							
	MADE	SHADE	GOFPANM	GOTLBO	Rcr-IJADE	IJAYA	SATLBO	TLABC
I_{ph} (A)	0.7608	0.7608	0.7608	0.7608	0.7608	0.7608	0.7608	0.7608
I_{sd} (μA)	0.3230	0.3230	0.3230	0.3316	0.3230	0.3228	0.3232	0.3230
R_s (Ω)	0.0364	0.0364	0.0364	0.0363	0.0364	0.0364	0.0363	0.0364
R_{sh} (Ω)	53.7185	53.7185	53.7185	54.1154	53.7185	53.7595	53.7256	53.7164
n	1.4812	1.4812	1.4812	1.4838	1.4812	1.4811	1.4812	1.4812
best RMSE	**9.8602E−04**	**9.8602E−04**	**9.8602E−04**	9.8744E−04	**9.8602E−04**	9.8603E−04	**9.8602E−04**	**9.8602E−04**
worst RMSE	**9.8602E−04**	**9.8602E−04**	**9.8602E−04**	1.9824E−03	**9.8602E−04**	1.0622E−03	9.9494E−03	1.0397E−03
mean RMSE	**9.8602E−04**	**9.8602E−04**	**9.8602E−04**	1.3349E−03	**9.8602E−04**	9.9204E−03	9.8780E−04	9.9852E−04
std RMSE	2.74E−15	2.22E−11	5.59E−15	2.09E−04	**5.12E−16**	1.40E−05	2.30E−06	1.86E−05
Max_NFE	**5000**	10,000	10,000	10,000	10,000	50,000	50,000	50,000
CPU time (s)	**0.1267**	3.0984	NA	NA	0.4887	13.1077	NA	0.9369

Table 3
IAE obtained by MADE for the single diode model.

Item	*V* (V)	I_{mea} (A)	I_{cal} (A)	*IAE*
1	−0.2057	0.764	0.764	0.000
2	−0.1291	0.762	0.763	0.001
3	−0.0588	0.7605	0.761	0.001
4	0.0057	0.7605	0.760	0.001
5	0.1185	0.76	0.759	0.001
6	0.1678	0.759	0.758	0.001
7	0.2132	0.757	0.757	0.000
8	0.2132	0.757	0.756	0.001
9	0.2545	0.7555	0.755	0.001
10	0.2924	0.754	0.754	0.000
11	0.3269	0.7505	0.751	0.001
12	0.3585	0.7465	0.747	0.001
13	0.3873	0.7385	0.740	0.002
14	0.4137	0.728	0.727	0.001
15	0.4373	0.7065	0.707	0.001
16	0.459	0.6755	0.675	0.001
17	0.4784	0.632	0.631	0.001
18	0.496	0.573	0.572	0.001
19	0.5119	0.499	0.499	0.000
20	0.5265	0.413	0.413	0.000
21	0.5398	0.3165	0.317	0.001
22	0.5521	0.212	0.212	0.000
23	0.5633	0.1035	0.103	0.001
24	0.5736	−0.01	−0.009	0.001
25	0.5833	−0.123	−0.124	0.001
26	0.59	−0.21	−0.209	0.001
∑*IAE*	–	–	–	0.021

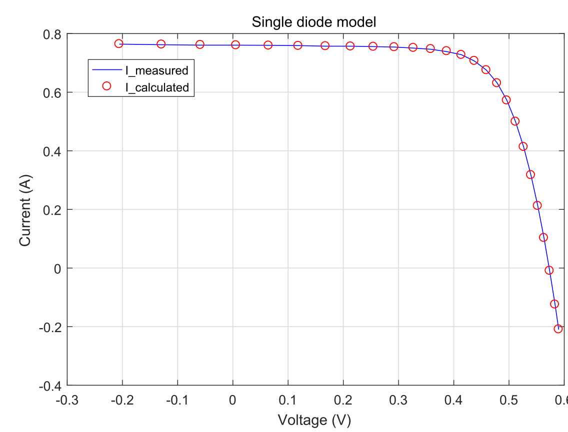

Fig. 4. Comparison on the *I-V* characteristics between the measured and calculated data of MADE for the single diode model.

these experimental data are typically used as standard datasets for parameter estimation of PV models.

