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Parameter estimation of solar PV models using self-adaptive differential evolution with dynamic mutation and pheromone strategy

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Abstract

In this paper we investigate the parameter estimation of solar photovoltaic (PV) models using the self-adaptive differential evolution algorithm with dynamic fitness-ranking mutation and pheromone strategy (SDE-FMP). The dynamic mutation divides the population into three groups according to fitness values and selects groups and their vectors with adaptive probabilities to create a mutant vector. The algorithm also encodes scaling factor and crossover rate values into target vectors to use in mutation and crossover operations and adjusts them with pheromones in the selection process. Experimental results show that the SDE-FMP algorithm can give the solutions with the lowest errors and is overall competitive with the compared methods regarding the mean errors.

1 Introduction

Solar photovoltaic models are mathematical representations of solar PV systems used to calculate electrical output under the model parameters that

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influence the system's performance. Accurate parameter estimation is crucial for designing and optimizing PV systems [1, 2]. Due to the non-linearity and complexity of the objective functions, various evolutionary algorithms have been proposed to solve the problems [3, 4, 5].

Differential evolution (DE), developed by Storn and Price in 1997 [6], is a global search algorithm for continuous optimization problems. It operates through mutation, crossover, and selection, and its performance depends on two control parameters: the scaling factor F and the crossover rate CR. Adaptive parameter techniques adjust the parameter values based on the overall feedback from the search process [7], while self-adaptive strategies encode the parameter values into the individuals and propagate them to others during the search process [8].

In this paper we estimate the parameters of PV models using the self-adaptive differential evolution algorithm with dynamic fitness-ranking mutation and pheromone strategy (SDE-FMP) and compares the performance with several evolutionary algorithms.

2 The SDE-FMP algorithm

The SDE-FMP algorithm incorporates a dynamic fitness-ranking mutation strategy that divides the population into three groups based on their fitness rank. It selects groups and vectors with adaptive probabilities to create a mutant vector, which enhances the diversity of the population. This mutation strategy learns to find suitable individuals for the mutation equation. The algorithm also employs a self-adaptive control parameter adaptation technique. It initially encodes pre-assigned values of F and CR into the target vector. These values are then adjusted using a pheromone inspired by ant colony optimization [9], allowing the algorithm to learn appropriate parameter values based on the feedback from the search process. Furthermore, the algorithm uses a resetting operation to manage the dominant pheromone and prevent premature convergence. The description of the SDE-FMP algorithm is as follows:

Step 1: Initialize the population of NP individuals and find the best solution vector x_{best} and its best function value f_{best}. Set number of function evaluations $nf = 0$.

Step 2: Encode the $F(i), CR(i)$ values to each target vector $x_i, i = 1, \ldots, NP$ by randomly choosing from the six combinations of (F, CR) where $F = 0.5, 0.7, 0.9$ and $CR = 0.1, 0.9$.

Step 3: Set all elements of vectors $PheromoneR_k, k = 1, 2, 3$ and a vector $PheromoneFCR$ to 1 and normalize them into $ProbR_k, k = 1, 2, 3$ and $ProbFCR$, respectively.

Step 4: Sort the population individuals according to fitness ranking and divide them into G_1, G_2, G_3 groups where G_1 represents the top best individuals, and G_3 contains the worst individuals.

Step 5: For $i = 1, 2, \ldots, NP$, choose $g_k \in \{G_1, G_2, G_3\}$ with the probabilities $ProbR_k, k = 1, 2, 3$ and uniformly pick distinct x_{R_k} vectors from corresponding g_k groups. Generate a mutant vector v_i by

$$v_i = x_{R_1} + F(i) \cdot (x_{R_2} - x_{R_3}) \tag{2.1}$$

Then, apply the crossover operation to get a trial vector u_i by

$$u_{i,j} = \begin{cases} v_{i,j} & ; \ s_j \leq CR(i) \ \text{ or } \ j = I_{rand} \\ x_{i,j} & ; \ \text{otherwise} \end{cases} \tag{2.2}$$

