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An Improved Differential Evolution to Extract Photovoltaic Cell Parameters

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ABSTRACT Parameter extraction of photovoltaic (PV) models plays a vital role in simulation, evaluation and control of PV systems. It requires to identify the parameters of different PV models quickly and accurately. In this paper, an improved differential evolution by reusing the past individual vectors and adaptive mutation strategy is proposed to extract PV parameters. In the proposed method, the successful difference vectors from previous generations are introduced to produce the offspring in the next generations to improve the performance of differential evolution. In addition, to obtain a nice result, an adaptive mutation strategy is considered to establish a good balance of exploration and exploitation. The proposed method is applied to identify the parameters of different PV models, such as single diode, double diode, and PV models. Comparison results demonstrate that the proposed method obtains the competitive performance on accuracy, reliability and convergence when compared with other state-of-the-art methods.

INDEX TERMS Parameter extraction, reusing vectors, adaptive strategy, differential evolution.

I. INTRODUCTION

To deal with the environmental pollution caused by the use of fossil fuels, most researches are working to develop a variety of renewable energy sources, such as wave, wind, nuclear and so on [1]. Solar energy has been recognized as promising renewable energy due to its availability and cleanliness [2]. Specifically, solar energy can be directly converted into electricity by photovoltaic (PV) systems and provide power to different loads [3]. However, PV systems are usually in an outdoor environment, and PV arrays are not always effective, which will affect the conversion efficiency of solar systems. For PV systems, it is vital to evaluate the PV arrays in operation using accurate models based on measured current-voltage data [4]. Several PV models have been designed and successfully used in simulating the behavior of PV systems. Among them, the single diode model (SDM) and the double diode model (DDM) are the most common and widely adopted [5]. For these PV models, the accuracy of them mainly depends on their model parameters. Hence, it requires accurate, efficient, and rapid determination of PV parameters. However, these parameters are unavailable and change due to aging, faults, and the operating conditions [6], it is still an extremely challenging work.

Traditional methods are considered as a typical method to extract the PV model parameters, such as, Newton-Raphson method [7], Lambert W-functions [8] and conductivity method (CM) [9]. The advantage of these methods is that the local search used can improve the accuracy of the solution, but they encounter the dilemma of trapping in local optimal. Additionally, most traditional methods are highly dependent on the initial parameters, lead to a lower efficiency if the initial guess is far away from the global optimal [10]. These deficiencies constrain the application of traditional methods to the parameter extraction of PV models.

In recent years, due to the characteristics of insensitive to objective functions and easy to implement, meta-heuristic methods have received widespread attention in the fields of the parameter extraction of PV models. Zhang *et al.* [11] used Backtracking Search Algorithm (BSA) for identifying parameters of PV models. Genetic Algorithm (GA) is a classical meta-heuristic algorithm and several improved GAs were applied to extract the parameters of PV models [12]–[14]. Nunes *et al.* [15] developed the guaranteed convergence particle swarm optimization (GCPSO) for solar cell extraction. Lin *et al.* [16] designed niche particle swarm optimization in

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parallel computing (NPSOPC) for solar cell parameters estimation. Gomes *et al.* [17] used shuffled complex evolution for identifying the intrinsic parameters of the PV generator. Chen *et al.* [18] presented an enhanced shuffled complex evolution algorithm with opposition-based learning strategy for this task. In [19], a self-adaptive teaching-learning-based optimization was designed by Yu *et al.* for PV parameter estimation. Li *et al.* [20] proposed an improved teaching-learning-based optimization (ITLBO) for this application. Liao *et al.* [21] designed a three phase TLBO to extract the parameter of the PV models. In [22], an improved chaotic whale optimization algorithm was designed and was applied to identify PV parameters. Guo *et al.* [23] designed two prey searching techniques to balance exploitation and exploration and enhanced the performance of whale optimization algorithm for this application. Jian *et al.* [24] developed a logistic chaotic JAYA algorithm for solar cell parameters identification. Yu *et al.* [25] presented a performance-guided JAYA algorithm for estimating the parameters in three diode model. In [26], an advanced onlooker-ranking-based adaptive differential evolution was proposed to extract the PV parameters. Li *et al.* [27] developed an enhanced adaptive differential evolution algorithm to estimate the PV parameters. In addition to the above methods, several researches adopted hybrid methods to solve this problem. A new hybrid algorithm based on grey wolf optimizer and cuckoo search was designed to solve the parameters estimation problem [28]. Chen *et al.* [29] combined cuckoo search algorithm with biogeography-based optimization to extract the PV models parameters.Although the above methods or their variants have obtained satisfied results, they still need further improvement. Additionally, the PV parameters extraction is a nonlinear and multi-modal problem, which makes it difficult to solve by conventional algorithms. Thus, designing an appropriate algorithm to effectively solve this problem and return accurate PV parameters remains a challenging task.

Differential evolution (DE) [30], proposed by Storn and Price in 1995, is an efficient population-based method. Over the past two decades, due to its simplicity and effectiveness, DE has been widely used in various areas, such as multimodal optimization [31], multiobjective optimization [32], solar cell optimization [33], and dynamic optimization [34], optimal power flow [35]. Also, to enhance the performance of DE, several advanced DE variants have been developed to solve the problems in various areas [36]. Among all DE variants, DE with the difference vector reuse (DVR) [37] is a new and improved method, having achieved promising results in the majority of test cases. However, it still encounters several shortcomings. For example, the stored difference vector records the individual information after mutation operation, ignoring the preservation of difference vector after the crossover operation of DE algorithm. Therefore, several valuable information may be lost. Additionally, parameters extraction of PV is a multi-model problem, which requires the algorithm to keep a balance between exploration and exploitation in different search stages.

In this paper, reusing the successful difference vectors in differential evolution with adaptive mutation strategy, named DVADE, is proposed to solve PV parameter estimation problems. In DVADE, reuse of the successful difference vectors is introduced to improve the performance of DE. This method can explore more promising regions in future generations as well as enhancing the population diversity. In addition, an adaptive mutation strategy is developed to keep a balance between exploration and exploitation. To be specific, at the early stage, the offsprings are generated by using "DE/rand/1" strategy, which is conducive to population diversity. At the later stage, the offsprings are produced around the best individual of the current generation, improving the exploitation ability of the algorithm. To verify the performance of the proposed DVADE, it is utilized to estimate the unknown parameters of multiple PV models. Simulation results demonstrate that DVADE obtains superior performance in terms of accuracy and reliability. Hence, DVADE can be considered as an effective alternative for estimation parameters of PV models.

The main contributions of this paper are given as follows:

- A reusing the successful difference vectors differential evolution with adaptive mutation strategy DVADE) is proposed to identify parameters of different PV models. In DVADE, the mechanism of reusing the successful difference vectors is introduced to generate the offsprings and explore the promising regions. For example, from Figure 1, the mutation operator uses previously successful difference vectors to generate trial vectors. Additionally, successful difference vectors will be stored in the archive after selection operator.

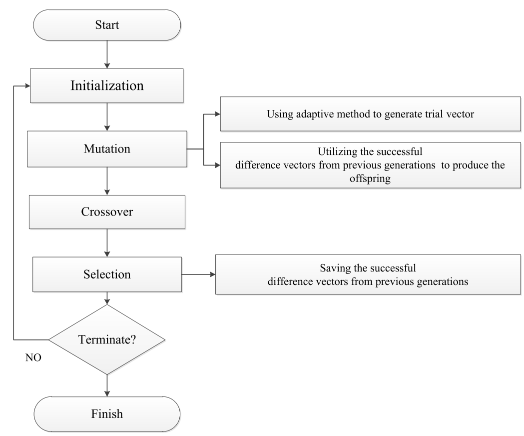


FIGURE 1. The flowchart of DVADE.