To make a fair comparison, the search range of each parameter is shown in Table 1, which is kept the same as used in other literature. The parameters of the algorithms are set as follows:

- Population size for MADE and SHADE: $NP = 20$;
- Max_NFE and ϵ:
  - For the single diode model and Photowatt-PWP201 module: Max_NFE = 5000 and ϵ = 0.05;
  - For the double diode model: Max_NFE = 10,000 and ϵ = 0.01;
  - For STM6-40/36 and STP6-120/36: Max_NFE = 7000 and ϵ = 1.5;

In addition, the algorithms are implemented in Matlab2016b and executed over 30 independent runs on a desktop PC with an Intel Core i5-4590 M processor @ 3.30 GHz, 8 GB RAM, under the Windows7 64-bit OS.

4.1. Results on the single diode model

For the single diode model, the results of MADE are compared with those of SHADE (Tanabe and Fukunaga, 2013), GOFPANM (Xu and Wang, 2017), GOTLBO (Chen et al., 2016), Rcr-IJADE (Gong and Cai,

Table 4
Comparison among different algorithms on the double diode model.

Parameter	Algorithm							
	MADE	SHADE	GOFPANM	GOTLBO	Rcr-IJADE	IJAYA	SATLBO	TLABC
I_{ph} (A)	0.7608	0.7608	0.7608	0.7608	0.7608	0.7601	0.7608	0.7608
I_{sd1} (μA)	0.7394	0.2260	0.7493	0.8002	0.2260	0.0050	0.2509	0.4239
I_{sd2} (μA)	0.2246	0.7494	0.2260	0.2205	0.7493	0.7509	0.5454	0.2401
R_s (Ω)	0.0368	0.0367	0.0367	0.0368	0.0367	0.0376	0.0366	0.0367
R_{sh} (Ω)	55.4329	55.4854	55.4854	56.0753	55.4854	77.8519	55.1170	54.6680
n_1	1.9963	1.4510	2.0000	2.0000	1.4510	1.2186	1.4598	1.9075
n_2	1.4505	2.0000	1.4510	1.4490	2.0000	1.6247	1.9994	1.4567
best RMSE	9.8261E−04	**9.8248E−04**	**9.8248E−04**	9.8318E−04	**9.8248E−04**	9.8293E−04	9.8280E−04	9.8415E−04
worst RMSE	9.8786E−04	2.1153E−03	1.3405E−03	1.7877E−03	**9.8602E−04**	1.4055E−03	1.0470E−03	1.5048E−03
mean RMSE	9.8608E−04	1.0867E−03	9.9548E−04	1.2436E−03	**9.8261E−04**	1.0269E−03	9.9811E−04	1.0555E−03
std RMSE	8.02E−05	2.60E−04	**6.52E−05**	2.09E−04	9.86E−05	9.83E−05	1.95E−05	1.55E−04
Max_NFE	**10,000**	20,000	20,000	20,000	20,000	50,000	50,000	50,000
CPU time (s)	**0.1890**	6.3452	NA	NA	0.8329	13.1719	NA	0.9347

2013), IJAYA (Yu et al., 2017a), SATLBO (Yu et al., 2017b) and TLABC (Chen et al., 2018). The experimental results are shown in Table 2, where the extracted parameters of different algorithms are the solution with the best RMSE among the 30 runs. Additionally, the best, worst, mean, and standard deviation of RMSE for different compared algorithms are also reported in Table 2. The Max_NFE and CPU time at one execution for different algorithms are given in the last row of the table. Note that NA means the results are not available.

