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Parameters extraction of solar cell models using a modified simplified swarm optimization algorithm

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The parameters of solar cells models have an effect on the simulation of solar cells and can be applied to monitor the working condition and diagnose potential faults for photovoltaic (PV) modules in a PV system. To accurately and efficiently extract the optimal parameters of solar cells in a limited CPU run time, a modified simplified swarm optimization (MSSO) algorithm is presented for the single diode and double diode models by minimizing the least square error between the calculated and experimental data. In MSSO, a new one-variable-update mechanism and survival-of-the-fittest policy are applied to enhance the ability of traditional SSO. To investigate the performance of MSSO, comparative studies with other well-known optimization algorithms, i.e., SSO, artificial bee colony (ABC) and simplified bird mating optimizer (SBMO), are presented, and extensive computational results are shown. The statistical data indicate that the MSSO method has the best performance among these methods in terms of efficiency, robustness and accuracy. Moreover, the current vs. voltage characteristics of the parameters extracted by MSSO coincide well with those of experimental data.

1. Introduction

In recent years, environmental protection has been increasingly concerned worldwide, leading to broad pursuit and investigation of new energy and clean fuel technologies (Singh, 2013). Solar energy is one of the desirable solutions with many advantages. Solar energy systems are non-polluting, safe, quiet and easy to be installed, and they can be constructed quickly (Xu et al., 2011). To evaluate the capacity and maximize the ability of a photovoltaic (PV) system before installation, a reliable and efficient PV simulator is required (Alam et al., 2015). As the most important part of PV simulator, the solar cell models should be set up first and the quality of the model affects the performance of the simulator directly. Additionally, for a PV system in operation, the parameters of solar cell can be applied to monitor the working condition and diagnose potential faults of PV modules (Bastidas-Rodriguez et al., 2015; Tina et al., 2016; Wang et al., 2016;).

The modeling of solar cells contains three main steps: selection of appropriate equivalent models, mathematical model formulation and accurate extraction of parameters values from the models (Oliva et al., 2014). Although several solar cell models have been proposed over the years, the single diode model (SDM) and the double diode model (DDM) are the most common equivalent electronic circuit models in practice. Since the current equations of solar cells models are implicit transcendental equations, which are difficult to be explicitly solved by conventional elementary functions. Therefore, in order to obtain a good approximation to the measured data acquired from a true solar cell, a feasible optimization method should be employed to estimate the parameters of solar cell models (Askarzadeh and Rezazadeh, 2012a).

Recently, various approaches have been presented for the optimal parameters extraction of solar cells models. These approaches can be divided into three types: analytical methods, numerical methods and soft-computing algorithms. Analytical methods are generally formulated by applying elementary functions (Chan et al., 1986; Chan and Phang, 1987; Lun et al., 2013; Saleem and Karmalkar, 2009), or the Lambert W-function (LW) (Jain and Kapoor, 2004; Jain et al., 2006; Zhang et al., 2011), they can work with not only a limited set of points, but also with a complete dataset. Despite the simplicity and relatively little time cost of analytical methods, the accuracy of analytical solutions is susceptible to

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measurement noise of the selected points. Moreover, analytical approaches often need to make approximations, which may also reduce accuracy (Ishaque et al., 2012). Numerical methods usually use non-linear optimization techniques, such as Newton-Raphson methods (NRM) (Easwarakhanthan et al., 1986), conductivity method (CM) (Chegaar et al., 2001) or the Levenberg–Marquardt (LM) algorithm (Ma et al., 2014) to obtain the parameters. These approaches, which need continuity, convexity and differentiability conditions for being applicable, are sensitive to the initial parameter values selected and easily trapped into local optima. The solar cell models parameters extraction problem is non-linear, multivariable and multi-modal, and it has numerous local optima (Gong and Cai, 2013). These characteristics make soft computing algorithms attractive due to their global search capability, such as genetic algorithm (GA) (Jervase et al., 2001; Zagrouba et al., 2010), particle swarm optimization (PSO) (Ye et al., 2009; Wei et al., 2011), simulated annealing (SA) (El-Naggar et al., 2012; Dkhichi et al., 2014), pattern search(PS) (AlHajri et al., 2012), cuckoo search(CS) (Ma et al., 2013), artificial bee swarm optimization(ABSO) (Askarzadeh and Rezazadeh, 2013a), harmony search (HS) (Askarzadeh and Rezazadeh, 2012a), differential evolution (DE) (Ishaque and Salam, 2011; Ishaque et al., 2012; Gong and Cai, 2013), artificial bee colony(ABC) (Oliva et al., 2014), and bird mating optimizer (BMO) (Askarzadeh and Rezazadeh, 2012b, 2013b; Askarzadeh et al., 2015). The results on the well-known solar cell benchmark prove that most of the soft computing algorithms have achieved better results than those of analytical approaches or numerical methods (Chan et al., 1986; Easwarakhanthan et al., 1986; Chegaar et al., 2001; Jervase et al., 2001; Wei et al., 2011; Zhang et al., 2011; Askarzadeh and Rezazadeh, 2012a, 2012b; Askarzadeh and Rezazadeh, 2013a; Dkhichi et al., 2014; Oliva et al., 2014; Askarzadeh et al., 2015).

However, the complex update mechanism (UM) of some aforementioned soft computing algorithms may increase computation cost for parameters extraction. For instance, PSO requires computing both the velocity and position equations for each solution, GA requires operating roulette wheel selection, ABC may calculate more than one fitness function at the step of onlookers, and SBMO needs ranking solutions in every generation. Additionally, updating mechanisms for most soft computing algorithms usually update all variables of each solution in every generation, which leads to efficiency loss. Furthermore, due to the large amount of PV modules in PV power station, it is much more convenient and flexible to adopt an embedded processor based circuit to extract the parameters in real time. However, the computation resource of embedded processor, e.g., advanced RISC machines (ARM), is quite limited, which leads to the high requirement of the computation efficiency of the algorithm. Hence, there is always a need for more efficiency and flexibility in soft computing algorithms for the solar cell models parameters extraction problem.

Simplified swarm optimization (SSO) is a rising population-based stochastic optimization algorithm, which was originally proposed by Yeh (2009). The SSO has a simple update mechanism and a flexible architecture. The results demonstrate that SSO has better performance than PSO, GA, EDA, ANN and ABC. Moreover, to address many optimization problems, SSO has proven its effectiveness in a number of optimization problems (Yeh, 2009, 2012a, 2012b, 2012c, 2013, 2015; Yeh and Lai, 2015; Chung and Wahid, 2012; Azizipanah-Abarghooee et al., 2013; Azizipanah-Abarghooee, 2013; Huang, 2015). Therefore, an alternative parameter extraction method using a modified simplified swarm optimization (MSSO) algorithm is proposed. A new one-variable-update mechanism and survival-of-the-fittest policy are applied to strengthen the effectiveness of the traditional SSO. Moreover, from the results, ABC and SBMO have excellent performance in solar cell models parameters extraction problem (Oliva et al., 2014; Askarzadeh et al., 2015). Hence, to verify the performance of MSSO, ABC, SBMO and the conventional SSO are selected to make comparisons in detail.

2. Problem formulation

The most popular equivalent models of solar cells are SDM and DDM, which are illustrated in Fig. 1. The parameters in the both models are the photocurrent (I_{ph}), diode current (I_D for SDM, I_{D1} and I_{D2} for DDM), diode ideality factors (n for SDM, n_1 and n_2 for DDM), and series (R_s) and shunt resistances (R_{sh}). Therefore, there are five parameters in the SDM and seven parameters in the DDM that should be extracted.