- An adaptive mutation strategy is adopted. On the one hand, the strategy encourages searching the whole region to find the optimal solution with high probability. On the other hand, it helps to enhance the exploitation ability, so as to improve the accuracy of the extracted parameters.
- The effectiveness of DVADE is exhibited through comprehensive experiments and parameter extraction of different PV models.

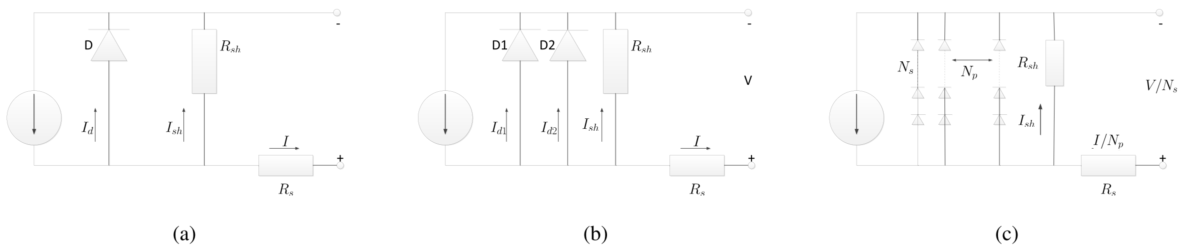


FIGURE 2. **Equivalent circuit of PV models: (a) SDM, (b) DDM, (c) SMM.**

The rest of this paper is organized as follows. Section II mainly introduces different PV models. Then, the original DE algorithm is described in Section III. In Section IV, the proposed approach is explained. Section V will discuss the simulation results. Finally, Section VI gives the conclusions.

II. FORMULATION OF PV MODELS

As mentioned, several mathematical models have been proposed to illustrate the behaviour of the solar cells. The SDM and the DDM are two commonly used models. In this section, the SDM, DDM and the PV module are detailed as below.

A. SINGLE DIODE MODEL

SDM is a common equivalent circuit model that represents the static characteristic of solar cell due to simplicity and accuracy [5]. As shown in Figure 2(a), SDM consists of a current source, a diode, a shunt resistor and a series resistor. Thus, the output electric current can be calculated as below:

$$I = I_{\mathrm{ph}} - I_{\mathrm{d}} - I_{\mathrm{sh}} \tag{1}$$

where I_{ph} represents the photo-generated current, I_{d} is the diode current, and I_{sh} denotes the shunt resistor current. Among them, I_{d} and I_{sh} can be calculated as:

$$I_{\mathrm{d}} = I_{\mathrm{o}}\left[\exp\left(\frac{V + IR_{\mathrm{s}}}{aV_{\mathrm{t}}}\right) - 1\right] \tag{2}$$

$$I_{\mathrm{sh}} = \frac{V + IR_{\mathrm{s}}}{R_{\mathrm{sh}}} \tag{3}$$

where I_{o}, a, R_{s} and R_{sh} are the diode reverse saturation current, the diode ideality factor, the series and the shunt resistance, respectively. V denotes the cell output voltage, and V_{t} is the junction thermal voltage calculated by Eq. (4)

$$V_{\mathrm{t}} = \frac{k \cdot T}{q} \tag{4}$$

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 is the temperature of junction in Kelvin.

Therefore, according to Eqs. (1)-(4), the output current I can be given by Eq. (5)

$$I = I_{\mathrm{ph}} - I_{\mathrm{o}}\left[\exp\left(\frac{V + IR_{\mathrm{s}}}{aV_{\mathrm{t}}}\right) - 1\right] - \frac{V + IR_{\mathrm{s}}}{R_{\mathrm{sh}}} \tag{5}$$

According to Eq.(5), five unknown parameters (I_{ph}, I_{o}, R_{s}, R_{sh}, and a) need to be identified for describing the solar cell behaviour.

B. DOUBLE DIODE MODEL

The SDM ignores the influence of recombination current loss in the depletion region; therefore, DDM is developed by considering this loss [38]. It is illustrated in Figure 2(b), where it can be seen that contains two diodes in parallel with current source and a shunt resistance. The output current I can be calculated as follows:

$$I = I_{\mathrm{ph}} - I_{\mathrm{d1}} - I_{\mathrm{d2}} - I_{\mathrm{sh}} \tag{6}$$

where I_{d1}, I_{d2} are respectively the first and second diode currents, which can be described as below:

$$I_{\mathrm{d1}} = I_{\mathrm{o1}}\left[\exp\left(\frac{V + IR_{\mathrm{s}}}{a_1 V_{\mathrm{t}}}\right) - 1\right] \tag{7}$$

$$I_{\mathrm{d2}} = I_{\mathrm{o2}}\left[\exp\left(\frac{V + IR_{\mathrm{s}}}{a_2 V_{\mathrm{t}}}\right) - 1\right] \tag{8}$$

where I_{o1}, I_{o2}, a_1 and a_2 represent diffusion current, saturation current, the first and second diode ideality factors, respectively. Therefore, the output current I of solar cells can be calculated by Eq. (9), and DDM has seven unknown parameters (I_{ph}, I_{o1}, I_{o2}, R_{s}, R_{sh}, a_1, and a_2) that need to be identified.

$$\begin{aligned} I = I_{\mathrm{ph}} - I_{\mathrm{o1}}&\left[\exp\left(\frac{V + IR_{\mathrm{s}}}{a_1 V_{\mathrm{t}}}\right) - 1\right] \\ &- I_{\mathrm{o2}}\left[\exp\left(\frac{V + IR_{\mathrm{s}}}{a_2 V_{\mathrm{t}}}\right) - 1\right] - \frac{V + IR_{\mathrm{s}}}{R_{\mathrm{sh}}} \end{aligned} \tag{9}$$

C. PHOTOVOLTAIC MODULE

As shown in Figure 2(c), the single diode PV module model (SMM) that consists of several solar cells connected in series and /or in parallel. The output current I can be calculated as follows:

$$\begin{aligned} I = I_{\mathrm{ph}}N_{\mathrm{p}} - I_{\mathrm{o}}N_{\mathrm{p}}&\left[\exp\left(\frac{V + IR_{\mathrm{s}}N_{\mathrm{s}}/N_{\mathrm{p}}}{aN_{\mathrm{s}}V_{\mathrm{t}}}\right) - 1\right] \\ &- \frac{V + IR_{\mathrm{s}}N_{\mathrm{s}}/N_{\mathrm{p}}}{R_{\mathrm{sh}}N_{\mathrm{s}}/N_{\mathrm{p}}} \end{aligned} \tag{10}$$

where N_{s} is the number of solar cells connected in series, and N_{p} indicate the number of solar cells connected in parallel. In this literature, $N_p = 1$.

