An Improved Differential Evolution Algorithm for Economic Load Dispatch Optimization of Power Systems

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ABSTRACT: *This paper proposed an improved differential evolution algorithm for solving economic load dispatch (ELD) problems of power systems. In the proposed algorithm, the double mutation operators are employed. One is used to maintain the diversity of the population; and the other is to accelerate the convergence speed. Meanwhile, an adaptive updating method of parameter and a chaotic local search is introduced to improve the performance of IDE. Finally, two types of ELD problems were used to test the efficiency of the proposed algorithm. Experimental results show that the proposed algorithm can effectively solve these problems.*

Keywords: Differential Evolution Algorithm, Double Mutation Operator, Economic Load Dispatch, Power Systems

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1. Introduction

Economic load dispatch (ELD) problem is one of the typical and important optimization problems in a power system. The objective of ELD is to reduce the total power generation cost and satisfies all unit equality and inequality constraints [1]. However, since generator sets usually have several nonlinear features, such as discontinuous operational zone, ramp rate limit and so on, it is difficult to minimize the operational costs while the power demands of all customers [2]. These features make the conventional exact mathematical include lambda iteration method, base point and participation factor method, gradient method, etc [3] be infeasible for the ELD problems. In recent years, as many optimization approaches progress, many intelligent algorithms have been applied to solve the ELD problem. These algorithms include Particle Swarm Optimization (PSO) [4], Artificial Bee Colony (ABC) Algorithm [5], Genetic Algorithm (GA) [6], Differential Evolution (DE) [7] and Bacterial Foraging Algorithm (BFA) [8] and Harmony Search Algorithm (HS) [9]. Each of the employed approaches may have some advantage and disadvantages.

For example, HS has good global exploration, but has low local exploitation. In this paper, we focus on exploiting differential evolution algorithm to achieve the better solution for the ELD problems.

Differential Evolution (DE) is a meta-heuristic algorithm for global optimization introduced by Price and Storn [10]. It is similar to other evolutionary algorithms (EAs) in that it employs a population and updates that population iteratively by using the mutation, crossover, and selection operation [11]. DE has demonstrated good convergence properties and is principally easy to understand. Therefore, the DE algorithm has gradually become more popular and has been applied in many practical applications, such as hydroelectric system scheduling [12], restoration in power distribution systems [13], image watermarking [14] and so on.

With above considerations, an improved differential evolution algorithm is proposed to solve economic load dispatch (ELD) problems of power systems in this paper. To ensure the diversity of the population and the convergence rate, two mutation operators are adopted, which are DE/rand/bin [10], DE/best/2/bin [10]. Meanwhile, an adaptive updating method of parameter and a chaotic local search is employed to improve the performance of IDE. To verify the proposed algorithm, computational experimental are conducted on the two types ELD problem, which are the basic ELD problem and ELD with valve point effect.

The remainder of this paper is arranged as follows. In Section 2, the economic load dispatch problems will be described. Section3 provides an introduction for differential evolution algorithm. Section 4 gives a detail description of the new proposed ELD algorithm. Section 5 discusses the experimental results. Finally, we end the paper with some conclusions in Section 6.

2. The economic load dispatch problems

Economic load dispatch (ELD) problem is an important issue about the power systems research and the practical application. The objective of it is to optimize the cost of the all generator sets and must ensure the total generated energy satisfy load demand. In general, the ELD can be stated as a minimization problem as follows [2, 15, 16]:

$$\text{minimize } C = \sum_{i=1}^{n} f_i(P_i)$$

$$\text{Subject to } D = \sum_{i=1}^{n} P_i \tag{1}$$

$$P_{imin} \le P_i \le P_{imax} \quad \text{for} \quad i = 1, 2, \ldots, n$$

C: the total generator cost

P_i: the electrical output of the generator i

f_i: the cost function of i th generator

D: the total demand power

n: the total generators

P_{imin}; the minimum output of generator i

P_{imax}: the maximum output of generator i

In fact, the ELD problems can be defined as minimizing the total cost C subject to the power balance constraint $D = \sum_{i=1}^{n} P_i$, $P_{imin} \le P_i \le P_{imax}$. Under ideal conditions, the relationship between the cost and the generated energy can be described as follows:

$$f_i(P_i) = a_i + bP_i + c_iP_i^2 \tag{2}$$

where a_i, b_i, c_i are the coefficients of generator fuel cost.