2.1. Single diode model

The single diode model for a solar cell is shown in Fig. 1(a). According to Kirchhoff's current law, the cell output current, I, can be calculated as:

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

where I_{ph}, I_D, and I_{sh} denote the photo-generated current, diode current and shunt resistance current, respectively. In addition, based on the Shockley equation, I_D is computed as:

$$I_D = I_{sd}\left[\exp\left(\frac{q(V + I \cdot R_s)}{n \cdot k \cdot T}\right) - 1\right] \tag{2}$$

where I_{sd} is the reverse saturation current, V is the solar cell output voltage, R_s is the series resistance, n is the diode ideality factor, k denotes Boltzmann's constant (1.380×10^{-23} J/K), q denotes the electronic charge (1.602×10^{-19} C) and T denotes the cell absolute temperature.

Moreover, the shunt resistance current, I_{sh}, is calculated using Eq. (3).

$$I_{sh} = \frac{V + I \cdot R_s}{R_{sh}} \tag{3}$$

where R_{sh} is the shunt resistance. By substituting from Eq. (2) and (3) into Eq. (1), the solar cell output current can be rewritten as follows:

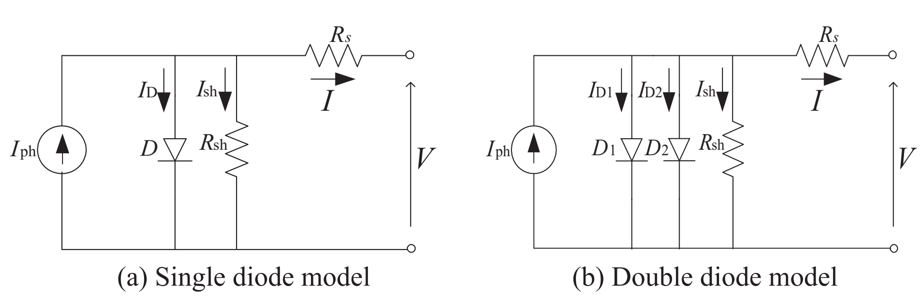


Fig. 1. Two equivalent models for a solar cell.

$$I = I_{ph} - I_{sd}\left[\exp\left(\frac{q(V + I \cdot R_s)}{n \cdot k \cdot T}\right) - 1\right] - \frac{V + I \cdot R_s}{R_{sh}} \tag{4}$$

Therefore, the parameter set to be extracted in SDM is ($I_{\rm ph}$, $I_{\rm sd}$, n, $R_{\rm s}$ and $R_{\rm sh}$).

2.2. Double diode model

Fig. 1(b) presents the double diode model for a solar cell. Using Kirchhoff's current law and Shockley equation, the output current of the DDM is calculated using Eq. (5):

$$\begin{aligned} I = I_{\rm ph} - I_{\rm sd1}\left[\exp\left(\frac{q(V + I \cdot R_{\rm s})}{n_1 \cdot k \cdot T}\right) - 1\right] \\ - I_{\rm sd2}\left[\exp\left(\frac{q(V + I \cdot R_{\rm s})}{n_2 \cdot k \cdot T}\right) - 1\right] - \frac{V + I \cdot R_{\rm s}}{R_{\rm sh}} \end{aligned} \tag{5}$$

where $I_{\rm sd1}$ and $I_{\rm sd2}$ are the diffusion and saturation currents, respectively, and n_1 and n_2 are the diode ideality factors. The other terms are introduced in Section 2.1. The DDM consists of seven unknown parameters, i.e., $I_{\rm ph}$, $I_{\rm sd1}$, $I_{\rm sd2}$, n_1, n_2, $R_{\rm s}$ and $R_{\rm sh}$.

2.3. Formulation of solar cells parameters extraction

The parameters extraction problem can be solved via an optimization approach. The proposed optimization algorithm is applied to minimize a pre-defined objective function value by tuning the parameters until the stopping criterion is reached. The optimal objective function then yields the optimal parameters values.

An appropriate objective function must be defined before the optimization procedure. In this study, the root mean square error (RMSE) is adopted to define the objective function. The RMSE is formulated as follows:

$$RMSE = \sqrt{\frac{1}{N}\sum\nolimits_{i=1}^{N}(f(V_e, I_e, x)^2)} \tag{6}$$

where $f_i(V_e, I_e, x)$ is the error function, which denotes the error between the experimental data and estimated values. N expresses the number of measured data points. The error function is given by Eq. (7) and Eq. (8) for SDM and DDM, respectively.

$$\begin{aligned} f(V_e, I_e, x) = I_e \\ - \left\{I_{ph} - I_{sd}\left[\exp\left(\frac{q(V_e + I_e \cdot R_s)}{n \cdot k \cdot T}\right) - 1\right] - \frac{V_e + I_e \cdot R_s}{R_{sh}}\right\} \end{aligned} \tag{7}$$

$$\begin{aligned} f(V_e, I_e, x) = I_e - \left\{I_{\rm ph} - I_{\rm sd1}\left[\exp\left(\frac{q(V_e + I_e \cdot R_{\rm s})}{n_1 \cdot k \cdot T}\right) - 1\right] \right. \\ \left. - I_{\rm sd2}\left[\exp\left(\frac{q(V_e + I_e \cdot R_{\rm s})}{n_2 \cdot k \cdot T}\right) - 1\right] - \frac{V + I \cdot R_{\rm s}}{R_{\rm sh}}\right\} \end{aligned} \tag{8}$$

In the above error functions, $V_{\rm e}$ and $I_{\rm e}$ are the experimental values of the voltage and current of the solar cell, respectively; x denotes the vector of unknown parameters. Therefore, x = ($I_{\rm ph}$, $I_{\rm sd}$, n, $R_{\rm s}$ and $R_{\rm sh}$) for SDM and x = ($I_{\rm ph}$, $I_{\rm sd1}$, $I_{\rm sd2}$, n_1, n_2, $R_{\rm s}$ and $R_{\rm sh}$) for DDM.

3. The SSO and proposed MSSO

An overview of SSO and the one-variable-update mechanism of the MSSO are discussed in detail in this section. Moreover, the detailed steps of MSSO are also presented.

3.1. The SSO

SSO is a new optimization method and can be categorized as swarm intelligence or evolutionary computing algorithm, which are two popular research topics in soft computing. From various large-scale NP-hard optimization applications, SSO had proved its ability to obtain good-quality solutions within a reasonable time (Yeh, 2012b, 2012c, 2013, 2015; Yeh and Lai, 2015). The update mechanism of SSO is described as follows:

Let $N_{\rm P}$ and $N_{\rm var}$ be the size of populations and variables, respectively; let $X_i = (x_{i,1}, x_{i,2}, \ldots, x_{i,\,N\rm var})$ be the ith population, and $x_{i,j}$ be the jth variable of X_i; let $P_i = (p_{i,1}, p_{i,2}, \ldots, p_{i,N\rm var})$ be the best ith solution in the evaluation history and $G = (g_1, g_2, \ldots, g_{N\rm var})$ be the best solution among all P_i. Assume c_w, c_p, c_g and c_r be the given probabilities of current variable value will be update to the same value (i.e., no change), P_i, G, and a new regenerated random feasible value, respectively. In each generation, SSO updates all variables in each solution by the following equations:

$$x_{i,j} = \begin{cases} x_{i,j} & \text{if } \rho \in [0, C_w = c_w) \\ p_{i,j} & \text{if } \rho \in [C_w, C_p = C_w + c_p) \\ g_j & \text{if } \rho \in [C_p, C_g = C_p + c_g) \\ x & \text{if } \rho \in [C_g, C_g + c_r = 1) \end{cases} \tag{9}$$

where $c_w + c_p + c_g + c_r = 1$, ρ is a random variable generated from [0, 1], $i = 1, 2, \ldots, N_{\rm sol}$, $j = 1, 2, \ldots, N_{\rm var}$, and x is a new regenerated random feasible value.