From Table 2, it can be seen that:

- Considering the best RMSE value, six algorithms, *i.e.*, MADE, SHADE, GOFPANM, Rcr-IJADE, SATLBO, and TLABC, obtain the best results.
- With respect to the mean RMSE, only MADE, SHADE, GOFPANM, and Rcr-IJADE are able to provide the best results.
- For the Max_NFE, the proposed MADE algorithm requires Max_NFE = 5000, which is much less than the compared methods.

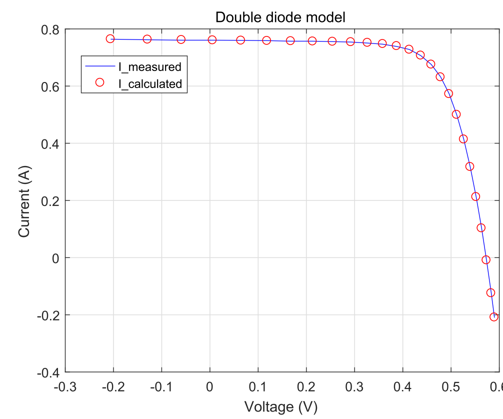

Fig. 5. Comparison on the I-V characteristics between the measured and calculated data of MADE for the double diode model.

- In terms of the CPU time, it can be observed that MADE is significantly less than other compared algorithms. The reason is that for the compared methods the main time consuming is cost by the objective function calculation. Since MADE only consumes Max_NFE = 5000, it requires the smallest CPU time.

Table 5
IAE obtained by MADE for the double diode model.

Item	*V* (V)	I_{mea} (A)	I_{cal} (A)	*IAE*
1	−0.2057	0.764	0.764	0.000
2	−0.1291	0.762	0.763	0.001
3	−0.0588	0.7605	0.761	0.001
4	0.0057	0.7605	0.760	0.001
5	0.0646	0.76	0.759	0.001
6	0.1185	0.759	0.758	0.001
7	0.1678	0.757	0.757	0.000
8	0.2132	0.757	0.756	0.001
9	0.2545	0.7555	0.755	0.001
10	0.2924	0.754	0.754	0.000
11	0.3269	0.7505	0.751	0.001
12	0.3585	0.7465	0.747	0.001
13	0.3873	0.7385	0.740	0.002
14	0.4137	0.728	0.727	0.001
15	0.4373	0.7065	0.707	0.001
16	0.459	0.6755	0.675	0.001
17	0.4784	0.632	0.631	0.001
18	0.496	0.573	0.572	0.001
19	0.5119	0.499	0.500	0.001
20	0.5265	0.413	0.414	0.001
21	0.5398	0.3165	0.317	0.001
22	0.5521	0.212	0.212	0.000
23	0.5633	0.1035	0.103	0.001
24	0.5736	−0.01	−0.009	0.001
25	0.5833	−0.123	−0.124	0.001
26	0.59	−0.21	−0.209	0.001
$\sum IAE$	–	–	–	0.023

Furthermore, in order to verify the accuracy of our approach, the individual absolute error (*IAE*)[1] and the *I-V* characteristic curve between the measured data I_{mea} and the calculated data I_{cal} are shown in Table 3 and Fig. 4, respectively. Note that I_{cal} is calculated by using the estimated PV parameters values of MADE into the objective function. It is easy to get an evidence that the measured data and the calculated data are highly consistent, which reflects the parameters estimated by the MADE are accurate enough.

4.2. Results on the double diode model

For the double diode model, there are seven parameters that need to be estimated. The parameter values and the RMSE values are reported in Table 4, where the results of MADE, SHADE (Tanabe and Fukunaga, 2013), GOFPANM (Xu and Wang, 2017), GOTLBO (Chen et al., 2016), Rcr-IJADE (Gong and Cai, 2013), IJAYA (Yu et al., 2017a), SATLBO (Yu et al., 2017b) and TLABC (Chen et al., 2018) are considered for comparison.

From Table 4, we observe that SHADE, GOFPANM, and Rcr-IJADE

[1] The individual absolute error is calculated as $IAE = |I_{mea} - I_{cal}|$.