In reality, due to valve point effect when the inlet valve of the generator is turn on, the costs of generators appear obvious nonlinearity. Therefore, with above considerations, sine function is added into Eq.(2) to show the exact relationship between the cost and the generated energy. The relationship can be defined as follows:

$$f_i(P_i) = a_i + bP_i + c_iP_i^2 + |e_i \bullet \sin(fi \bullet (P_{imin} - P_i))| \tag{3}$$

where e_i, f_i are the coefficients for generator i, P_i^{min} is the minimum output of generator i.

3. Differential evolution

Differential evolution (DE) algorithm is an effective global optimization algorithm in the field of evolutionary computation. It has the features of simple concept, high efficiency, easy to use. DE has been widely used to solve various optimization problems and practical applications. Like other evolutionary algorithms, DE algorithm adopts a population-based iterative statistical search process, and in each generation mutation, crossover, selection operators are used to move the current population toward the global optimal [11]. The classical DE algorithm includes 3 parameters: the population size *NP*, the scale factor *F*, the crossover rate *CR*. The main process of DE algorithm is as follows [10]:

Step 1: Population initialization and related parameters.

Step 2: Mutate the population according to the mutation strategy.

Step 3: Crossover.

Step 4: Selection.

Step 5: If the convergence criterion is satisfied, terminate the algorithm; otherwise, go back to step 1.

The components that affect the performance of DE include two main parts: the mutation strategy and the control of parameters. For the mutation strategy, the traditional mutation operation is to randomly select three individuals to construct the random vector to make the population mutate, but which has low efficiency. Thus, many researchers have proposed many different mutation operators [10] to get the high solving efficiency. However, there still lacks a mutation operator, which can adaptively maintain a reasonable balance between exploration and exploitation during the search process. The DE algorithm is very sensitive to the parameters. There is no parameter setting that is suitable for various problems. Moreover, the parameters setting also closely correlate with the choice of mutation strategy. So the traditional DE has the weakness of low convergence, weak convergence and the dependency for parameter. DE is not good at solving the complex optimal problems.

4. The improved DE algorithm for ELD

At present, most DE algorithms apply a single mutation strategy and combine the adjusting of parameters to mutate the population. Since DE uses a single mutation strategy, it leads to the shortage of the overall searching ability of the DE and does not sufficiently search for the large searching scope. DE uses only a part of features of population to evolve the population, which results in the too narrow solution space; especially the DE is easily trapped in local optimal, the diversity of the population loss, and the weak convergence during the evolutionary process. Therefore, an improved DE (IDE) is proposed in this paper. The two distinctive mutation operators are incorporated into DE to enhance the search ability of it. The updating way of parameters in reference [17] is adopted to further enrich the diversity of the population. Meanwhile, to improved the quality of the solution, a chaotic search algorithm [18] is introduced to further exploit the solution obtained by IDE. The procedure of IDE is described as follows, while the flow chart of it is displayed in Fig.1

Step 1: Initialization

Step 1.1: Population initialization. Initialize the population size NP and population based on ELD problems with Eq.(4).

$$x_{ij,G} = x_{imax} + rand \times (x_{imax} - x_{imin}) \tag{4}$$

where x_{ij} is the jth element of the ith individual, x_{imax}, x_{imin} is the maximum and minimum of, x_{ij}, respectively. $i = 1,2,...,NP$, $j = 1,2,...,m$, m is the number of generators.

Step 1.2: Parameter initialization. Initialize the scale factor F, the crossover rate CR, the selective factor α, the maximum iteration *Maxgens*, the current evolution number G=1.