The SSO is flexible and can be integrated with any other update mechanism and is efficient without needing tedious or complex calculations, which makes it appropriate to various problems.

3.2. The MSSO

From the update mechanism listed in Eq. (9), the SSO is more suitable for limited data values, e.g., discrete data. To make the SSO more applicable to the continuous variables in the solar cell models parameters extraction problem, the MSSO is proposed. In MSSO, a one-variable-update mechanism is proposed to replace the UM of SSO, with only one random variable of a solution being updated at each generation. Assuming k is one random variable and $k \in [1, 2, \ldots, N_{\rm var}]$, the Eq. (9) is revised as follows:

$$x_{i,k} = \begin{cases} x_{i,k} + \rho_1 \cdot \rho_2 \cdot w \cdot x_{i,k} & \textit{if } k = gBest \\ x_{i,k} + \rho_1 \cdot \rho_2 \cdot w \cdot u_k & \textit{if } \rho_1 \in [0, C_w) \textit{ and } k \neq gBest \\ x_{i,k} + \rho_2 \cdot (x_{gBest,k} - x_{i,k}) & \textit{if } \rho_1 \in [C_w, C_g) \textit{ and } k \neq gBest \\ x_k & \textit{if } \rho_1 \in [C_g, 1) \textit{ and } k \neq gBest \end{cases} \tag{10}$$

where ρ_1 and ρ_2 are random numbers generated from the uniform distribution within [0, 1] and [−0.5, 0.5], respectively; $w = (2 \cdot N_{\rm var})^{-1}$, $u_k = x_k^{\max} - x_k^{\min}$, where $x_k^{\max}$ and $x_k^{\min}$ are the upper bound and lower bound of the kth variable, x_k is one variable of a random feasible value, and C_w and C_g are the predefined probability coefficients.

Compared with the traditional SSO, MSSO removes all *pBests* from Eq. (9) and improves the all variables update mechanism. MSSO divided the variables into two types, i.e., g*Best* and not g*Best*. First, for the g*Best*, the parthenogenesis strategy is adopted to enhance the exploration of the g*Best*, i.e., the first subitem in Eq. (10). The parthenogenesis is a well-known type of the reproduction in nature and has been applied in some evolutionary algorithms (Askarzadeh et al., 2015; Barukčić et al., 2010; Wu and Wang, 2013); Second, in the second subitem of Eq. (10), according to the C_w, a random variable is updated to its neighbor; Third, a random variable is updated from the interval between itself and g*Best* based on C_g. In addition, random movement is utilized to generate a new random variable, which may result in more exploration, i.e., the fourth subitem in Eq. (10). Moreover, in the traditional SSO, the new updated solution replaces the old one even if the new one is worse. Hence, the survival of the fittest policy is applied to ensure that only a better updated variable can replace the old one.

The pseudocode steps of MSSO are presented as follows:

STEP0. Generate $X_i = (x_{i,1}, x_{i,2}, \ldots, x_{i,\mathrm{Nvar}})$ randomly, calculate the fitness $F(X_i)$ based on Eqs. (6)–(8) as discussed in Section 2.3, and find $gBest \in \{1, 2, \ldots, \mathrm{Nsol}\}$ such that $F(X_{gBest}) \leqslant F(X_i)$, where $i = 1, 2, \ldots, \mathrm{Nsol}$.
STEP1. Let $i = 1$.
STEP2. Let $F^* = F(X_i)$, generate a random number $k \in [1, 2, \ldots, N\mathrm{var}]$, let $x_{i,k}^* = x_{i,k}$, and update $x_{i,k}$ based on Eqs. (10) and calculate $F(X_i)$.
STEP3. If $F(X_i) > F^*$, then let $x_{i,k} = x_{i,k}^*$ and $F(X_i) = F^*$ and go to STEP 5.
STEP4. If $F(X_i) < F(X_{gBest})$, then let $gBest = i$.
STEP5. If CPU time is met, then halt and X_{gBest} is the final solution;
STEP6. If $i < N\mathrm{sol}$, then let $i = i + 1$ and go to STEP 2. Otherwise, go to STEP 1.

4. Results and discussion

In this section, several soft computing algorithms are selected to evaluate the performance of MSSO for parameters extraction problem in detail. As originally proposed by Karaboga (2005), ABC is one of the well-known swarm-based algorithms that is based on the particular intelligent behavior of honeybee swarms. BMO is originally proposed by Askarzadeh, and inspired by the mating strategies of bird species (Askarzadeh and Rezazadeh, 2012a, 2012b, 2013a, 2013b). SBMO simplifies BMO by eliminating complicated task for tuning parameters and also improves some rules (Askarzadeh et al., 2015). Previous studies show that ABC and SBMO have excellent performance in the solar cell models parameters extraction problem (Oliva et al., 2014; Askarzadeh et al., 2015). Therefore, ABC, SBMO and SSO are selected to be compared with the proposed approach in detail on a solar cell benchmark. In addition, the MSSO is applied for parameters extraction of an industrial 6″ passivated emitter and rear cell (PERC cell) to further validate its effectiveness.

4.1. The experimental conditions for benchmark

The I–V characteristics of a 57-mm diameter commercial (R.T.C. France) silicon solar cell is used since the experimental data are extensively adopted by researchers as benchmark to test and compare the performance of techniques for parameters extraction. The data are measured from the system under 1 sun (1000 W/m^2) at 33 °C (Easwarakhanthan et al., 1986). There are 26 measurement points, i.e., N = 26, represented by (V_e, I_e) as follows:

(−0.2057, 0.764), (−0.1291, 0.762), (−0.0588, 0.7605), (0.0057, 0.7605), (0.0646, 0.76),
(0.1185, 0.759), (0.1678, 0.757), (0.2132, 0.757), (0.2545, 0.7555), (0.2924, 0.754),
(0.3269, 0.7505), (0.3585, 0.7465), (0.3873, 0.7385), (0.4137, 0.728), (0.4373, 0.7065),
(0.459, 0.6755), (0.4784, 0.632), (0.496, 0.573), (0.5119, 0.499), (0.5265, 0.413),
(0.5398, 0.3165), (0.5521, 0.212), (0.5633, 0.1035), (0.5736, −0.01), (0.5833, −0.123), and
(0.59, −0.21).

According to the literature survey, the bounds of the solar cell models parameters are shown in Table 1.

Table 1
Bounds of the solar cell models parameters.

Models	Parameters	Lower bound	Upper bound
SDM	I_{ph} (A)	0	1
	I_{sd} (μA)	0	1
	n	1	2
	R_s (Ω)	0	0.5
	R_{sh} (Ω)	0	100
DDM	I_{ph} (A)	0	1
	I_{sd1} (μA)	0	1
	I_{sd2} (μA)	0	1
	n_1	1	2
	n_2	1	2
	R_s (Ω)	0	0.5
	R_{sh} (Ω)	0	100

To compare the performance of the above-mentioned methods, a time limit is adopted as the stopping criterion. In this study, ten short independent run time periods are used for objectively observing the trends and changes in the optimization process, i.e., from 0.1 s to 1.0 s, the step is 0.1 s. The run time unit is CPU seconds. All the algorithms are coded in standard C programming language since this code can be easily ported to embedded processors in future studies. The computing tasks are implemented on a laptop with an Intel Core i7-5500U @2.40 GHz CPU, 8 GB RAM and Windows 7 64-bit operating system. In each comparison, there are 55 individual runs for each test, and only the top 50 are recorded to remove outliers.

The adjustable parameters for SSO, MSSO, ABC and SBMO are listed as follows:

SSO: $C_w = 0.35$, $C_p = 0.65$, $C_g = 0.85$, $N_{sol} = 150$;
MSSO: $C_w = 0.6$, $C_p = 0.90$, $N_{sol} = 150$;
ABC: $N_p = 150$, *limit* is $N_p * 5$ for SDM and $N_P * 7$ for DDM, and
SBMO: $N = 30$.