D. PARAMETER EXTRACTION OF PV MODELS

Parameter identification problem of PV models can be modeled as an optimization problem, and the aim is to accurately extract the unknown parameters that characterize the SDM, DDM, and SMM. Hence, the minimum difference between the experimental and the simulated data is the main task of parameter extraction. Similar to [39], the overall root mean square error (RMSE) is used to quantify the difference between the measured and simulated current. Hence, the objective function is formulated as follows:

$$\mathrm{RMSE}(\mathbf{x}) = \sqrt{\frac{1}{N}\sum_{k=1}^{N} f(V_k, I_k, \mathbf{x})^2} \tag{11}$$

where N represents the number of experimental data. $\mathbf{x}$ is a vector, which consists of several unknown parameters that need to be identified. In this paper, the objective functions of different PV models can be formulated as follows:

- For SDM:

$$\begin{cases} f(V, I, \mathbf{x}) = I_{\mathrm{ph}} - I_{\mathrm{o}}\left[\exp\left(\dfrac{V+IR_{\mathrm{s}}}{aV_{\mathrm{t}}}\right) - 1\right] \\ \quad -\dfrac{V+IR_{\mathrm{s}}}{R_{\mathrm{sh}}} - I \\ \mathbf{x} = \left\{I_{\mathrm{ph}}, I_{\mathrm{o}}, R_{\mathrm{s}}, R_{\mathrm{sh}}, a\right\} \end{cases} \tag{12}$$

- For DDM:

$$\begin{cases} f(V, I, \mathbf{x}) = I_{\mathrm{ph}} - I_{\mathrm{o1}}\left[\exp\left(\dfrac{V+IR_{\mathrm{s}}}{a_1 V_{\mathrm{t}}}\right) - 1\right] \\ -I_{\mathrm{o2}}\left[\exp\left(\dfrac{V+IR_{\mathrm{s}}}{a_2 V_{\mathrm{t}}}\right) - 1\right] - \dfrac{V+IR_{\mathrm{s}}}{R_{\mathrm{sh}}} - I \\ \mathbf{x} = \left\{I_{\mathrm{ph}}, I_{\mathrm{o1}}, I_{\mathrm{o2}}, R_{\mathrm{s}}, R_{\mathrm{sh}}, a_1, a_2\right\} \end{cases} \tag{13}$$

- For SMM:

$$\begin{cases} f(V, I, \mathbf{x}) = I_{\mathrm{ph}}N_{\mathrm{p}} - I_{\mathrm{o}}N_{\mathrm{p}} \\ \quad \left[\exp\left(\dfrac{V+IR_{\mathrm{s}}N_{\mathrm{s}}/N_{\mathrm{p}}}{aN_{\mathrm{s}}V_{\mathrm{t}}}\right) - 1\right] \\ -\dfrac{V+IR_{\mathrm{s}}N_{\mathrm{s}}/N_{\mathrm{p}}}{R_{\mathrm{sh}}N_{\mathrm{s}}/N_{\mathrm{p}}} - I \\ \mathbf{x} = \left\{I_{\mathrm{ph}}, I_{\mathrm{o}}, R_{\mathrm{s}}, R_{\mathrm{sh}}, a\right\} \end{cases} \tag{14}$$

III. DIFFERENTIAL EVOLUTION

Differential evolution (DE) is a reliable yet powerful function optimizer, and mainly contains four steps, *i.e.*, initialization, mutation, crossover, and selection to modify individuals during the search process. In what follows, we will give a brief overview of these steps in DE.

Before beginning, all individuals are generated randomly within the specified range and form the population. Subsequently, the differential mutation operator is applied to create the donor vector. Two commonly used mutation strategies are described below:

- "DE/rand/1"

$$v_i = x_{r1} + F \cdot (x_{r2} - x_{r3}) \tag{15}$$

- "DE/best/1"

$$v_i = x_{best} + F \cdot (x_{r2} - x_{r3}) \tag{16}$$

where r_1, r_2 and r_3 represent different random indices selected from the population, which are different from the base index i. F is the scale factor for controlling the difference vectors. x_{best} denotes the vector with best fitness value of current generation.

Next, the crossover operation takes place to generate the trial vectors. The trial vector u_i can be expressed as follows:

$$u_{i,j} = \begin{cases} v_{i,j}, & \text{if } \mathrm{rand}_j(0,1) \le CR(i) \text{ or } j = j_{rand} \\ x_{i,j}, & \text{otherwise} \end{cases} \tag{17}$$

where $CR(i) \in (0, 1)$ is the crossover rate. $\mathrm{rand}_j(0, 1)$ is a uniformly distributed random number within $[0, 1]$. $j_{rand} \in \{1, 2, \ldots, D\}$ is a random index. D is the number of decision variables.

Finally, greedy selection operation between the target and the trial vector is implemented:

$$x_i' = \begin{cases} u_i, & \text{if } f(u_i) \le f(x_i) \\ x_i, & \text{otherwise} \end{cases} \tag{18}$$

where $f(\cdot)$ is the objective function to be minimized.

IV. OUR APPROACH

In this section, the motivation of our approach is introduced firstly. Then, a reusing the successful difference vectors in differential evolution with adaptive mutation strategy, namely DVADE, is proposed to extract the parameters of PV models. The details of DVADE are described below.

A. MOTIVATION

In [37], the past difference vectors are reused to significantly improve the performance of DE. Since the stored difference vector is generated before the crossover operation, some information is lost in the difference vectors, which may lead to the deviation of the offspring from the promising region, resulting in low search efficiency. In addition, the parameters extraction of PV models is a multi-modal problem. Thus, how to balance between the exploration and exploitation of DE to obtain the extracted parameters quickly, accurately and reliably still needs further study. Taking into account these disadvantages, an improved differential evolution by reusing the successful individual vectors and employing adaptive mutation strategy is proposed, which is referred to as DVADE. First, the successful differential vector is proposed to generate the offspring, which avoids searching unpromising areas. Second, an adaptive mutation strategy is introduced to adopt different mutation operators at different stages of the evolutionary process to enhance the quality of the acquired optima. The core idea of DVADE is elucidated in the following subsection.

B. MODIFIED SUCCESSFUL DIFFERENCE VECTOR

In [37], a difference vector $\vec{\Delta} = x_{r2} - x_{r3}$ will be saved into the archive if it is adopted to generate a successful offspring. However, DE contains the operation of mutation and crossover. Therefore, such technique in [37] motivates us to preserve the difference vectors after crossover operation for enhancing search efficiency. A modified difference vector operation is calculated by Eq.(19):

$$\vec{\Delta} = x_i' - x_i, \quad \text{if } f(x_i') \leq f(x_i) \tag{19}$$

where x_i is the i-th individual in the current population. x_i' is the trial vector.

Compared with the difference vector proposed in [37], $\vec{\Delta}$ is obtained by subtracting x_i' from x_i in the vector sense. It is worth highlighting that trial vector include the individual information after mutation and crossover operation, and the difference vector obtained from it will record the previously successful search directions. Hence, reuse of these successful difference vectors will lead to the discovery of more feasible regions with a high probability in future generation.

C. ADAPTIVE MUTATION STRATEGY

In DE, the mutation strategy has a marked influence on the performance for dealing with different optimization problems. In other words, it is not suitable to adopt the same mutation for different problems. For this purpose, an adaptive mutation strategy is presented to select different mutation operations at different search stages to ensure the exploration and exploitation ability of DE.

Section III describes two commonly used mutation strategies, which have different features and are suitable to different search stages. For example, "DE/rand/1" has a strong exploration ability and should be used in the early stages. In addition, "DE/best/1" is beneficial to exploitation ability and the accuracy of estimated parameters, so it should be employed in the later stages. Adaptive mutation strategy is described as follows:

$$\text{mutation operation} = \begin{cases} \text{“DE/rand/1”}, & \text{if } \dfrac{NFE}{MAX\_NFE} \leq 0.5 \\ \text{“DE/best/1”}, & \text{otherwise} \end{cases} \tag{20}$$

where NFE is the number of function evaluation and MAX_NFE represents the maximum NFE.