Step 2: Update the parameters. Update *F* and *CR* with Eq.(5) and Eq.(6).

$$F_{i,G+1} = \begin{cases} 0.1 + 0.9 \times rand_1 & if \quad rand_2 < \tau_1 \\ F_{i,G} & or \end{cases} \tag{5}$$

$$CR_{i,G+1} = \begin{cases} rand_3 & if \quad rand_4 < \tau_2 \\ CR_{i,G} & or \end{cases} \tag{6}$$

where τ_1 and τ_2 are threshold value. $rand_1$- $rand_4$ are the random number between [0, 1].

Step 3: Mutation. Mutating the population based on the following method.

If rand <α, mutate the individual with Eq.(7); otherwise, use Eq.(8) to mutate.

$$v_i = x_{r1,G} + \mathrm{Fi} \bullet (x_{r2,G} - x_{r3,G}) \tag{7}$$

$$v_i = x_{best, G} + F_i \bullet (x_{r1, G} - x_{r2, G} + x_{r3, G} - x_{r4, G}) \tag{8}$$

where $x_{r1, G}$, $x_{r2, G}$, $x_{r3, G}$, $x_{r4, G}$ are the random individuals, $x_{best, G}$ is the best individual of the current population.

Step 4: Crossover.

$$u_{ij} = \begin{cases} x_{ij} & if \quad rand < CR_i \\ v_{ij} & or \end{cases} \tag{9}$$

where u_{ij} is the crossover individual, *rand* is a random number between [0, 1].

Step 5: Selection.

$$x_{i,G+1} = \begin{cases} u_i & if \quad f(u_i) < f(x_{i,G}) \\ x_{i,G} & or \end{cases} \tag{10}$$

where $f(\bullet)$ is the fitness function.

Step 6: Local search to the best solution by the chaotic search algorithm.

Step 7: *G*=*G*+1. If G>*Maxgens*, or find the optimization, then the search is over; otherwise, go back to step 2.

In above procedure, two mutation operators are employed, where Eq.(7) is DE/rand/bin [10] which has strong ergodicity, could sufficiently search the solution space and maintains the diversity of the population. So the proportion of it is large. Eq.(8) is DE/best/2/bin [10] , which combines the four random individuals and the best individual in current population, could exploit the neighborhood of the best individual and speed up the convergence rate. The selective factor α decided the proportion of the two mutation operators, whose setting is important for the performance of the proposed algorithm. The updating method of parameter efficiently maintains the diversity of the population and gets rid of the dependency of the parameter setting. It improves the robustness of the proposed algorithm.