Table 6
Comparison among different algorithms on the Photowatt-PWP201 module.

Parameter	Algorithm						
	MADE	SHADE	GOFPANM	Rcr-IJADE	IJAYA	SATLBO	TLABC
I_{ph} (A)	1.0305	1.0305	1.0305	1.0305	1.0305	1.0305	1.0306
I_{sd} (μA)	3.4823	3.4823	3.4823	3.4823	3.4703	3.4827	3.4715
R_s (Ω)	1.2013	1.2013	1.2013	1.2113	1.2016	1.2013	1.2017
R_{sh} (Ω)	981.9823	981.9822	981.9823	981.9822	977.3752	982.4038	972.9357
n	48.6428	48.6428	48.6428	48.6428	48.6298	48.6433	48.6313
best RMSE	**2.4250E−03**	**2.4251E−03**	**2.4250E−03**	**2.4250E−03**	**2.4251E−03**	**2.4251E−03**	**2.4251E−03**
worst RMSE	**2.4251E−03**	**2.4251E−03**	**2.4251E−03**	**2.4251E−03**	2.4393E−03	2.4291E−03	2.4458E−03
mean RMSE	**2.4251E−03**	**2.4251E−03**	**2.4251E−03**	**2.4251E−03**	**2.4251E−03**	2.4254E−03	2.4265E−03
std RMSE	3.07E−17	1.93E−16	2.92E−16	**2.90E−17**	3.78E−06	7.41E−07	4.00E−06
Max_NFE	**5000**	10,000	10,000	10,000	50,000	50,000	50,000
CPU time (s)	**0.1356**	3.1405	NA	0.5353	12.9754	NA	0.9347

Table 7
IAE obtained by MADE for the Photowatt-PWP201 module.

Item	$V(V)$	$I_{mea}(A)$	$I_{cal}(A)$	*IAE*
1	0.1248	1.0315	1.029	0.003
2	1.8093	1.03	1.027	0.003
3	3.3511	1.026	1.026	0.000
4	4.7622	1.022	1.024	0.002
5	6.0538	1.018	1.022	0.004
6	7.2364	1.0155	1.020	0.005
7	8.3189	1.014	1.016	0.002
8	9.3097	1.01	1.010	0.000
9	10.2163	1.0035	1.001	0.003
10	11.0449	0.988	0.985	0.003
11	11.8018	0.963	0.960	0.003
12	12.4929	0.9255	0.923	0.002
13	13.1231	0.8725	0.873	0.001
14	13.6983	0.8075	0.807	0.001
15	14.2221	0.7265	0.728	0.002
16	14.6995	0.6345	0.636	0.002
17	15.1346	0.5345	0.536	0.002
18	15.5311	0.4275	0.429	0.002
19	15.8929	0.3185	0.319	0.001
20	16.2229	0.2085	0.208	0.001
21	16.5241	0.101	0.098	0.003
22	16.7987	−0.008	−0.008	0.000
23	17.0499	−0.111	−0.111	0.000
24	17.2793	−0.209	−0.209	0.000
25	17.4885	−0.303	−0.302	0.001
$\sum IAE$	–	–	–	0.046

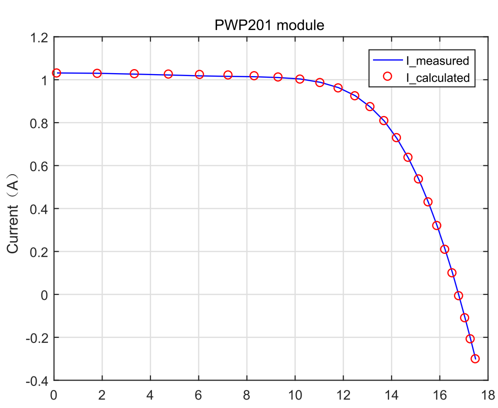

Fig. 6. Comparison on the *I-V* characteristics between the measured and calculated data of MADE for the Photowatt-PWP201 module.

obtain the best RMSE values, followed by MADE, SATLBO, IJAYA, GOTLBO and TLABC. Although MADE does not get the best RMSE value, it is still able to provide highly competitive results with only 10,000 NFE. Whereas all other compared methods require much more computational resources. Besides, MADE spends the least CPU time (0.1890 s).