From Eq. (20), the search stage is judged by the number of function evaluation, so different mutation operation can be selected in different stages. In the early stages, "DE/rand/1" bears the exploration capability and searches the entire area extensively, improving the population diversity. In the latter stages, adopting "DE/best/1" strategy to generate the offspring around the best individual to obtain the optima quickly, accurately and reliably, thus enhancing the exploitation capability of DE.

Algorithm 1 The Framework of DVADE

Input: Control parameters: NP, NFE, MAX_NFE
Output: The optimal solution
Set $NFE = 0$, $Iter = 1$ and the archive $\mathcal{A} = \varnothing$;
Randomly generate the population $\mathcal{P}$;
Evaluate the fitness of the population ;
$NFE = NFE + NP$;
while $NFE < MAX\_NFE$ **do**
  for $i = 1$ *to* NP **do**
    if $Iter < 2$ **then**
      Randomly select $r1, r2, r3 \in \{1, NP\}$, and $r1 \neq r2 \neq r3$;
      Generate a difference vector: $\vec{\Delta}_i = x_{r2} - x_{r3}$;
    end
    else
      Randomly select $r1 \in \{1, NP\}$;
      if $rand \leq 0.5$ **then**
        Randomly select difference vector $\vec{\Delta}_k$ from $\mathcal{A}$;
        $\vec{\Delta}_i = \vec{\Delta}_k$;
      end
      else
        Randomly select $r2, r3 \in \{1, NP\}$, and $r1 \neq r2 \neq r3$;
        Generate a difference vector: $\vec{\Delta}_i = x_{r2} - x_{r3}$;
      end
    end
    if $\frac{NFE}{MAX\_NFE} \leq 0.5$ **then**
      $v_i = x_{r1} + F * \vec{\Delta}_i$;
    end
    else
      $v_i = x_{best} + F * \vec{\Delta}$;
    end
    Generate the trial vector x_i' by using Eq.(17);
    if $f(x_i') \leq f(x_i)$ **then**
      $\vec{\Delta}_i = x_i' - x_i$;
      $\mathcal{A} = \mathcal{A} \cup \vec{\Delta}_i$;
      $x_i = x_i'$;
    end
  end
  $NFE = NFE + 1$;
  if $size(\mathcal{A}) \geq NP$ **then**
    Discard $size(\mathcal{A}) - NP$ difference vectors;
  end
end
return the best individual x_{best} from the final population.

D. THE FRAMEWORK OF DVADE

By incorporating the reusing successful difference vector and adaptive mutation strategy, the framework of DVADE is described in Algorithm 1, where NP is the population size; *NFE* and *MAX_NFE* represent the number of function evaluations and the maximal number of function evaluations, respectively.

In lines 2-4, the main work is to randomly generate population and estimate their fitness value, and update *NFE*. Subsequently, in lines 8-9, if $Iter < 2$, three indices are randomly selected and the difference vector is generated. In lines 11-17, if $rand \leq 0.5$, the difference vector is randomly selected from $\mathcal{A}$, otherwise it is formed from the current population. In lines 18-21, in the early stages, offspring is generated by utilizing Eq. (15), while utilizing Eq. (16) in the latter stages. In lines 23-26, suppose x_i' is better than x_i, the new difference vector is recorded and stored to the archive for reuse, which is the main difference from [37]. Line 27 is to update *NFE*. In lines 28-29, if the size of $\mathcal{A}$ exceed *NP*, $size(\mathcal{A}) - NP$ difference vectors will be discarded.

V. SIMULATION RESULTS AND ANALYSIS

In this section, the performance of DVADE is evaluated on parameters extraction of different PV models, *i.e.*, SDM, DDM, and SMM. The current-voltage data of SDM and DDM acquired from [7] is used in our experiment, which is measured on a 57 mm diameter commercial RTC France solar cell (under 1000 W/m^2 at 33 °C). The SMM contains three PV module models: Photowatt-PWP201, mono-crystalline STM6-40/36 and ploy-crystalline STP6-120/36, which consist of 36 cells in series. The data of Photowatt-PWP201 (under 1000 W/m^2 at 45 °C) is obtained from [7]. While the data of mono-crystalline STM6-40/36 acquired from [40] and ploy-crystalline STP6-120/36 acquired from [41], are measured at 51 °C and 55 °C, respectively. The parameter range of different PV models is adopted in [27].

For DVADE, the input parameter of *MAX_NFE* is equal to 10,000 for SDM and Photowatt-PWP201 module. *MAX_NFE* is 20,000 for DDM, while for STM6-40/36 and STP6-120/36 modules, *MAX_NFE* is set to be 15,000. Due to the expensive equipment, no practical experiments are carried out in this paper. Instead, Matlab2016b software is used to verify the performance of the algorithm. It is worth highlighting that each algorithm is carried out 30 independent runs and the experiments are performed on a desktop PC with Intel Core i7-7700 processor @ 3.6GHz, 8GB RAM, under the windows 10 64-bit OS.

To verify the superior performance of DVADE, seven well-established algorithms, including improved JAYA (IJAYA) [39], performance-guide JAYA (PGJAYA) [25], multiple learning backtracking search algorithm (MLBSA) [42], self-adaptive teaching-learning-based optimization (SATLBO) [19], generalized oppositional teaching learning based optimization (GOTLBO) [38], teaching-learning-based artificial bee colony (TLABC) [43], and improved teaching-learning-based optimization (ITLBO) [20], are selected for comparison. In addition, DE [30] is also selected to compare since our method is an improved DE variant. Table 1 lists related parameter settings of the compared algorithms.

TABLE 1. Parameter setting of compared algorithms.

Algorithm	Parameter setting
IJAYA	$NP = 20$
PGJAYA	$NP = 20$
MLBSA	$NP = 50$
SATLBO	$NP = 40$
GOTLBO	$NP = 50,\ Jumping\ rate\ J_r = 0.3$
TLABC	$NP = 50,\ limit = 200,\ F = rand(0,1)$
ITLBO	$NP = 50$
DE	$NP = 50,\ F = 0.5, CR = 0.9$
DVADE	$NP = 50,\ F = 0.5, CR = 0.9$

A. RESULTS ON THE SDM

First, five unknown parameters and RMSE results obtained by DVADE and other state-of-the-art algorithms in SDM are demonstrated in Table 2. The RMSE shows the accuracy of extracting the parameters. From Table 2, PGJAYA, MLBSA, SATLBO, TLABC, ITLBO and DVADE achieve the best RMSE (**9.8602E-04**), but DVADE consumes the least amount of computing resources (**10000**). In addition, although GOTLBO adopted the same computing resources, the RMSE result were worse than DVADE.

The estimated parameters of DVADE are utilized to draw the *I-V* characteristic curve. Figure 3(a) depicts the characteristic diagram of simulated data and the measured data. It is obvious that the simulated data obtained DVADE are in good agreement with the experimental data, which demonstrates the high estimation accuracy of the DVADE.

B. RESULTS ON THE DDM

The estimated parameters and RMSE results achieved by DVADE and other algorithms in DDM are listed in Table 3. Obviously, there are seven parameters to be estimated, so the parameter estimation of the DDM is more complex than the SDM. From Table 3, ITLBO and DVADE achieve the best RMSE value (**9.8248E-04**), but DVADE consumes the least computing resources (**20000**). MLBSA, PGJAYA, SATLBO, IJAYA, GOTLBO, DE and TLABC ranked 3-9 respectively. Thus, the results in Table 3 show that DVADE can still get the best results with less resource consumption.