5. Experimental results and analysis

5.1 Experimental setting

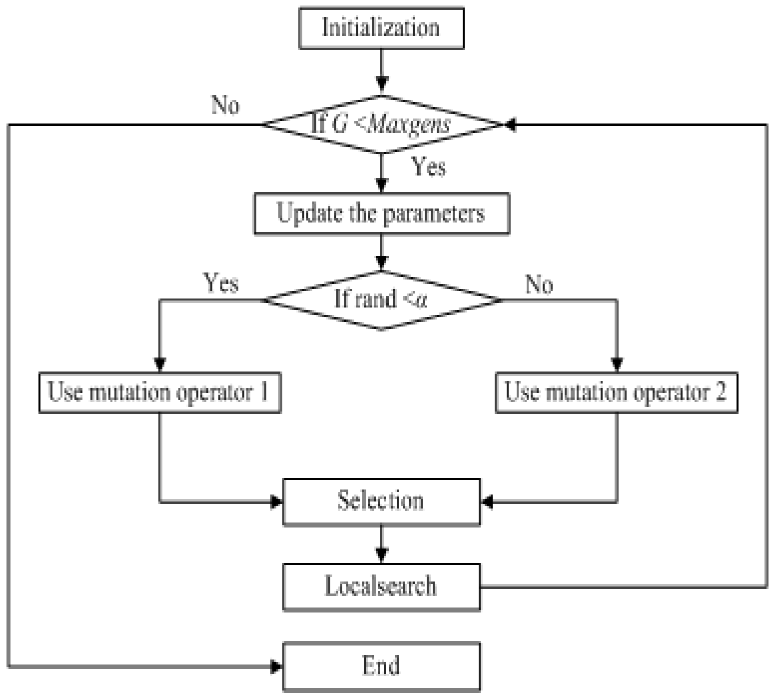


Figure 1. The flow chart of IDE

To evaluate the efficiency of the proposed IDE algorithm, several typical ELD problems are employed to as benchmark instances. These instances include two parts: basic ELD problem, the ELD with valve point effect. To fairly compare with other algorithms, we implement three classical algorithms; those are particle PSO [19], DE [20], jDE [17]. And other compared algorithms come from relevant literatures. The proposed algorithm was coded in Matlab2010a and run on a PC with an Intel Core i5-2450 CPU and 2G RAM under Windows 7.

The parameter is important for the performance of IDE, which includes the initial scale factor F and crossover rate CR and the selective factor α. *F* and *CR* are all set 0.5. α is set differently for different ELD problems, so it has displayed in each ELD problem. Other parameters included the maximum iteration *Maxgens*, the population size *NP* are set according to different ELD problem. In order to study the statistical properties of the proposed algorithm, every problem is executed by the proposed algorithm for 20 times. The parameters of above three compared algorithms come from relevant literatures.

5.2 Experimental results

5.2.1 The basic ELD problem

The dimension of the basic ELD problem is set 38. Other parameters can be seen from Table 1. The load demand is set 6000MW. In this problem, we will ignore the valve point effect and others constraints. Moreover, the consumption in during transmission is free. The population size *NP* is set 40, *Maxgens*=3000. The selective factor is set 0.6. Table 2 lists the results which include the mean (Mean), the best value (Best), the worst value (Worst), the variance (Std). In this, the convergence rate of the proposed algorithm is compared with PSO, DE, jDE in Fig.1 Table 3 lists the best solution of the IDE, PSO, DE, jDE. In Table 4, we compare the best value of IDE with other reported algorithms for this ELD problem. These algorithms include LL [21], HHS [22], IPSO [23].

It is can be observed from Table 2 that the obtained results by IDE are better than other three algorithms. Meanwhile, regarding the mean cost and maximum cost, the performance of the proposed algorithm indicates that it is steady and robust, which demonstrated that the strong capability of handling the basic ELD problem. It also observed that the worst solution of IDE outperforms than the best solutions found by the other approaches. It can be seen from Table 4 that the best solution obtained by IDE is better than other reported algorithms found. In Fig.2, we can seen that the convergence rate of the proposed algorithm is superior to others. It illustrates that the mutation operator DE/best/2/bin have important effect on accelerating the convergence speed.

i	P_i^{min}	P_i^{min}	a_i	b_i	c_i
1	220	550	0.3133	796.9	64782
2	220	550	0.3133	796.9	64782
3	200	500	0.3127	795.5	64670
4	200	500	0.3127	795.5	64670
5	200	500	0.3127	795.5	64670
6	200	500	0.3127	795.5	64670
7	200	500	0.3127	795.5	64670
8	200	500	0.3127	795.5	64670
9	114	500	0.7075	915.7	172832
10	114	500	0.7075	915.7	172832
11	114	500	0.7515	884.2	176003
12	114	500	0.7083	884.2	173028
13	114	500	0.4211	1250.1	91340
14	90	365	0.5145	1298.6	63440
15	82	365	0.5691	1298.6	65468
16	120	325	0.5691	1290.8	77282
17	65	315	2.5881	238.1	190928
18	65	315	3.8734	1149.5	285372
19	65	315	3.6842	1269.1	271676
20	120	272	0.4921	696.1	39197
21	120	272	0.5728	660.2	45576
22	110	260	0.3572	803.2	28770
23	80	190	0.9415	818.2	36902
24	10	150	52.123	33.5	105510
25	60	125	1.1421	805.4	22233
26	55	110	2.0275	77.1	30953
27	35	75	3.0744	833.6	17044
28	20	70	16.765	2188.7	81079
29	20	70	26.35	124.24	124757
30	20	70	30.575	8376.1	121915
31	20	70	25.098	1305.2	120780
32	20	60	33.722	710.6	104441
33	25	60	23.915	1633.9	8324
34	18	60	32.562	969.6	111281
35	8	60	18.362	2625.8	64142
36	25	60	23.915	1633.9	103519
37	20	38	8.482	694.7	13547
38	20	38	9.693	655.9	13518