where $j = 1, \ldots, D$, s_j is a uniform random number in $(0, 1)$ and, I_{rand} is a randomly fixed integer from 1 to D. Next, evaluate $f(u_i)$ and update $nf = nf + 1$. If $f(u_i) < f(x_i)$, select u_i to replace x_i and update each $PheromoneR_k$ at the lth position of $g_k = G_l$ by adding 1 to the associated pheromone vector position as $PheromoneR_k(l) = PheromoneR_k(l) + 1$ and update $PheromoneFCR$ at the associated l index of combination as $PheromoneFCR(l) = PheromoneFCR(l) + 1$. Otherwise, re-encode the new random $F(i), CR(i)$ values for x_i according to $ProbFCR$. If u_i is also better than x_{best}, replace x_{best} with u_i.

Step 6: If $\sum PheromoneR_k \geq r_g$ for some k, reset $PheromoneR_k = 1$ for all k. If $\sum PheromoneFCR \geq r_p$, reset $PheromoneFCR = 1$ where r_g and r_p are the resetting periods for $PheromoneR_k$ and $PheromoneFCR$, respectively.

Step 7: Normalize $PheromoneR_k$ and $PheromoneFCR$ to be $ProbR_k$ and $ProbFCR$, respectively.

Step 8: Repeat Steps 4-7 until reaching the maximum number of function evaluations $maxnf$ and report the obtained x_{best} and f_{best} values.

3 Experimental design

We experiment on several types of PV models, including the single diode model (SDM), double diode model (DDM), triple diode model (TDM), and PV module model (MM), to estimate their parameters. The objective functions for these models are to minimize the root mean square error (RMSE) of the error functions between the measured and computed electrical current data as follows:

$$RMSE(x) = \sqrt{\frac{1}{N}\sum_{i=1}^{N} f(V_{L_i}, I_{L_i}, x)} \tag{3.3}$$

where N is the number of data, V_L is the cell output voltage, I_L is the cell output current, and x is the parameter vector of the model.

The measured electrical current data sets are taken from [10] and the error functions $f(V_L, I_L, x)$ are the following.

Single diode model (SDM):

$$f(V_L, I_L, x) = I_{ph} - I_{sd}\left[\exp\left(\frac{q(V_L + R_s I_L)}{akT}\right) - 1\right] - \frac{V_L + R_s I_L}{R_{sh}} - I_L \tag{3.4}$$

where $x = (I_{ph}, I_{sd}, R_s, R_{sh}, a)$.

Double diode model (DDM):

$$\begin{aligned} f(V_L, I_L, x) = I_{ph} &- I_{sd_1}\left[\exp\left(\frac{q(V_L + R_s I_L)}{a_1 kT}\right) - 1\right] - I_{sd_2}\left[\exp\left(\frac{q(V_L + R_s I_L)}{a_2 kT}\right) - 1\right] \\ &- \frac{V_L + R_s I_L}{R_{sh}} - I_L \end{aligned} \tag{3.5}$$

where $x = (I_{ph}, I_{sd_1}, I_{sd_2}, R_s, R_{sh}, a_1, a_2)$.

Triple diode model (TDM):

$$\begin{aligned} f(V_L, I_L, x) = I_{ph} &- I_{sd_1}\left[\exp\left(\frac{q(V_L + R_s I_L)}{a_1 kT}\right) - 1\right] - I_{sd_2}\left[\exp\left(\frac{q(V_L + R_s I_L)}{a_2 kT}\right) - 1\right] \\ &- I_{sd_3}\left[\exp\left(\frac{q(V_L + R_s I_L)}{a_3 kT}\right) - 1\right] - \frac{V_L + R_s I_L}{R_{sh}} - I_L \end{aligned} \tag{3.6}$$

where $x = (I_{ph}, I_{sd_1}, I_{sd_2}, I_{sd_3}, R_s, R_{sh}, a_1, a_2, a_3)$.

PV module model (MM):

$$f(V_L, I_L, x) = I_{ph} - I_{sd}\left[\exp\left(\frac{q\left(\frac{V_L}{N_s} + \frac{R_s I_L}{N_p}\right)}{akT}\right) - 1\right] - \frac{\left(\frac{V_L}{N_s} + \frac{R_s I_L}{N_p}\right)}{R_{sh}} - \frac{I_L}{N_p} \tag{3.7}$$

where $x = (I_{ph}, I_{sd}, R_s, R_{sh}, a)$.