The above parameters for ABC and SBMO are adopted from Oliva et al. (2014) and Askarzadeh et al. (2015), respectively.

At the end of each time period, several values are recorded. To compare the accuracy of the solutions, the average, minimal (the best), maximal (the worst) and standard deviation of the fitness values are recorded and calculated, which are denoted by F_{avg}, F_{min}, F_{max} and F_{std}, respectively. Moreover, the number of fitness values obtained by the algorithm that is less than a threshold value is also calculated, namely N_g. The threshold values are set as 9.682E−04 for SDM and 9.860E−04 for DDM, respectively. To compare the efficiency of those methods, the average of the corresponding fitness calculation number (N_{avg}), the average of the fitness calculation number that finds the final gBest (n_{avg}) are calculated. Moreover, the best value in each comparison is highlighted in bold.

4.2. Results on single diode model for benchmark

For the SDM, the experimental results in fitness value of SSO, MSSO, ABC and SBMO are summarized in Table 2.

From Table 2, it is evident that the proposed MSSO method has the best performance in F_{avg}, F_{max} and F_{std} among all of the compared methods in any running time period. For the F_{min}, MSSO also obtains the best result in most cases except the first case where the best result is obtained by SMBO. Moreover, the minimal fitness value in all the running time periods is obtained by MSSO, i.e., 9.8607E−04.

The number of fitness value is better than the threshold value obtained by SSO, MSSO, ABC and SBMO, shown in Table 3. The total number of Ng found by SSO, MSSO, ABC and SBMO is 0, 49, 1 and 2,

Table 2
The fitness value obtained by SSO, MSSO, ABC and SBMO for the SDM.

Statistics	Time (s)	SSO	MSSO	ABC	SBMO
F_{avg}	0.1	1.7500E−03	**1.0112E−03**	1.1098E−03	1.3384E−03
	0.2	1.6218E−03	**9.9126E−04**	1.0715E−03	1.4170E−03
	0.3	1.6867E−03	**9.8879E−04**	1.0328E−03	1.3397E−03
	0.4	1.7892E−03	**9.8785E−04**	1.0407E−03	1.2834E−03
	0.5	1.6365E−03	**9.8711E−04**	1.0221E−03	1.3041E−03
	0.6	1.6889E−03	**9.8688E−04**	1.0053E−03	1.2757E−03
	0.7	1.7397E−03	**9.8680E−04**	1.0045E−03	1.2599E−03
	0.8	1.8298E−03	**9.8704E−04**	1.0003E−03	1.2027E−03
	0.9	1.6020E−03	**9.8666E−04**	1.0018E−03	1.2418E−03
	1.0	1.7307E−03	**9.8663E−04**	1.0013E−03	1.2342E−03
F_{min}	0.1	9.9974E−04	9.8791E−04	9.9191E−04	**9.8695E−04**
	0.2	9.9194E−04	**9.8618E−04**	9.9029E−04	9.8625E−04
	0.3	9.9461E−04	**9.8613E−04**	9.8638E−04	9.8856E−04
	0.4	9.8964E−04	**9.8618E−04**	9.8669E−04	9.8700E−04
	0.5	9.9471E−04	**9.8609E−04**	9.8813E−04	9.8611E−04
	0.6	9.9033E−04	**9.8608E−04**	9.8641E−04	9.8883E−04
	0.7	9.9763E−04	**9.8609E−04**	9.8619E−04	9.8676E−04
	0.8	9.9116E−04	**9.8607E−04**	9.8628E−04	9.8610E−04
	0.9	9.8640E−04	**9.8612E−04**	9.8742E−04	9.8793E−04
	1.0	9.8913E−04	**9.8608E−04**	9.8675E−04	9.8631E−04
F_{max}	0.1	2.4640E−03	**1.0473E−03**	1.2642E−03	1.8414E−03
	0.2	2.3625E−03	**1.0021E−03**	1.2027E−03	1.8958E−03
	0.3	2.4431E−03	**9.9578E−04**	1.1307E−03	1.7530E−03
	0.4	2.4519E−03	**9.9363E−04**	1.1527E−03	1.7300E−03
	0.5	2.3836E−03	**9.8988E−04**	1.0838E−03	1.7239E−03
	0.6	2.4489E−03	**9.8900E−04**	1.0429E−03	1.7068E−03
	0.7	2.4475E−03	**9.8786E−04**	1.0371E−03	1.6382E−03
	0.8	2.4470E−03	**9.8967E−04**	1.0297E−03	1.4759E−03
	0.9	2.4474E−03	**9.8890E−04**	1.0225E−03	1.5613E−03
	1.0	2.4483E−03	**9.8802E−04**	1.0404E−03	1.5045E−03
F_{stdev}	0.1	4.6281E−04	**1.5531E−05**	8.5036E−05	2.7263E−04
	0.2	4.0640E−04	**4.2831E−06**	6.2635E−05	2.5943E−04
	0.3	5.0697E−04	**2.5211E−06**	3.4431E−05	2.2067E−04
	0.4	5.3206E−04	**1.7190E−06**	4.0285E−05	2.0426E−04
	0.5	4.2654E−04	**9.1681E−07**	2.6141E−05	2.2895E−04
	0.6	4.9529E−04	**7.5803E−07**	1.5193E−05	2.0814E−04
	0.7	4.6378E−04	**4.7414E−07**	1.3385E−05	1.7813E−04
	0.8	5.1380E−04	**9.6834E−07**	1.1810E−05	1.4996E−04
	0.9	4.6724E−04	**6.2126E−07**	9.6713E−06	1.3902E−04
	1.0	4.9275E−04	**5.2095E−07**	1.3543E−05	1.2845E−04

Table 3
The Ng obtained by SSO, MSSO, ABC and SBMO for the SDM.

Time (s)	SSO	MSSO	ABC	SBMO
0.1	0	0	0	0
0.2	0	**1**	0	0
0.3	0	**1**	0	0
0.4	0	**2**	0	0
0.5	0	**2**	0	1
0.6	0	**10**	0	0
0.7	0	**4**	1	0
0.8	0	**9**	0	1
0.9	0	**10**	0	0
1.0	0	**10**	0	0
SUM	0	**49**	1	2

respectively. Above all, MSSO has the best accuracy and robustness performance among all of the compared algorithms.

Table 4 shows the efficiency of the algorithms, and larger numbers of N_{avg} and n_{avg} indicate that the approach runs more times in the same running period. Accordingly, the proposed MSSO is the most efficient among all the compared algorithms because the average fitness calculation numbers (N_{avg} and n_{avg}) obtained by MSSO are larger than those obtained by other algorithms.

On the whole, for the SDM parameters extraction problem, the performance of the proposed MSSO algorithm is better than that of SSO, ABC and SBMO with more accuracy, robustness and efficiency.

The extracted parameters for SDM along with the RMSE of the comparison methods and those of several other well-known soft computing approaches, such as LMSA (Dkhichi et al., 2014), ABSO (Askarzadeh and Rezazadeh, 2013a), HS (Askarzadeh and Rezazadeh, 2012a, 2012b), PSO (Wei et al., 2011), and GA (Jervase et al., 2001), are listed in Table 5. In addition, several typical analytical methods and numerical methods, which have been applied on the SDM parameters extraction benchmark in literatures, are added to make a comparison. They are analytical five-point (An.5-Pt.) (Chan et al., 1986) and LW (Zhang et al., 2011) that belong to analytical methods, as well as NRM (Easwarakhanthan

Table 4
The efficiency of the proposed SSO, MSSO, ABC and SBMO for the SDM.