Table 1. The parameters of the basic ELD problems

Algorithm	Best	Mean	Worst	Std
PSO[19]	9523431.38	9537029.10	9549653.64	1.31e+04
DE [20]	9407838.53	9408187.93	9408490.84	3.28e+02
jDE [17]	9406681.70	9406684.13	9.40668754	3.04e+00
IDE	9406671.36	9406671.36	9406671.36	6.65e-06

Table 2. Statistical results for PSO, DE, jDE, IDE

i	PSO[19]	DE[20]	jDE[17]	IDE
1	359.44	422.53	423.64	424.36
2	410.06	437.08	425.39	424.36
3	385.67	424.90	427.34	427.41
4	423.86	419.71	427.24	427.41
5	443.25	419.91	427.01	427.41
6	373.22	415.25	428.69	427.41
7	362.56	412.95	427.76	427.41
8	320.83	125.46	425.75	427.41
9	270.07	114.94	114.07	114.00
10	182.64	114.00	114.02	114.00
11	212.86	135.28	119.20	118.31
12	163.77	110.00	126.40	126.08
13	172.12	110.00	110.00	110.00
14	112.25	90.00	90.00	90.00
15	114.39	82.00	82.00	82.00
16	136.15	120.21	120.00	120.00
17	167.47	160.06	159.45	159.33
18	65.12	65.00	65.00	65.00
19	68.31	65.04	65.00	65.00
20	192.22	271.66	271.99	272.00
21	233.85	267.99	271.98	272.00
22	177.54	259.23	260.00	260.00
23	136.14	132.51	130.12	130.00
24	14.69	10.24	10.00	100.00
25	105.46	122.03	112.40	112.69
26	99.05	109.75	110.00	110.00
27	55.98	35.63	36.89	37.27
28	20.22	20.00	20.00	20.00
29	22.38	20.00	20.00	20.00
30	20.04	20.00	20.00	20.00

31	20.00	20.00	20.00	20.00
32	21.00	20.11	20.00	20.00
33	25.77	25.09	25.00	25.00
34	21.04	18.03	18.00	18.00
35	10.09	8.03	8.00	8.00
36	25.17	25.00	25.00	25.00
37	29.93	22.14	21.68	21.70
38	25.21	22.78	20.91	20.99

Table 3. The best solution with PSO, DE, jDE, IDE

Algorithm	Best
PSO [19]	9523431.38
DE [20]	9407838.53
jDE [17]	9406681.70
IDE	9406671.36
LL [21]	9447354
IPSO[23]	9500448
HHS[22]	9417325