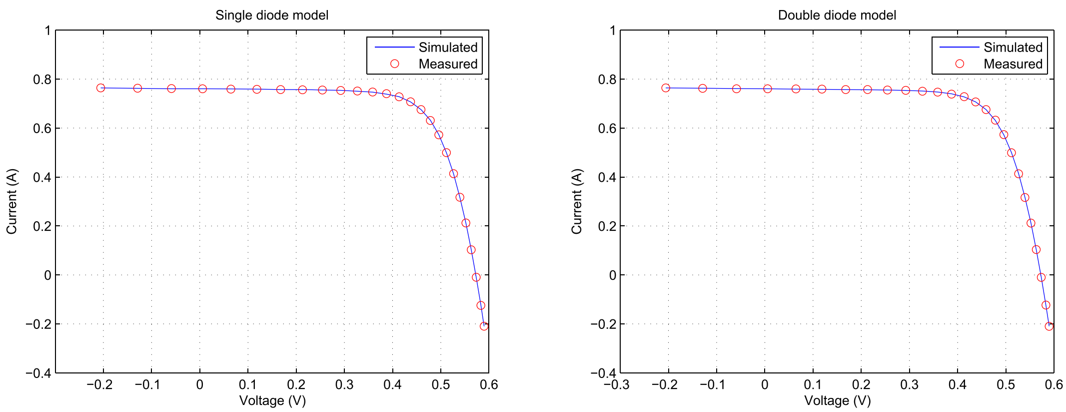
Figure 3(b) depicts the characteristic diagram of simulated data and the measured data of DDM. It is obvious that the simulated data from DVADE are highly in coincidence with the experimental data over the whole voltage range. The above results demonstrate that DVADE has also achieved high estimation accuracy in parameter extraction of the DDM.

C. RESULTS ON THE SMM

For the SMM, this section uses three different modules (Photowatt-PWP201, STM6-40/36 and STP6-120/36) to verify the performance of DVADE, and the relevant results are shown in Tables 4, 5, 6, respectively. From Table 4, all algorithm can obtain the best RMSE values (**2.4251E-03**), but DE and DVADE consume the least computing resources. For STM6-40/36, Table 5 shows that DVADE achieves the best

TABLE 2. Comparison of DVADE with other algorithms on SDM.

Algorithm	I_{ph} (A)	I_o (μA)	R_s (Ω)	R_{sh} (Ω)	a	RMSE	NFE
IJAYA	0.7608	0.3228	0.0364	53.7595	1.4811	9.8603E-03	50000
PGJAYA	0.7608	0.3230	0.0364	53.7185	1.4812	**9.8602E-04**	50000
MLBSA	0.7608	0.3230	0.0364	53.7185	1.4812	**9.8602E-04**	50000
SATLBO	0.7608	0.3232	0.0364	53.7256	1.4812	**9.8602E-04**	50000
GOTLBO	0.7608	0.3316	0.0363	54.1154	1.4838	9.8744E-04	10000
TLABC	0.7608	0.0323	0.0364	53.7164	1.4812	**9.8602E-04**	50000
ITLBO	0.7608	0.3230	0.0364	53.7185	1.4812	**9.8602E-04**	50000
DE	0.7608	0.3229	0.0364	53.7192	1.4812	9.8602E-04	50000
DVADE	0.7608	0.3230	0.0364	53.7185	1.4812	**9.8602E-04**	**10000**



(a) (b)

FIGURE 3. Comparison between the simulated and measured data obtained by DVADE: (a) SDM, (b) DDM.

TABLE 3. Comparison of DVADE with other algorithms on DDM.

Algorithm	I_{ph} (A)	I_{o_1} (μA)	R_s (Ω)	R_{sh} (Ω)	a_1	I_{o_2} (μA)	a_2	RMSE	NFE
IJAYA	0.7601	0.0050	0.0376	77.8519	1.2186	0.7509	1.6247	9.8293E-04	50000
PGJAYA	0.7608	0.2103	0.0368	55.8135	1.4450	0.8853	2.0000	9.8263E-04	50000
MLBSA	0.7608	0.2273	0.0367	55.4612	1.4515	0.7384	2.0000	9.8249E-04	50000
SATLBO	0.7608	0.2509	0.0366	55.1170	1.4598	0.5454	1.9994	9.8280E-04	50000
GOTLBO	0.7608	0.8002	0.0368	56.0753	2.0000	0.2205	1.4490	9.8318E-04	20000
TLABC	0.7608	0.4239	0.0367	54.6680	1.9075	0.2401	1.4567	9.8415E-04	50000
ITLBO	0.7608	0.2260	0.0367	55.4854	1.4510	0.7493	2.0000	**9.8248E-04**	50000
DE	0.7606	0.3696	0.0366	54.5069	1.9997	0.2719	1.4665	9.8347E-04	20000
DVADE	0.7608	0.2261	0.0367	55.4826	1.4511	0.7479	2.0000	**9.8248E-04**	**20000**

RMSE value (**1.7298E-03**) under the fewest number of fitness evaluation (NFE = 15000). Similarly, DVADE obtains the best RMSE value (**1.6601E-02**) in Table 6 under the least computing resources (NFE = 15000). Thus, DVADE obtains a very high estimation accuracy for SMM. Moreover, from Tables 4, 5, 6, PGJAYA, MLBSA, SATLBO, GOTLBO, TLABC, ITLBO can get the best RMSE results under more computing resources (NFE = 50000). This shows that the existing three models are simple, but also encourages us to adopt more complex models for evaluating the performance of the algorithms in the future.

Figure 4 illustrates the curves fitting results of SMM. The simulated data obtained by DVADE are also in quite good agreement with the measured data, regardless of the model. Hence, the above experiment results again shed light on the accuracy of the extracted parameters obtained by DVADE.

D. STATISTICAL RESULTS AND CONVERGENCE CURVE

Table 7 shows the statistical results including minimum (Min), maximum (Max), average accuracy (Mean), as well as the standard deviation (Std). The following conclusions can be drawn from Table 7:

- In terms of the Min of RMSE value, many algorithms obtained the best results for SDM, Photowatt-PWP201, STM6-40/36 and STP6-120/36, whereas ITLBO and DVADE achieved the best RMSE value (**9.8286E-04**) for DDM. These observations indicate that DVADE can obtain the best Min of RMSE value for these five different models. In addition, most of the comparison algorithms have poor results for parameter estimation in DDM, which demonstrates the complexity of the DDM model.
- In terms of the Max RMSE value, ITLBO and DVADE obtained the best RMSE value overall in

TABLE 4. Comparison of DVADE with other algorithms on Photowatt-PWP201.

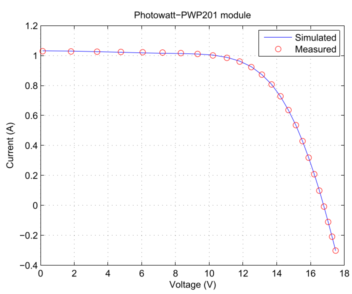
Algorithm	I_{ph} (A)	I_o (μA)	R_s (Ω)	R_{sh} (Ω)	a	RMSE	NFE
IJAYA	1.0305	3.4703	1.2016	977.3752	48.6298	**2.4251E-03**	50000
PGJAYA	1.0305	3.4818	1.2013	981.8545	48.6424	**2.4251E-03**	50000
MLBSA	1.0305	3.4823	1.2013	981.9823	48.6428	**2.4251E-03**	50000
SATLBO	1.0305	3.4827	1.2013	982.4038	48.6433	**2.4251E-03**	50000
GOTLBO	1.0305	3.4991	1.2008	989.6889	48.6611	**2.4251E-03**	50000
TLABC	1.0306	3.4715	1.2017	972.9357	48.6313	**2.4251E-03**	50000
ITLBO	1.0305	3.4823	1.2013	981.9823	48.6428	**2.4251E-03**	50000
DE	1.0305	3.4831	1.2013	981.9827	48.6428	**2.4251E-03**	**10000**
DVADE	1.0305	3.4823	1.2013	981.9824	48.6428	**2.4251E-03**	**10000**

TABLE 5. Comparison of DVADE with other algorithms on STM6-40/36.