I_{ph} is the photo-generated current, I_{sd} is the reverse saturation current of diode, V_L is the value of the output voltage, R_s is the series resistance, R_{sh} is the shunt resistance, a is the diode ideality factor, $q = 1.60217646 \times 10^{-19}$ is the charge of electron, $k = 1.3806503 \times 10^{23}$ is the Boltzmann constant, T is the cell temperature in Kelvin and $N_s = 36$ is the number of solar cell series connected in $N_p = 25$ parallels.

We use the suitable resetting periods of $r_g = 500$ and $r_p = 300$ obtained by the preliminary study and a population size of $NP = 30$ to compare the performance of the SDE-FMP algorithm with 16 other evolutionary algorithms [10]. The maximum number of function evaluations is $maxnf = 50000$, and each algorithm performs 30 independent runs as in the original paper. We report the mean, standard deviation, minimum, and maximum values of the obtained RMSE values.

4 Experimental results

Tables 1, 2, 3, and 4 compare the performance of SDE-FMP with the other 16 algorithms. The results of the compared methods are from [10]. The SDE-FMP provides the mean of RSME close to the DPDE, SEDE, EBLSHADE, SHADE, and SaDE and is better than the other 11 methods. In addition, SDE-FMP achieves the minimum RSME values for SDM, TDM, and MM. The best solutions obtained by SDE-FMP are listed in Table 5.

5 Discussion

The SDE-FMP algorithm employs a pheromone strategy to improve the search performance by adapting the probabilities for selecting subgroups during the mutation process. The algorithm applies the pheromone to self-adaptive control parameters F and CR by indicating the potential to create better trial vectors, where the most successful pairs of F and CR have higher pheromone levels to propagate for the next generations. Moreover, pheromone resetting is employed to prevent dominance and to balance the cycle of gathering and using pheromones. Therefore, the pheromone strategy enhances SDE-FMP search performance, making it

Table 1: The performance comparison on the single diode model

Algorithm	RSME			
	Max	Min	Mean	Std
DPDE	9.86021877891588E-04	9.86021877891470E-04	9.86021877891542E-04	2.57114481592195E-17
SEDE	9.86021877891648E-04	9.86021877891473E-04	9.86021877891578E-04	4.22402064939716E-17
EBLSHADE	9.86021877891583E-04	9.86021877891483E-04	9.86021877891545E-04	2.42631519358872E-17
LSHADE	9.86021877891603E-04	9.86021877891474E-04	9.86021877891549E-04	2.72471385985015E-17
SHADE	9.86021877891570E-04	9.86021877891481E-04	9.86021877891518E-04	2.57659061125260E-17
SaDE	9.89440002089708E-04	9.86021877891506E-04	9.86277976468403E-04	8.53130107161545E-07
EPSDE	1.22714416502895E-03	9.86021877891541E-04	1.01823735705123E-03	5.75465144864996E-05
JADE	1.17588906881870E-03	9.86021877891519E-04	9.94227417958838E-04	3.50267077536333E-05
CJADE	1.14224435541393E-03	9.86021877891503E-04	9.91340156245408E-04	2.85054397325118E-05
jDE	9.86021877891636E-04	9.86021877891525E-04	9.86021877891575E-04	2.47754982777884E-17
OXDE	1.77750698837158E-03	9.86096600253304E-04	1.31283442937857E-03	2.25406676232243E-04
IJAYA	9.94787957078899E-04	9.86170617423864E-04	9.89046399032753E-04	2.29879624197496E-06
MLBSA	9.86021911979861E-04	9.86021877891628E-04	9.86021879375819E-04	6.43810065443421E-12
CLPSO	2.27619493726483E-03	9.86030199090211E-04	1.51325943249177E-03	4.54627816384801E-04
GWO	3.67123515055235E-02	3.39766544964050E-03	1.78937525259178E-02	8.57327959490325E-03
WDO	2.91023323658502E-02	7.87742382966782E-03	1.70060850254307E-02	5.83191048167574E-03
SDE-FMP	9.86021877891528E-04	**9.86021877891437E-04**	9.86021877891483E-04	2.09972994934996E-17