Statistics	Time (s)	SSO	MSSO	ABC	SBMO
N_{avg}	0.1	9.9460E+04	**1.1260E+05**	7.9947E+04	8.3393E+04
	0.2	1.9025E+05	**2.2381E+05**	1.6474E+05	1.6126E+05
	0.3	2.9940E+05	**3.5434E+05**	2.5422E+05	2.5048E+05
	0.4	3.9904E+05	**4.6701E+05**	3.4572E+05	3.2677E+05
	0.5	4.8238E+05	**5.9840E+05**	4.3374E+05	4.1439E+05
	0.6	5.8824E+05	**7.0865E+05**	5.2267E+05	4.9016E+05
	0.7	6.7215E+05	**8.2493E+05**	6.2151E+05	5.6423E+05
	0.8	7.8575E+05	**9.5614E+05**	7.2230E+05	6.5050E+05
	0.9	8.6635E+05	**1.0691E+06**	8.0838E+05	7.2866E+05
	1.0	9.6579E+05	**1.2012E+06**	9.1005E+05	8.1244E+05
n_{avg}	0.1	8.8947E+04	**1.0829E+05**	7.4679E+04	8.3388E+04
	0.2	1.7114E+05	**2.1698E+05**	1.5669E+05	1.6126E+05
	0.3	2.6379E+05	**3.4247E+05**	2.3312E+05	2.5047E+05
	0.4	3.5949E+05	**4.5216E+05**	3.0633E+05	3.2675E+05
	0.5	4.1080E+05	**5.7537E+05**	3.8787E+05	4.1429E+05
	0.6	5.2220E+05	**6.7778E+05**	4.6793E+05	4.9006E+05
	0.7	5.8896E+05	**8.0285E+05**	5.3093E+05	5.6416E+05
	0.8	6.8967E+05	**9.1769E+05**	5.8795E+05	6.5042E+05
	0.9	7.9552E+05	**1.0295E+06**	6.3724E+05	7.2862E+05
	1.0	8.4744E+05	**1.1315E+06**	7.4728E+05	8.1231E+05

Table 5
The results of parameters extraction for the SDM by various methods.

Approaches	Parameters					
	I_{ph} (A)	I_{sd} (μA)	n	R_s (Ω)	R_{sh} (Ω)	RMSE
SSO	0.760803	0.321044	1.480468	0.036392	53.152466	*9.8640E−04*
MSSO	0.760777	0.323564	1.481244	0.036370	53.742465	***9.8607E−04***
ABC	0.760784	0.321523	1.480601	0.036398	53.639071	*9.8619E−04*
SBMO	0.760779	0.321626	1.480639	0.036393	53.575366	*9.8610E−04*
LMSA	0.76078	0.31849	1.47976	0.03643	53.32644	*9.8640E−04*
ABSO	0.76080	0.30623	1.47583	0.03659	52.2903	*9.9124E−04*
HS	0.7607	0.30495	1.47538	0.03663	53.5946	*9.9510E−04*
PSO	0.7607	0.4	1.5033	0.0354	59.012	1.3900E−03
GA	0.7619	0.8087	1.5751	0.0299	42.3729	1.8704E−02
An.5-Pt.	0.7606	0.2417	1.4513	0.0422	106.3829	7.9602E−03
LW	0.7611	0.2422	1.4561	0.0373	42	9.6964E−03
NRM	0.7608	0.3223	1.4837	0.0364	53.7634	1.0072E−02
CM	0.7608	0.4039	1.5039	0.0364	49.5050	2.8573E−03

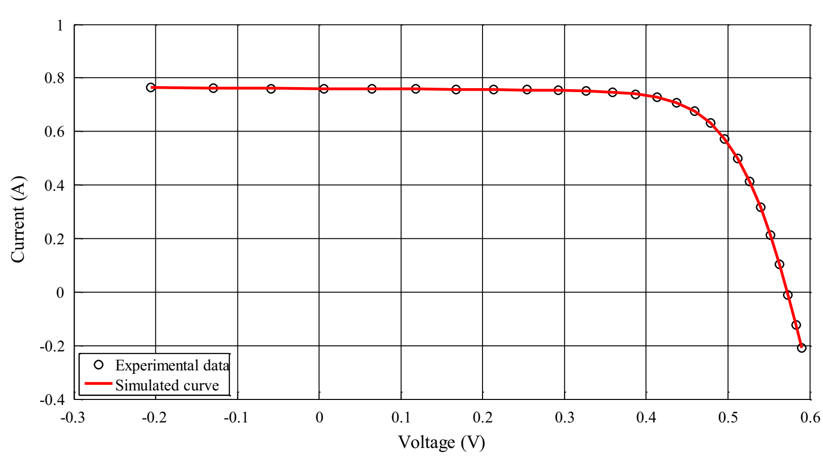


Fig. 2. Comparison between the experimental data and the simulated curve for the SDM.

et al., 1986) and CM (Chegaar et al., 2001) that belong to numerical methods. As can be seen from Table 5, the RMSEs obtained by most of the soft computing approaches are less than 1E−03, which are better than those of analytical approaches or numerical methods. Furthermore, the proposed MSSO has the best results among all the compared approaches.

In addition, the I–V characteristics calculated by using the optimal solution of MSSO are illustrated in Fig. 2. From the figure, it can be observed that the deviation between the calculated data and the experimental data is very minor and the RMSE is only 9.8607E−04. Consequently, MSSO obtains a high accurate solution.

4.3. Results on double diode model for benchmark

The corresponding fitness values obtained by SSO, MSSO, ABC and SBMO for the DDM are shown in Table 6. This table shows that the performance of MSSO is superior to those of SSO, ABC and SBMO in F_{avg}, F_{max}, and F_{stdev} for each stopping criterion of the runtime. For the F_{min} case, MSSO also has the best result at all the runtime periods except 0.4 s, where the best result is obtained by ABC. Furthermore, the minimal fitness value in all the running time periods is obtained by MSSO, i.e., 9.8281E−04.

The Ng found by the proposed MSSO is much better than those of SSO, ABC and SBMO, as shown in Table 7. The Ng obtained by MSSO is 77, as marked in bold, while that obtained by ABC is 23, and that by SBMO is only 1.

From Table 8, it is clear that the proposed MSSO is the most efficient among all compared algorithms because the average fitness calculation numbers (N_{avg}) and the average fitness calculation number that finds the final *gBest* (n_{avg}) obtained by MSSO are larger than those obtained by other compared algorithms.

Table 6
The fitness value obtained by SSO, MSSO, ABC and SBMO for the DDM.