By carefully looking at the best RMSE, we find that MADE gets worse result than SHADE. We may ask that "Does the NMM procedure or the ranking based elimination strategy deteriorate the performance of SHADE for parameter extraction of the double diode model?" Based on this consideration, we checked the *intermediate* results and observed that after refining the solution with NMM, MADE found a better solution with $f(\mathbf{x}) = 9.8077E-04$, and its corresponding parameters are $\mathbf{x}=$.

$$\{0.76078126, 1, 0.26506674, 0.03663464, 55.21304804, 2.23693056, 1.46359979\}$$

However, for this solution, $n_1 = 2.23693056$ is out of its search range [1, 2]. In SHADE, if the parameter is out of its range, it will be re-initialized within its range. In this way, the solutions obtained by NMM that are out of the search range will be penalized. This may result in that MADE obtains slightly worse best RMSE than SHADE. However, according to the mean and standard values, we can see that MADE is more robust than SHADE.

In addition, Table 5 and Fig. 5 show the IAE values and the *I-V* characteristic curve between the measured data and calculated data of MADE, respectively. It is clear that the error of the measured and calculated data are relatively small.

4.3. Results on the PV modules

4.3.1. Results on the Photowatt-PWP201 module

For the Photowatt-PWP201 module, MADE is compared with SHADE (Tanabe and Fukunaga, 2013), GOFPANM (Xu and Wang, 2017), Rcr-IJADE (Gong and Cai, 2013), IJAYA (Yu et al., 2017a), SATLBO (Yu et al., 2017b), and TLABC (Chen et al., 2018). The results are shown in Table 6. Note that the results of GOFPANM, Rcr-IJADE, IJAYA, SATLBO, and TLABC are obtained from their respective references. Additionally, the calculated results (I_{cal}) of MADE are tabulated in Table 7 and the corresponding *I-V* characteristic curve is plotted in Fig. 6.

From Table 6, it is clear that all compared algorithms can provide the similar best RMSE values, but MADE takes the least CPU time. In addition, MADE, SHADE, GOFPANM, Rcr-IJADE, and IJAYA obtain the same mean RMSE values. However, the Max_NFE of MADE is only 5000, which is much less than those of SHADE (10,000), GOFPANM (10,000), Rcr-IJADE (10,000), IJAYA (50,000), SATLBO (50,000), and TLABC (50,000). From Table 7 and Fig. 6, the results also confirm that

Table 8
Comparison among different algorithms on the STM6-40/36 module.

Parameter	Algorithm					
	MADE	SHADE	Rcr-IJADE	CWOA	STBLO	BMO
I_{ph} (A)	1.6639	1.6639	1.6639	1.7000	1.7000	1.6646
I_{sd} (μA)	1.7387	1.7386	1.7387	1.6338	1.4127	1.4311
R_s (Ω)	0.0043	0.0043	0.0043	0.0050	0.0050	0.0050
R_{sh} (Ω)	15.9283	15.9282	15.9283	15.4000	15.4000	14.9371
n	1.5203	1.5203	1.5203	1.5000	1.5000	1.4994
best RMSE	**1.7298E−03**	**1.7298E−03**	**1.7298E−03**	1.8000E−03	1.9000E−03	1.9000E−03
worst RMSE	**1.7298E−03**	1.7423E−03	**1.7298E−03**	NA	NA	NA
mean RMSE	**1.7298E−03**	1.7306E−03	**1.7298E−03**	NA	NA	NA
std RMSE	**8.49E−14**	2.44E−06	**1.18E−14**	NA	NA	NA
Max_NFE	**7000**	10,000	10,000	NA	NA	NA
CPU time (s)	**0.1692**	3.0881	0.4700	NA	NA	NA

Table 9
IAE obtained by MADE for the STM6-40/36 module.