Table 2: The performance comparison on the double diode model

Algorithm	RSME			
	Max	Min	Mean	Std
DPDE	9.83081420487992E-04	9.82484827161920E-04	9.82549779378988E-04	1.51333797156833E-07
SEDE	9.86021877891717E-04	9.82484851785253E-04	9.82728715430221E-04	7.41063337122926E-07
EBLSHADE	9.85928137945412E-04	9.82484851785141E-04	9.82749045776290E-04	6.72880234913202E-07
LSHADE	1.62452064094912E-03	9.82484851785100E-04	1.00415275543719E-03	1.17170972653862E-04
SHADE	2.26240671239624E-03	9.82484851784974E-04	1.04896881769883E-03	2.42993773026528E-04
SaDE	1.08509791228107E-03	9.84240112384937E-04	9.99735517003374E-04	2.72408263108179E-05
EPSDE	1.95496643408352E-03	9.86021901689630E-04	1.28515635877505E-03	2.62384386534029E-04
JADE	1.57674854487247E-03	9.86906876039984E-04	1.15646172465113E-03	1.43958951102558E-04
CJADE	1.98466758544154E-03	9.82484851784997E-04	1.12784739325351E-03	2.44803094997921E-04
jDE	1.05199829970035E-03	9.82541953030198E-04	9.87065089117113E-04	1.23333730879820E-05
OXDE	1.77986325577303E-03	9.83640182460851E-04	1.11692975227259E-03	1.74454292405715E-04
IJAYA	1.37100768422358E-03	9.85844525575868E-04	1.02770326249421E-03	7.81621512051265E-05
MLBSA	9.89501961945283E-04	9.82659499655910E-04	9.85578064938901E-04	1.50173363877032E-06
CLPSO	1.87101620596843E-03	9.86849689979796E-04	1.37557234033593E-03	2.71525165066017E-04
GWO	4.80409789639781E-02	6.14858473503986E-03	1.96039276512751E-02	9.61765315943461E-03
WDO	3.02431128479055E-02	2.73977553535096E-03	1.61789339342861E-02	6.08673163422464E-03
SDE-FMP	9.87351423961884E-04	9.82484851785297E-04	9.84970251043055E-04	1.52126128318098E-06

a promising approach to providing accurate parameter estimation for solar PV models.

6 Conclusion

In this paper we proposed a self-adaptive differential evolution algorithm with dynamic fitness-ranking mutation and pheromone strategy called SDE-FMP. Its key features included adaptive probabilities for mutation, self-adaptive control parameters, and the resetting operation to prevent premature convergence and stagna-

Table 3: The performance comparison on the triple diode model

Algorithm	RSME			
	Max	Min	Mean	Std
DPDE	9.86188097663681E-04	9.82484851785319E-04	9.83096769943567E-04	1.02284590208062E-06
SEDE	9.86095212876115E-04	9.82484851787748E-04	9.83225064327061E-04	1.07424567734332E-06
EBLSHADE	1.93808030016925E-03	9.82484851785187E-04	1.05516981797004E-03	2.27110030882710E-04
LSHADE	2.48412567808144E-03	9.82484870461156E-04	1.15390557975761E-03	3.76112139022221E-04
SHADE	1.98300783041678E-03	9.82484851785053E-04	1.22008055753712E-03	3.31296315372992E-04
SaDE	1.86818015140939E-03	9.83456937225773E-04	1.18943670575384E-03	2.45200777718747E-04
EPSDE	2.67714771423133E-03	1.02863078261565E-03	1.61808310313064E-03	4.25492825641048E-04
JADE	1.94800129833457E-03	1.02030923233994E-03	1.27865479201068E-03	2.15607042449324E-04
CJADE	2.70382824876446E-03	9.82484851785089E-04	1.39458198090656E-03	5.22176960835074E-04
jDE	1.13881450816934E-03	9.83033980617441E-04	1.00809667724542E-03	4.96686277183878E-05
OXDE	1.83554751589953E-03	9.82583263324295E-04	1.17314451788972E-03	2.36949910626828E-04
IJAYA	1.42658031764047E-03	9.85756777793189E-04	1.08360873131578E-03	1.41134047622091E-04
MLBSA	1.05467170486918E-03	9.82521011980619E-04	9.90063102634409E-04	1.35226248209557E-05
CLPSO	2.58351492051508E-03	9.95021678044232E-04	1.53488103358296E-03	4.30259477503636E-04
GWO	3.96151076986646E-02	8.87800175689218E-03	2.30943677929877E-02	7.76522602593209E-03
WDO	3.68560186033246E-02	7.07484913004008E-03	1.84195368723705E-02	7.93519629136375E-03
SDE-FMP	3.23013733906880E-03	**9.76217388664965E-04**	1.05360352826245E-03	4.11088278669508E-04