Statistics	Time (s)	SSO	MSSO	ABC	SBMO
F_{avg}	0.1	2.1273E−03	**1.0435E−03**	1.0456E−03	1.8228E−03
	0.2	2.0383E−03	**9.9854E−04**	1.0180E−03	1.6219E−03
	0.3	1.8919E−03	**9.8969E−04**	1.0161E−03	1.4530E−03
	0.4	1.9009E−03	**9.8893E−04**	9.9990E−04	1.3615E−03
	0.5	1.8974E−03	**9.8833E−04**	9.9696E−04	1.2838E−03
	0.6	1.9172E−03	**9.8751E−04**	9.9848E−04	1.2956E−03
	0.7	1.8253E−03	**9.8735E−04**	9.9418E−04	1.1965E−03
	0.8	1.5774E−03	**9.8709E−04**	9.9260E−04	1.2146E−03
	0.9	1.8857E−03	**9.8657E−04**	9.9220E−04	1.1348E−03
	1.0	1.9469E−03	**9.8658E−04**	9.9066E−04	1.1195E−03
F_{min}	0.1	1.0899E−03	**9.8669E−04**	9.8992E−04	9.9918E−04
	0.2	9.9129E−04	**9.8603E−04**	9.8790E−04	9.9401E−04
	0.3	1.0745E−03	**9.8341E−04**	9.8476E−04	9.8485E−04
	0.4	9.9708E−04	9.8512E−04	**9.8427E−04**	9.8770E−04
	0.5	1.0374E−03	**9.8405E−04**	9.8575E−04	9.9190E−04
	0.6	1.0390E−03	**9.8281E−04**	9.8596E−04	9.8670E−04
	0.7	9.9179E−04	**9.8367E−04**	9.8404E−04	9.8604E−04
	0.8	1.0078E−03	**9.8328E−04**	9.8418E−04	9.8703E−04
	0.9	1.0250E−03	**9.8282E−04**	9.8428E−04	9.8933E−04
	1.0	9.9149E−04	**9.8327E−04**	9.8387E−04	9.8734E−04
F_{max}	0.1	3.5709E−03	**1.1296E−03**	1.1466E−03	2.4107E−03
	0.2	3.4574E−03	**1.0204E−03**	1.0857E−03	2.2075E−03
	0.3	2.9087E−03	**9.9646E−04**	1.0875E−03	1.8752E−03
	0.4	2.9948E−03	**9.9497E−04**	1.0268E−03	1.8557E−03
	0.5	2.9355E−03	**9.9530E−04**	1.0114E−03	1.6305E−03
	0.6	2.8618E−03	**9.9249E−04**	1.0203E−03	1.7545E−03
	0.7	2.6680E−03	**9.9307E−04**	1.0160E−03	1.5691E−03
	0.8	2.3314E−03	**9.9179E−04**	1.0118E−03	1.5723E−03
	0.9	2.8072E−03	**9.8984E−04**	1.0046E−03	1.4237E−03
	1.0	2.5481E−03	**9.9026E−04**	1.0025E−03	1.3411E−03
F_{stdev}	0.1	6.5438E−04	**3.7512E−05**	3.8616E−05	3.9406E−04
	0.2	7.0509E−04	**8.4671E−06**	2.3440E−05	3.7083E−04
	0.3	5.0064E−04	**2.7379E−06**	2.3620E−05	2.7026E−04
	0.4	5.8715E−04	**2.4376E−06**	1.1752E−05	2.6295E−04
	0.5	5.2060E−04	**2.6699E−06**	7.7660E−06	1.9380E−04
	0.6	5.3604E−04	**1.8349E−06**	9.1066E−06	2.1564E−04
	0.7	4.3961E−04	**1.8992E−06**	8.1252E−06	1.6217E−04
	0.8	4.3153E−04	**1.9924E−06**	5.7790E−06	1.6802E−04
	0.9	4.6152E−04	**1.5368E−06**	6.3045E−06	1.1093E−04
	1.0	4.6349E−04	**1.7124E−06**	4.8839E−06	1.0758E−04

Table 7
The Ng obtained by SSO, MSSO, ABC and SBMO for the DDM.

Time (s)	SSO	MSSO	ABC	SBMO
0.1	0	0	0	0
0.2	0	0	0	0
0.3	0	1	1	1
0.4	0	**4**	2	0
0.5	0	**10**	1	0
0.6	0	**4**	1	0
0.7	0	**10**	4	0
0.8	0	**16**	4	0
0.9	0	**15**	4	0
1.0	0	**17**	6	0
SUM	0	**77**	23	1

Table 8
The efficiency of the proposed SSO, MSSO, ABC and SBMO for the DDM.

Statistics	Time (s)	SSO	MSSO	ABC	SBMO
N_{avg}	0.1	6.6422E+04	**8.3645E+04**	7.2425E+04	6.3727E+04
	0.2	1.3247E+05	**1.6286E+05**	1.3803E+05	1.1876E+05
	0.3	1.9373E+05	**2.5252E+05**	2.1736E+05	1.8292E+05
	0.4	2.5824E+05	**3.2992E+05**	2.8684E+05	2.3815E+05
	0.5	3.3164E+05	**4.1821E+05**	3.6500E+05	3.0159E+05
	0.6	3.8771E+05	**4.9588E+05**	4.3479E+05	3.5600E+05
	0.7	4.6378E+05	**5.7514E+05**	5.0179E+05	4.1187E+05
	0.8	5.2270E+05	**6.6489E+05**	5.8374E+05	4.7777E+05
	0.9	5.8809E+05	**7.3996E+05**	6.5659E+05	5.3116E+05
	1.0	6.5513E+05	**8.3028E+05**	7.3443E+05	5.9519E+05
n_{avg}	0.1	6.0624E+04	**8.1246E+04**	6.8723E+04	6.3681E+04
	0.2	1.2240E+05	**1.5758E+05**	1.3060E+05	1.1864E+05
	0.3	1.7906E+05	**2.4429E+05**	2.0511E+05	1.8270E+05
	0.4	2.4030E+05	**3.1740E+05**	2.7388E+05	2.3717E+05
	0.5	3.1369E+05	**4.0163E+05**	3.5462E+05	3.0116E+05
	0.6	3.6663E+05	**4.8079E+05**	4.1561E+05	3.5570E+05
	0.7	4.3495E+05	**5.5680E+05**	4.6720E+05	4.1129E+05
	0.8	4.8640E+05	**6.4235E+05**	5.4833E+05	4.7590E+05
	0.9	5.6233E+05	**7.1520E+05**	6.0727E+05	5.2787E+05
	1.0	6.2912E+05	**8.0237E+05**	6.7401E+05	5.9431E+05

Table 9
The results of parameters extraction for the DDM by various methods

Approaches	Parameters							
	I_{ph} (A)	I_{sd1} (μA)	I_{sd2} (μA)	n_1	n_2	R_s (Ω)	R_{sh} (Ω)	RMSE
SSO	0.760651	0.287201	0.065979	1.510345	1.433838	0.036255	55.853271	*9.9129E−04*
MSSO	0.760748	0.234925	0.671593	1.454255	1.995305	0.036688	55.714662	***9.8281E−04***
ABC	0.760813	0.192684	0.999587	1.438003	1.983721	0.036861	55.933515	*9.8387E−04*
SBMO	0.760786	0.200798	0.74373	1.441256	1.947888	0.036917	55.104367	*9.8485E−04*
ABSO	0.76078	0.26713	0.38191	1.46512	1.98152	0.03657	54.6219	*9.8344E−04*
HS	0.76176	0.12545	0.2547	1.49439	1.49989	0.03545	46.82696	1.2600E−03
PSO	0.7623	0.4767	0.01	1.5172	2	0.0325	43.1034	1.6600E−02
GA	0.7608	0.0001	0.0001	1.3355	1.481	0.0364	53.7185	3.6040E−01

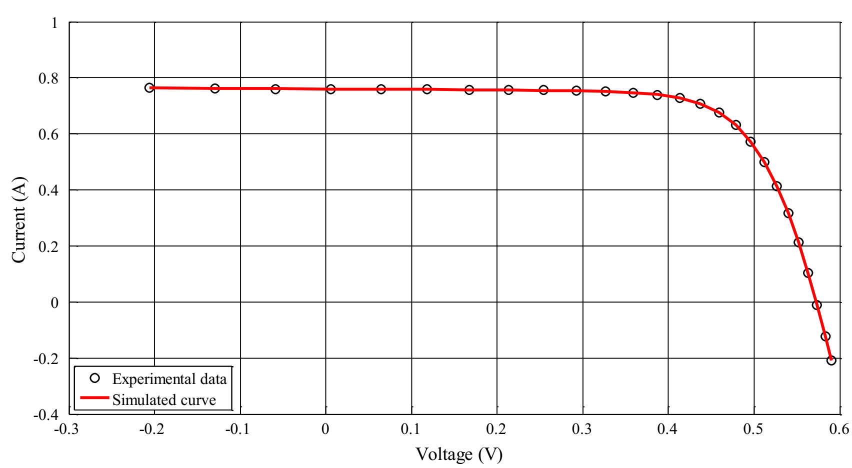


Fig. 3. Comparison between the experimental data and the simulated curve for the DDM.