Item	V (V)	I_{mea} (A)	I_{cal} (A)	*IAE*
1	0	1.663	1.663	0.000
2	0.118	1.663	1.663	0.000
3	2.237	1.661	1.660	0.001
4	5.434	1.653	1.654	0.001
5	7.26	1.65	1.651	0.001
6	9.68	1.645	1.645	0.000
7	11.59	1.64	1.639	0.001
8	12.6	1.636	1.634	0.002
9	13.37	1.629	1.627	0.002
10	14.09	1.619	1.618	0.001
11	14.88	1.597	1.603	0.006
12	15.59	1.581	1.582	0.001
13	16.4	1.542	1.542	0.000
14	16.71	1.524	1.521	0.003
15	16.98	1.5	1.499	0.001
16	17.13	1.485	1.485	0.000
17	17.32	1.465	1.466	0.001
18	17.91	1.388	1.388	0.000
19	19.08	1.118	1.118	0.000
20	21.02	0	0.000	0.000
$\sum IAE$	–	–	–	0.021

Table 11
IAE obtained by MADE for the STP6-120/36 module.

Item	V (V)	I_{mea} (A)	I_{cal} (A)	*IAE*
1	0	7.48	7.471	0.009
2	9.06	7.45	7.453	0.003
3	9.47	7.42	7.447	0.027
4	10.32	7.44	7.439	0.001
5	11.17	7.41	7.420	0.010
6	11.81	7.38	7.396	0.016
7	12.36	7.37	7.363	0.007
8	12.74	7.34	7.331	0.009
9	13.16	7.29	7.284	0.006
10	13.59	7.23	7.218	0.012
11	14.17	7.1	7.088	0.012
12	14.58	6.97	6.958	0.012
13	14.93	6.83	6.815	0.015
14	15.39	6.58	6.568	0.012
15	15.71	6.36	6.349	0.011
16	16.08	6	6.037	0.037
17	16.34	5.75	5.777	0.027
18	16.76	5.27	5.274	0.004
19	16.9	5.07	5.082	0.012
20	17.1	4.79	4.786	0.004
21	17.25	4.56	4.546	0.014
22	17.41	4.29	4.274	0.016
23	17.65	3.83	3.832	0.002
24	19.21	0	0.001	0.001
$\sum IAE$	–	–	–	0.279

Table 10
Comparison among different algorithms on the STP6-120/36 module.

Parameter	Algorithm					
	MADE	SHADE	Rcr-IJADE	CWOA	STBLO	BMO
I_{ph} (A)	7.4725	7.4725	7.4725	1.2000	1.1679	1.2333
I_{sd} (μA)	2.3350	2.3353	2.3350	7.4760	7.4814	7.4763
R_s (Ω)	0.0046	0.0046	0.0046	0.0049	0.0055	0.0049
R_{sh} (Ω)	22.2199	22.2169	22.2199	9.7942	9.8000	9.7000
n	1.2601	1.2601	1.2601	1.2069	1.2048	1.2092
best RMSE	**1.6601E−02**	**1.6601E−02**	**1.6601E−02**	1.7601E−02	1.6211E−02	1.6985E−02
worst RMSE	**1.6601E−02**	5.6820E−02	**1.6601E−02**	NA	NA	NA
mean RMSE	**1.6601E−02**	2.4820E−02	**1.6601E−02**	NA	NA	NA
std RMSE	**1.69E−15**	1.39E−02	1.29E−14	NA	NA	NA
Max_NFE	**7000**	10,000	10,000	NA	NA	NA
CPU time (s)	**0.1780**	3.1030	0.4580	NA	NA	NA