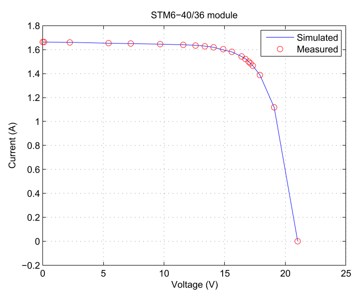
Algorithm	I_{ph} (A)	I_o (μA)	R_s (Ω)	R_{sh} (Ω)	a	RMSE	NFE
IJAYA	1.6637	1.8353	0.0040	15.9449	1.5263	1.7548E-03	50000
PGJAYA	1.6639	1.7389	0.0043	15.9290	1.5203	**1.7298E-03**	50000
MLBSA	1.6639	1.7387	0.0043	15.9283	1.5203	**1.7298E-03**	50000
SATLBO	1.6639	1.7387	0.0043	15.9283	1.5203	**1.7298E-03**	50000
GOTLBO	1.6639	1.7387	0.0043	15.9283	1.5203	**1.7298E-03**	50000
TLABC	1.6639	1.7387	0.0043	15.9283	1.5203	**1.7298E-03**	50000
ITLBO	1.6639	1.7387	0.0043	15.9283	1.5203	**1.7298E-03**	50000
DE	1.6626	3.0768	0.0024	19.3247	1.5858	2.1965E-03	15000
DVADE	1.6639	1.7387	0.0043	15.9283	1.5203	**1.7298E-03**	**15000**

TABLE 6. Comparison of DVADE with other algorithms on STP6-120/36.

Algorithm	I_{ph} (A)	I_o (μA)	R_s (Ω)	R_{sh} (Ω)	a	RMSE	NFE
IJAYA	7.4672	2.2536	0.0046	27.5925	1.2571	1.6731E-02	50000
PGJAYA	7.4725	0.0000	0.0046	22.2184	1.2601	**1.6601E-02**	50000
MLBSA	7.4725	2.3350	0.0046	22.2199	1.2601	**1.6601E-02**	50000
SATLBO	7.4725	2.3350	0.0046	22.2199	1.2601	**1.6601E-02**	50000
GOTLBO	7.4725	2.3350	0.0046	22.2199	1.2601	**1.6601E-02**	50000
TLABC	7.4725	2.3349	0.0046	22.2117	1.2601	**1.6601E-02**	50000
ITLBO	7.4725	2.3350	0.0046	22.2199	1.2601	**1.6601E-02**	50000
DE	7.4711	4.2598	0.0043	1304.8044	1.3125	1.8704E-02	15000
DVADE	7.4725	2.3350	0.0046	22.2199	1.2601	**1.6601E-02**	**15000**



(a)



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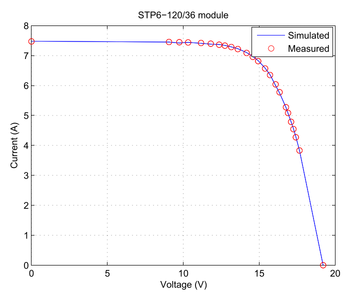


(c)

FIGURE 4. Comparison between the simulated measured data obtained by DVADE: (a) Photowatt-PWP201, (b) STM6-40/36, (c) STP6-120/36.

different models. Moreover, in regard to the Mean RMSE value, PGJAYA, MLBSA, ITLBO and DVADE achieved the best RMSE value in the five different models.

- With respect to Std of RMSE value, ITLBO and DVADE obtained the best RMSE value overall in different models, but ITLBO consumed more computing resources.
- In regard to CPU time, DE consumed the least operation time among all comparison algorithms, but obtained the poor results. Instead, DVADE consumed the second least operation time and achieved the best Std of RMSE value in different models.

From the above analysis results, it can be seen that under the premise of spending running time, the proposed algorithm (DVADE) has obtained superior results in five different models.

For further investigating the performance of these algorithms, the convergence curves of the comparison algorithms are plotted in Figure 5. The proposed DVADE has faster

TABLE 7. The statistical results of SDM, DDM, and SMM.

Model	Algorithm	RMSE				CPU time (s)
		Min	Max	Mean	Std	-
SDM	IJAYA	9.8603E-04	1.0622E-03	9.9204E-04	1.40E-05	397.83
	PGJAYA	**9.8602E-04**	9.8603E-04	**9.8602E-04**	1.45E-09	4.41
	MLBSA	**9.8602E-04**	**9.8602E-04**	**9.8602E-04**	9.15E-12	397.39
	SATLBO	**9.8602E-04**	9.9494E-04	9.8780E-04	2.30E-06	4.95
	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**	**2.79E-17**	5.95
	DE	9.8660E-04	1.4291E-03	1.1184E-03	1.25E-04	**1.55**
	DVADE	**9.8602E-04**	**9.8602E-04**	**9.8602E-04**	**5.16E-17**	1.77
DDM	IJAYA	9.8293E-04	1.4055E-03	1.0269E-03	9.83E-05	393.60
	PGJAYA	9.8263E-04	9.9499E-04	9.8582E-04	2.54E-06	4.84
	MLBSA	9.8249E-04	9.8798E-04	9.8518E-04	1.35E-06	401.25
	SATLBO	9.8280E-04	1.0470E-03	9.9811E-04	1.95E-05	5.70
	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**	9.8807E-04	9.8448E-04	1.59E-06	6.60
	DE	9.8315E-04	1.2171E-03	1.0136E-03	6.28E-05	**2.81**
	DVADE	**9.8286E-04**	**9.8604E-04**	**9.8425E-04**	**1.03E-06**	3.69
Photowatt-PWP201	IJAYA	**2.4251E-03**	2.4393E-03	2.4289E-03	3.78E-06	385.56
	PGJAYA	**2.4251E-03**	2.4268E-03	**2.4251E-03**	3.07E-07	4.33
	MLBSA	**2.4251E-03**	2.4253E-03	**2.4251E-03**	4.34E-08	397.53
	SATLBO	**2.4251E-03**	2.4291E-03	2.4254E-03	7.41E-07	4.87
	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**	**1.20E-17**	5.83
	DE	**2.4251E-03**	2.4295E-03	2.4253E-03	9.49E-07	**1.35**
	DVADE	**2.4251E-03**	**2.4251E-03**	**2.4251E-03**	**5.52E-17**	1.76
STM6-40/36	IJAYA	1.7548E-03	2.5223E-03	1.9305E-03	1.91E-04	350.14
	PGJAYA	**1.7298E-03**	1.7302E-03	**1.7298E-03**	7.82E-08	4.15
	MLBSA	**1.7298E-03**	1.7851E-03	1.7382E-03	1.45E-05	366.53
	SATLBO	**1.7298E-03**	1.7299E-03	**1.7298E-03**	1.22E-08	4.74
	GOTLBO	**1.7298E-03**	1.1244E-02	4.2347E-03	2.68E-03	4.49
	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**	**7.13E-18**	5.55
	DE	2.2054E-03	3.3817E-03	2.8855E-03	2.64E-04	**1.86**
	DVADE	**1.7298E-03**	**1.7298E-03**	**1.7298E-03**	**9.05E-18**	2.55
STP6-120/36	IJAYA	1.6731E-02	1.7304E-02	1.6891E-02	1.12E-04	365.12
	PGJAYA	**1.6601E-02**	1.6611E-02	1.6602E-02	2.57E-06	4.34
	MLBSA	**1.6601E-02**	1.8269E-02	1.6731E-02	3.01E-04	388.09
	SATLBO	**1.6601E-02**	**1.6601E-02**	**1.6601E-02**	2.02E-09	4.98
	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**	**8.44E-17**	5.79
	DE	2.0793E-02	4.1024E-02	2.9457E-02	5.43E-03	**1.94**
	DVADE	**1.6601E-02**	**1.6601E-02**	**1.6601E-02**	**2.03E-16**	2.61

convergence speed than all the other algorithms SDM, DDM, STM6-40/36 and STP6-120/36 models.