The extracted parameters for DDM and the RMSE of the compared methods and those of several other well-known soft computing approaches, such as ABSO (Askarzadeh and Rezazadeh, 2013a), HS (Askarzadeh and Rezazadeh, 2012a, 2012b), PSO (Wei et al., 2011) and GA (Jervase et al., 2001), are summarized in Table 9. This table shows that most of the soft computing approaches can gain the RMSEs less than 1E−03. Moreover, the proposed MSSO has the best RMSE among all the compared methods.

The *I–V* characteristics calculated by using the optimal solution of MSSO are illustrated in Fig. 3. Apparently, the calculated data are remarkably consistent with the experimental data.

4.4. Results on PERC cell

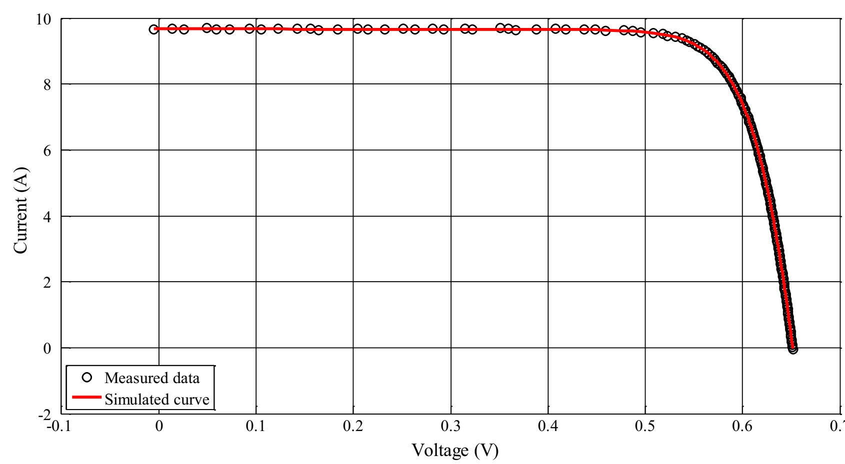
To validate the effectiveness of the proposed MSSO on industrial 6″ solar cells, the *I-V* characteristics of a PERC cell is applied for parameter extraction. The *I-V* characteristics of the PERC cell is

Table 10
The parameters of the PERC cell.

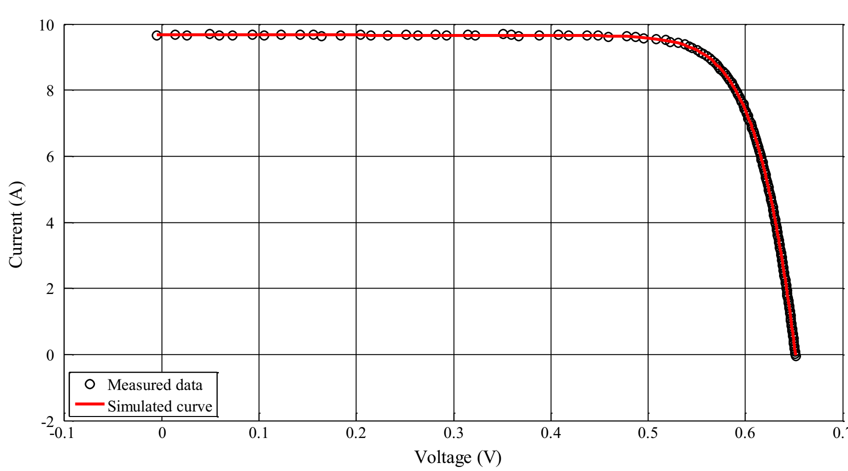
Area (cm^2)	I_{SC} (A)	V_{OC} (V)	I_{MPP} (A)	V_{MPP} (V)	FF (%)	Eff (%)
242.84	9.667	0.6514	9.2129	0.5507	80.57	20.89

Table 11
The extracted parameters of the SDM and DDM for the PERC cell.

Model	Parameters									
	I_{ph} (A)	I_{sd} (μA)	I_{sd1} (μA)	I_{sd2} (μA)	n	n_1	n_2	R_s (Ω)	R_{sh} (Ω)	RMSE
SDM	9.667444	0.003307	–	–	1.163208	–	–	0.001095	257.410117	1.6884 E−02
DDM	9.667314	–	0.003332	0.000106	–	1.163599	1.967633	0.001094	280.305312	1.6893 E−02



(a) Single diode model



(b) Double diode model

Fig. 4. Comparison between the experimental data and the simulated curve for the PERC cell.

measured at standard testing condition (STC) and the mainly parameters of the cell are listed in Table 10.

The extracted parameters and the RMSE by using MSSO of the SDM and DDM for the PERC cell are summarized in Table 11. The parameters are put into the two modules to simulate the I–V characteristics curves. The comparison results between the measured data and the simulated curve of the SDM and the DDM for the PERC cell are illustrated in Fig. 4, respectively. As can be observed, the two models are in good agreement with the experimental data, respectively. Therefore, the proposed MSSO is also able to extract parameters of PERC cells.

5. Conclusions

In this work, a modified SSO with an efficient update mechanism was proposed to extract the solar cell models parameters accurately and efficiently. In MSSO, only one random variable of each solution is updated in every generation. The survival of the fittest policy is also employed. The MSSO is firstly compared with SSO, ABC and SBMO in detail on a solar cell benchmark. Then, the MSSO is further applied for parameters extraction of a PERC cell to further validate performance. For benchmark, statistical data about fitness value and efficiency obtained by MSSO are recorded and compared with those of SSO, ABC and SBMO. The comparison demonstrates that MSSO is much better than SSO, ABC and SBMO, with greater accuracy, robustness and efficiency for the two well-known solar cell models. In addition, the results reveal the calculated data by MSSO are significantly consistent with the experimental data. For the application on the PERC cell, the MSSO can obtain an accurate approximation to measured data for both models. Consequently, the proposed MSSO is an effective approach to address the parameters extraction of solar cell models.

In future studies, this work should be ported to an embedded processor based online system for extracting the parameters of solar cells or PV modules.