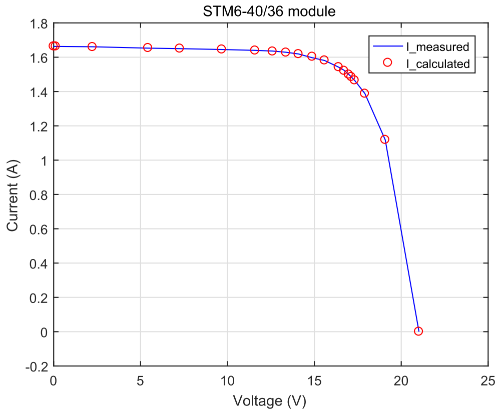

Fig. 7. Comparison on the *I-V* characteristics between the measured and calculated data of MADE for the STM6-40/36 module.

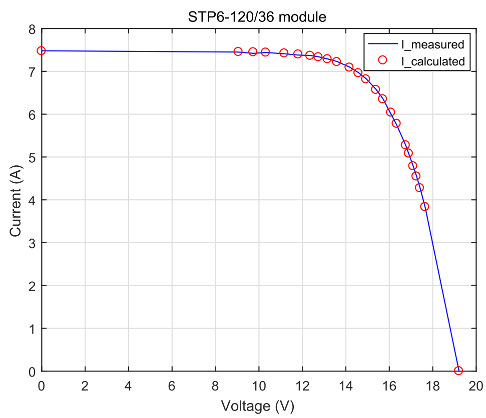

Fig. 8. Comparison on the *I-V* characteristics between the measured and calculated data of MADE for the STP6-120/36 module.

the calculated results obtained by MADE keep very good agreement with the measurements.

4.3.2. Results on the other modules

To further verify the performance of the proposed algorithm, we extend the MADE to estimate the parameters of other two PV modules: mono-crystalline STM6-40/36 and poly-crystalline STP6-120/36. The results are respectively reported in Table 8 and Table 10, where MADE is compared with SHADE (Tanabe and Fukunaga, 2013), Rcr-IJADE (Gong and Cai, 2013), CWOA (Oliva et al., 2017), STBLO (Niu et al., 2014), and BMO (Askarzadeh and Rezazadeh, 2013). Note that the results of CWOA, STBLO, and BMO are obtained from Oliva et al. (2017). In addition, Tables 9 and 11 report the *IAE* results of MADE for STM6-40/36 and STP6-120/36, respectively. In Figs. 7 and 8, the *I-V* characteristics of MADE are plotted for STM6-40/36 and STP6-120/36, respectively.

Similar to the results for the Photowatt-PWP201 module, MADE is able to provide highly competitive results compared with other six algorithms. However, MADE consumes the smallest Max_NFE and the least CPU time among the seven algorithms. In Tables 9 and 11, and Figs. 7 and 8, the results demonstrate that the calculated values obtained by MADE can fit the measured values very well for both the STM6-40/36 and STP6-120/36 modules.

5. Conclusion

Parameter estimation is crucial to PV systems optimization. In this paper, a memetic adaptive DE (MADE) is proposed to effectively address the parameter estimation problems of PV models. In our approach, SHADE, NMM, and ranking-based elimination strategy are combined together. The performance of MADE is extensively evaluated by estimating the parameters of different PV models, i.e., the single diode model, the double diode model, and three PV modules. Compared with other meta-heuristic methods in the literature, MADE obtains highly competitive results, yet only consumes the smallest computational resources. The reasons can be summarized into threefold: (i) SHADE is able to avoid trapping into the local optimum and provides good initial guess for the NMM local procedure; (ii) NMM is able to refine the solution, and hence accelerates the convergence speed; and (iii) the ranking-based elimination strategy can eliminate the worse solutions in the archive, in this way, the convergence speed can be further enhanced. Thus, MADE can be an efficient alternative for other complex optimization problems in PV systems.

In future work, we will try to combine more efficient heuristics (Lu et al., 2018) with NMM to solve the maximum power point tracking in PV systems (Li et al., 2018; Babu et al., 2018).

The source code can be obtained from the authors upon request.

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