Moreover, in order to demonstrate the distribution of results acquired by different algorithms in 30 independent runs, the boxplot of different PV models is shown in Figure 6. It can be observed that the proposed DVADE exhibits the best performance compared with other compared algorithms in terms of robustness.

E. RESULTS ON SURVEY EXPERIMENTAL DATA

In the previous experiments, the validity and robustness of DVADE for extracting parameters of different PV modules have been verified. In this subsection, DVADE was adopted to identify the parameters of both models (SDM and DDM) of the Sharp ND-R250A5 PV module to further estimate the practicability and reliability.

The experiment data are obtained from three diverse operating conditions: $924W/m^2$ at 68 °C, $747W/m^2$ at 67 °C, and $544W/m^2$ at 53 °C. The range of parameters are given as: $I_{ph} \in [0, 10]$ (A), $I_o, I_{o1}, I_{o2} \in [1E-12, 1E-05]$ (A), $n, n_1, n_2 \in [0.5, 2.5]$, $R_s \in [0.001, 2]$ (Ω), and $R_{sh} \in [0, 5000]$ (Ω). According to Eq.(12) and (13), there are five and seven unknown parameters to be extracted, respectively.

The optimal extracted parameter for SDM and DDM of the Sharp ND-R250A5 under different operating conditions are presented in Table 8 and 9. The algorithm was carried out 30 independent runs and MAX_NFE is set to be 15,000. Additionally, to demonstrate the accuracy of the

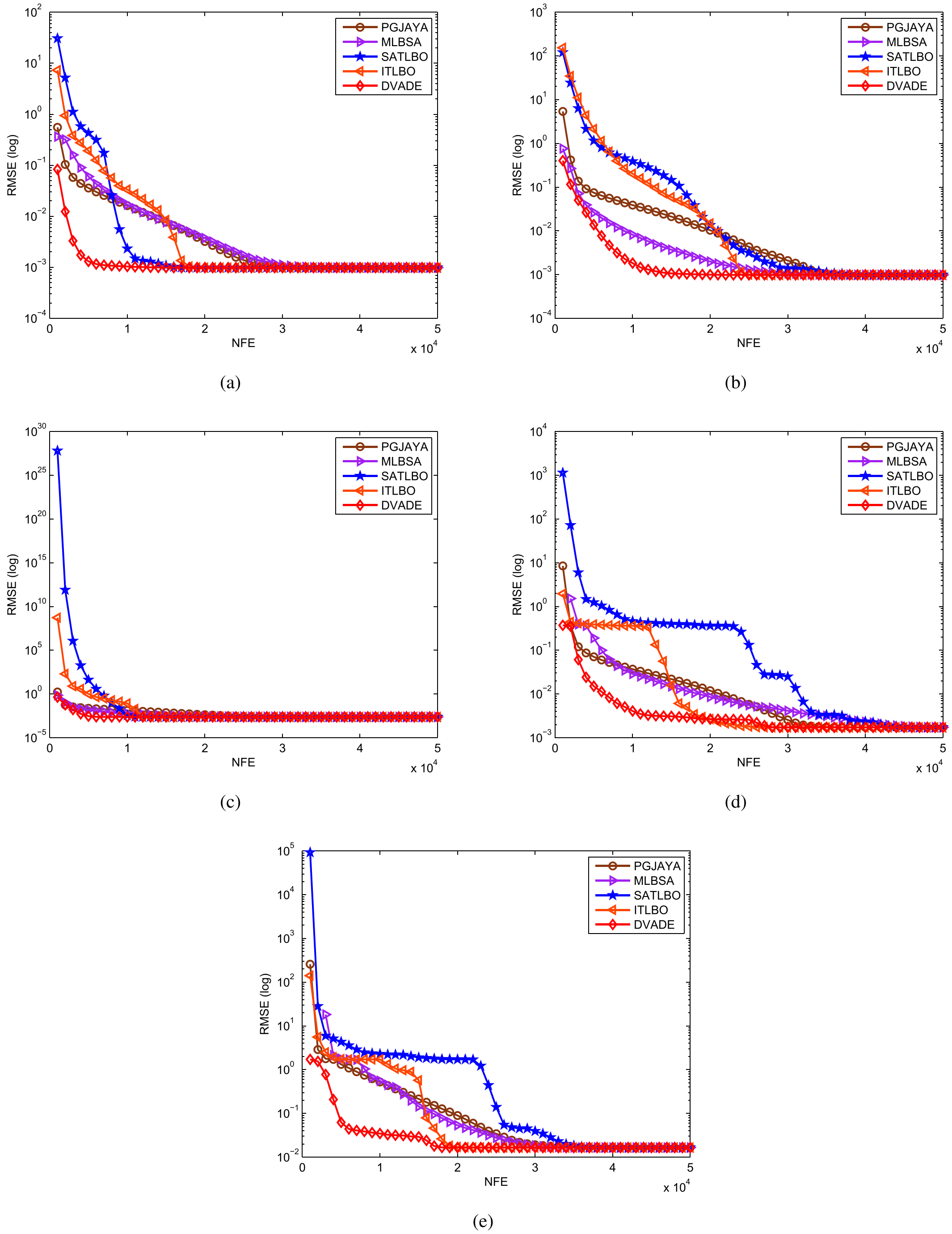


FIGURE 5. Convergence curves of different algorithms on PV models: (a) SDM, (b) DDM, (c) Photowatt-PWP201, (d) STM6-40/36, (e) STP6-120/36.

extracted parameters, Figure 7 plots the $I-V$ characteristics from the extracted parameters for three operating conditions with the SDM and DDM.