Table 4: The performance comparison on the PV module model

Algorithm	RSME			
	Max	Min	Mean	Std
DPDE	2.42507486809514E-03	2.42507486809506E-03	2.42507486809511E-03	1.82238517018742E-17
SEDE	2.42507486809517E-03	2.42507486809509E-03	2.42507486809513E-03	2.17422878257460E-17
EBLSHADE	2.42507486809518E-03	2.42507486809508E-03	2.42507486809512E-03	2.46515015886099E-17
LSHADE	2.42507486809518E-03	2.42507486809509E-03	2.42507486809513E-03	2.18256489502315E-17
SHADE	2.42507486809516E-03	2.42507486809507E-03	2.42507486809512E-03	2.34541878724134E-17
SaDE	3.06001676859194E-03	2.43091042530733E-03	2.63068772908896E-03	1.77991649947236E-04
EPSDE	4.11335702942234E-03	2.42507486809519E-03	2.83362014927839E-03	4.04984120837293E-04
JADE	5.85295310096216E-03	2.42507486809520E-03	3.10556163005014E-03	9.36587211190641E-04
CJADE	3.54042566803523E-03	2.42507486809510E-03	2.57747124647016E-03	3.51132480915387E-04
jDE	2.45948842357608E-03	2.42507486809520E-03	2.43202911190868E-03	1.13263165908818E-05
OXDE	1.55867964441641E-01	3.11174611519435E-03	4.39113039850298E-02	4.97826425974914E-02
IJAYA	3.02981693428441E-03	2.42704684024839E-03	2.77966916360691E-03	2.13245576790259E-04
MLBSA	3.34990953853000E-03	2.42507486812449E-03	2.55905715197564E-03	2.16738361792119E-04
CLPSO	1.81549024235258E-01	2.50956761661887E-03	3.29017944426902E-02	4.37690814529868E-02
GWO	4.32498125803442E-01	8.68816654445963E-02	2.06847899418349E-01	8.36839970750963E-02
WDO	3.57718382379418E-01	1.04839219281605E-01	2.23497726291873E-01	8.44825632265307E-02
SDE-FMP	2.42507486809506E-03	**2.42507486809497E-03**	2.42507486809502E-03	2.44639968187715E-17

tion. The experimental results demonstrated that SDE-FMP overall outperforms the compared methods and provided high-precision solutions for the PV models.

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Table 5: The best solutions obtained by SDE-FMP algorithm

Parameter	SDM	DDM	TDM	MM
I_{ph}	0.76077553	0.76078108	0.76040594	1.03051430
I_{sd_1}	0.32302081	0.74934798	0.00559402	3.48226307
I_{sd_2}	-	0.22597419	0.73206617	-
I_{sd_3}	-	-	0.22627135	-
R_s	0.03637709	0.03674043	0.03674203	0.83421598
R_{sh}	53.71854541	55.48544421	54.38171834	27.27728716
a_1	1.48118359	2.00000000	1.45134021	1.35118986
a_2	-	1.45101674	2.00000000	-
a_3	-	-	1.45134114	-
RMSE	9.86021877891437E-04	9.82484851785297E-04	9.76217388664965E-04	2.42507486809497E-03

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