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References

Alam, D.F., Yousri, D.A., Eteiba, M.B., 2015. Flower pollination algorithm based solar PV parameter estimation. Energy Convers. Manage. 101, 410–422.
AlHajri, M.F., El-Naggar, K.M., AlRashidi, M.R., Al-Othman, A.K., 2012. Optimal extraction of solar cell parameters using pattern search. Renew. Energy 44, 238–245.
Askarzadeh, A., Rezazadeh, A., 2012a. Parameter identification for solar cell models using harmony search-based algorithms. Sol. Energy 86 (11), 3241–3249.
Askarzadeh, A., Rezazadeh, A., 2012b. A new heuristic optimization algorithm for modeling of proton exchange membrane fuel cell: bird mating optimizer. Int. J. Energy Res. 37 (10), 1196–1204.
Askarzadeh, A., Rezazadeh, A., 2013a. Artificial bee swarm optimization algorithm for parameters identification of solar cell models. Appl. Energy 102, 943–949.
Askarzadeh, A., Rezazadeh, A., 2013b. Extraction of maximum power point in solar cells using bird mating optimizer-based parameters identification approach. Sol. Energy 90, 123–133.
Askarzadeh, A., dos Santos, Coelho, L., 2015. Determination of photovoltaic modules parameters at different operating conditions using a novel bird mating optimizer approach. Energy Convers. Manage. 89, 608–614.
Azizipanah-Abarghooee, R., 2013. A new hybrid bacterial foraging and simplified swarm optimization algorithm for practical optimal dynamic load dispatch. Int. J. Elect. Power 49, 414–429.
Azizipanah-Abarghooee, R., Niknam, T., Gharibzadeh, M., Golestaneh, F., 2013. Robust, fast and optimal solution of practical economic dispatch by a new enhanced gradient-based simplified swarm optimisation algorithm. IET Gener. Transm. Dis. 7 (6), 620–635.
Barukčić, M., Nikolovski, S., Jović, F., 2010. Hybrid evolutionary-heuristic algorithm for capacitor banks allocation. J. Electr. Eng. 61 (6), 332–340.
Bastidas-Rodriguez, J.D., Franco, E., Petrone, G., Ramos-Paja, C.A., Spagnuolo, G., 2015. Model-based degradation analysis of photovoltaic modules through series resistance estimation. IEEE Trans. Ind. Electron. 62 (11), 7256–7265.
Chan, D.S.H., Phillips, J.R., Phang, J.C.H., 1986. A comparative study of extraction methods for solar cell model parameters. Solid-State Electron. 29 (3), 329–337.
Chan, D.S.H., Phang, J.C.H., 1987. Analytical methods for the extraction of solar-cell single-and double-diode model parameters from IV characteristics. IEEE Trans. Electron Dev. 34 (2), 286–293.
Chegaar, M., Ouennoughi, Z., Hoffmann, A., 2001. A new method for evaluating illuminated solar cell parameters. Solid-State Electron. 45 (2), 293–296.
Chung, Y.Y., Wahid, N., 2012. A hybrid network intrusion detection system using simplified swarm optimization (SSO). Appl. Soft Comput. 12 (9), 3014–3022.
Dkhichi, F., Oukarfi, B., Fakkar, A., et al., 2014. Parameter identification of solar cell model using Levenberg–Marquardt algorithm combined with simulated annealing. Sol. Energy 110, 781–788.
Easwarakhanthan, T., Bottin, J., Bouhouch, I., Boutrit, C., 1986. Nonlinear minimization algorithm for determining the solar cell parameters with microcomputers. Int. J. Sol. Energy 4 (1), 1–12.
El-Naggar, K.M., AlRashidi, M.R., AlHajri, M.F., Al-Othman, A.K., 2012. Simulated annealing algorithm for photovoltaic parameters identification. Sol. Energy 86 (1), 266–274.
Gong, W., Cai, Z., 2013. Parameter extraction of solar cell models using repaired adaptive differential evolution. Sol. Energy 94, 209–220.
Huang, C.L., 2015. A particle-based simplified swarm optimization algorithm for reliability redundancy allocation problems. Reliab. Eng. Syst. Saf. 142, 221–230.
Ishaque, K., Salam, Z., 2011. An improved modeling method to determine the model parameters of photovoltaic (PV) modules using differential evolution (DE). Sol. Energy 85 (9), 2349–2359.
Ishaque, K., Salam, Z., Mekhilef, S., Shamsudin, A., 2012. Parameter extraction of solar photovoltaic modules using penalty-based differential evolution. Appl. Energy 99, 297–308.
Jain, A., Kapoor, A., 2004. Exact analytical solutions of the parameters of real solar cells using Lambert W-function. Sol. Energy Mater. Solid C 81 (2), 269–277.
Jain, A., Sharma, S., Kapoor, A., 2006. Solar cell array parameters using Lambert W-function. Sol. Energy Mater. Solid C 90 (1), 25–31.
Jervase, J.A., Bourdoucen, H., Al-Lawati, A., 2001. Solar cell parameter extraction using genetic algorithms. Meas. Sci. Technol. 12 (11), 1922–1925.
Karaboga, D., 2005. An idea based on honey bee swarm for numerical optimization Technical report-tr06. Erciyes University, Engineering Faculty, Computer Engineering Department.
Lun, S.X., Du, C.J., Yang, G.H., Wang, S., Guo, T.T., Sang, J.S., Li, J.P., 2013. An explicit approximate I-V characteristic model of a solar cell based on padé approximants. Sol. Energy 92, 147–159.
Ma, J., Ting, T.O., Man, K.L., Zhang, N., Guan, S.-U., Wong, P.W.H., 2013. Parameter estimation of photovoltaic models via cuckoo search. J. Appl. Math. 2013, 8.
Ma, T., Yang, H., Lu, L., 2014. Development of a model to simulate the performance characteristics of crystalline silicon photovoltaic modules/strings/arrays. Sol. Energy 100, 31–41.
Oliva, D., Cuevas, E., Pajares, G., 2014. Parameter identification of solar cells using artificial bee colony optimization. Energy 72, 93–102.
Saleem, H., Karmalkar, S., 2009. An analytical method to extract the physical parameters of a solar cell from four points on the illuminated curve. IEEE Electron. Dev. Lett. 30 (4), 349–352.
Singh, G.K., 2013. Solar power generation by PV (photovoltaic) technology: a review. Energy 53, 1–13.
Tina, G.M., Cosentino, F., Ventura, C., 2016. Monitoring and diagnostics of photovoltaic power plants. Renewable Energy in the Service of Mankind, vol. II. Springer International Publishing, pp. 505–516.
Wang, W., Liu, A.C.F., Chung, H.S.H., Lau, R.W.H., Zhang, J., Lo, A.W.L., 2016. Fault diagnosis of photovoltaic panels using dynamic current-voltage characteristics. IEEE Trans. Power Electr. 31 (2), 1588–1599.
Wei, H., Cong, J., Lingyun, X., Deyun, S., 2011. Extracting solar cell model parameters based on chaos particle swarm algorithm. In: International Conference on Electric Information and Control Engineering, pp. 398–402.
Wu, J., Wang, H., 2013. A parthenogenetic algorithm for the founder sequence reconstruction problem. J. Comput. 8 (11), 2934–2941.
Xu, X., Wang, H., Zuo, Y., 2011. Method for diagnosing photovoltaic array fault in solar photovoltaic system. In: Power and Energy Engineering Conference, pp. 1–5.
Ye, M., Wang, X., Xu, Y., 2009. Parameter extraction of solar cells using particle swarm optimization. J. Appl. Phys. 105 (9), 094502–094508.
Yeh, W.C., 2009. A two-stage discrete particle swarm optimization for the problem of multiple multi-level redundancy allocation in series systems. Expert Syst. Appl. 36 (5), 9192–9200.
Yeh, W.C., 2012a. Novel swarm optimization for mining classification rules on thyroid gland data. Inf. Sci. 197, 65–76.
Yeh, W.C., 2012b. Optimization of the disassembly sequencing problem on the basis of self-adaptive simplified swarm optimization. IEEE Trans. Syst. Man Cybern. A Syst. Hum. 42 (1), 250–261.
Yeh, W.C., 2012c. Simplified swarm optimization in disassembly sequencing problems with learning effects. Comput. Oper. Res. 39 (9), 2168–2177.
Yeh, W.C., 2013. New parameter-free simplified swarm optimization for artificial neural network training and its application in the prediction of time series. IEEE Trans. Neural Netw. Learn. Syst. 24 (4), 661–665.
Yeh, W.C., 2015. An improved simplified swarm optimization. Know.-Based Syst. 82, 60–69.
Yeh, W.C., Lai, C.M., 2015. Accelerated simplified swarm optimization with exploitation search scheme for data clustering. PLoS ONE 10 (9), e0137246.
Zagrouba, M., Sellami, A., Bouaicha, M., Ksouri, M., 2010. Identification of PV solar cells and modules parameters using the genetic algorithms: application to maximum power extraction. Sol. Energy 84 (5), 860–866.
Zhang, C., Zhang, J., Hao, Y., Lin, Z., Zhu, C., 2011. A simple and efficient solar cell parameter extraction method from a single current-voltage curve. J. Appl. Phys. 110 (6), 064504.