As shown in Tables 8 and 9, DVADE obtained the low RMSE values at three operating conditions, which indicated that the proposed algorithm can accurately extract the unknown parameters regardless of irradiance and temperature levels. From Figure 7, the $I-V$ characteristics achieved from the extracted optimal parameters are in good agreement with the experimental data regardless of irradiance

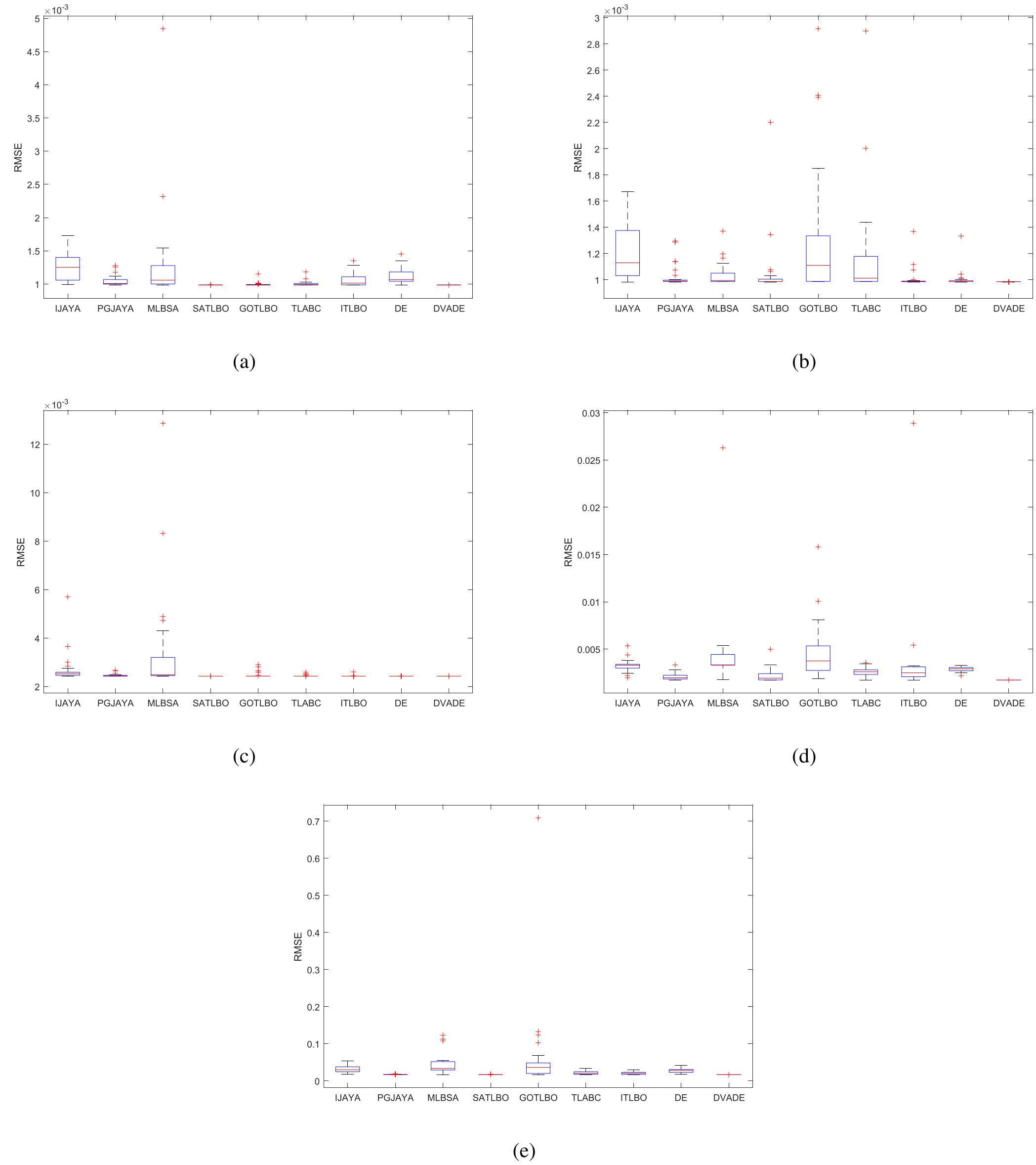


FIGURE 6. Boxplot of best RMSE over 30 runs of different algorithm for different PV models: (a) SDM, (b) DDM, (c) Photowatt-PWP201, (d) STM6-40/36, (e) STP6-120/36.

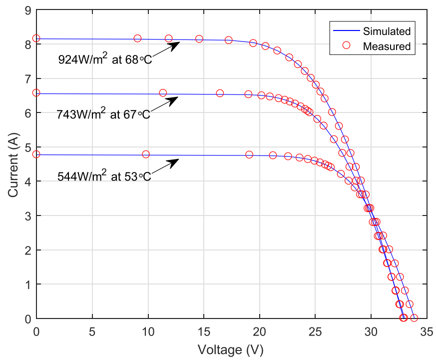
TABLE 8. Estimated optimal parameters and RMSE values for different operating conditions with SDM (Sharp ND-R250A5).

Operating conditions	I_{ph} (A)	I_o (μA)	R_s (Ω)	R_{sh} (Ω)	a	RMSE
$924W/m^2$ at 68 °C	8.1547	1.7649E-06	0.5849	5000	1.2154	1.1031E-02
$743W/m^2$ at 67 °C	6.5664	2.7092E-07	0.6212	5000	1.1054	1.2854E-02
$544W/m^2$ at 53 °C	4.7736	7.8378E-08	0.6054	5000	1.122	6.7698E-03

TABLE 9. Estimated optimal parameters and RMSE values for different operating conditions with DDM (Sharp ND-R250A5).

Operating conditions	I_{ph} (A)	I_{o_1} (μA)	R_s (Ω)	R_{sh} (Ω)	a_1	I_{o_2} (μA)	a_2	RMSE
$924W/m^2$ at 68 °C	8.1547	1.0000E-12	0.5849	5000	1.5232	1.7649E-06	1.2154	1.1031E-02
$743W/m^2$ at 67 °C	6.5667	2.4484E-07	0.6214	5000	1.1021	3.2004E-08	1.1648	1.2854E-02
$544W/m^2$ at 53 °C	4.7736	7.5613E-08	0.6055	5000	1.1211	3.0382E-09	1.1611	6.7993E-03

and temperature levels. In summary, the proposed DVADE can identify the optimal parameters of PV models at diverse irradiation and temperature levels and can be considered as an alternative technique for parameters estimation of PV models.



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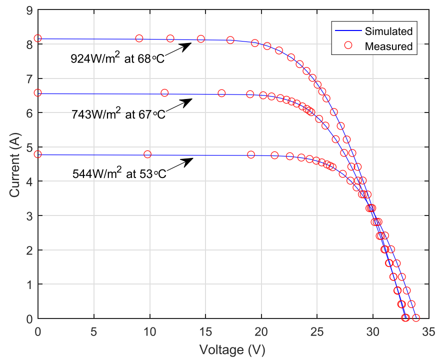

(b)

FIGURE 7. Comparison between the measured and simulated data obtained by DVADE at different operating conditions for SDM and DDM: (a) SDM, (b) DDM.

VI. CONCLUSION

In this paper, a reusing the successful difference vectors in differential evolution with adaptive mutation strategy (DVADE) is proposed to extract the unknown parameters of different PV models. In DVADE, reuse of the past difference vectors can generate the promising individual and markedly improve the performance of differential evolution. Additionally, to make a trade-off between exploration and exploitation, an adaptive mutation strategy is used. ''DE/rand/1'' is used to enhance the exploration ability in the early stages while ''DE/best/1'' is employed at a later stage to improve the accuracy of parameters. To evaluate the performance of the proposed algorithm, five PV models, *i.e.*, the single diode model, the double diode model and three PV panel models are selected as test suite. In addition, it is also tested on a survey experimental data measured at different operating conditions. The simulation results achieved by DVADE are compared with eight state-of-art algorithms. From the comparison results, DVADE shows prominent performance in terms of accuracy, convergence and reliability. Hence, the proposed DVADE can be considered as an effective alternative to extract the parameters of PV models.

In the future, adaptive selection of difference vectors should be designed to improve the efficiency of the algorithm. In addition, DVADE algorithm will be used to solve more complex PV model parameter extraction problem.

The source code used in this paper can be obtained from the authors upon request.

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