Table 4. Comparison with other reported algorithms for the best value

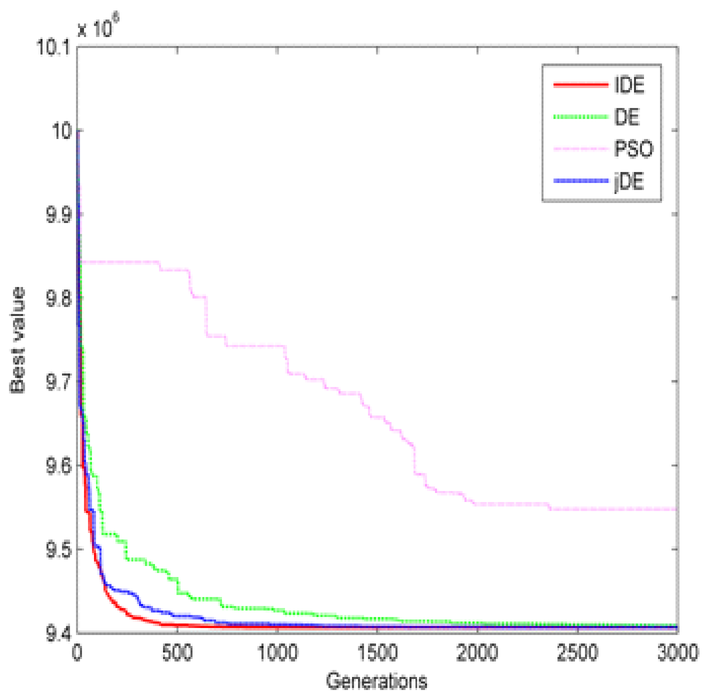


Figure 2. The convergence curve of the basic ELD problem

5.2.2 The ELD problem with valve point effect

In this problem, 13 generators will be considered. This ELD problem takes into account the influence of the valve point effect. The load demand is set 1800MW and 2520MW. The relevant parameters can be seen from Table 5. The best known solution is lists in Table 6 and 7. Furthermore, the consumption in during transmission is also free. The population size *NP* is set 40, *Maxgens*=3000. The selective factor is set 0.7. Table 8 and Table 9 list the statistical results which include the mean (Mean), the best value (Best), the worst value (Worst), the variance (Std). Table 10 lists the best value for PSO, DE, jDE, IDE and other reported algorithms, which include IFEP [24], CDE [25], DSPSO [26], HHS [22]. Meanwhile, the convergence rate of the proposed algorithm is compared with PSO, DE, jDE in Fig.3

i	P_i^{min}	P_i^{min}	a	b	c	e	f
1	0	680	0.00028	8.1	550	300	0.035
2	0	360	0.00056	8.1	309	200	0.042
3	0	360	0.00056	8.1	307	200	0.042
4	60	180	0.00324	7.74	240	150	0.063
5	60	180	0.00324	7.74	240	150	0.063
6	60	180	0.00324	7.74	240	150	0.063
7	60	180	0.00324	7.74	240	150	0.063
8	60	180	0.00324	7.74	240	150	0.063
9	60	180	0.00324	7.74	240	150	0.063
10	40	120	0.00284	8.6	126	100	0.084
11	40	120	0.00284	8.6	126	100	0.084
12	55	120	0.00284	8.6	126	100	0.084
13	55	120	0.00284	8.6	126	100	0.084

Table 5. The parameters of the ELD problem with valve point effect

i	P_i
1	628.3185
2	149.5997
3	222.7419
4	109.8666
5	109.8666
6	109.8666
7	109.8666
8	60.0000
9	109.8666
10	40.000
11	40.000
12	55.000
13	55.000
$\Sigma P_i = 1800$ C = 17960.3661	

Table 6. The best known solution of the ELD problem with valve point effect (1800MW)

i	p_i
1	628.3185
2	299.5997
3	294.4840
4	159.7331
5	159.7331
6	159.7331
7	159.7331
8	159.7331
9	159.7331
10	77.3999
11	77.3999
12	92.3999
13	92.3999
$\Sigma P_i = 2520$ $C = 17960.3661$	

Table 7. The best known solution of the ELD problem with valve point effect (1800MW)

i	p_i
1	628.3185
2	299.5997
3	294.4840
4	159.7331
5	159.7331
6	159.7331
7	159.7331
8	159.7331
9	159.7331
10	77.3999
11	77.3999
12	92.3999
13	92.3999
$\Sigma P_i = 2520$ $C = 24164.0508$	

Table 8. The best known solution of the ELD problem with valve point effect (2520MW)

Algorithm	Best	Mean	Wost	Std
PSO[19]	18440.47	18497.97	18587.11	6.77e+01
DE [20]	17972.81	17972.81	17972.81	8.64e-02
JDE[17]	17972.81	17972.81	17972.81	2.21e-07
IDE	17968.91	17968.91	17968.91	4.61e-10

Table 9. Statistical results with PSO, DE, jDE, IDE for the ELD problem with valve point effect (1800MW)

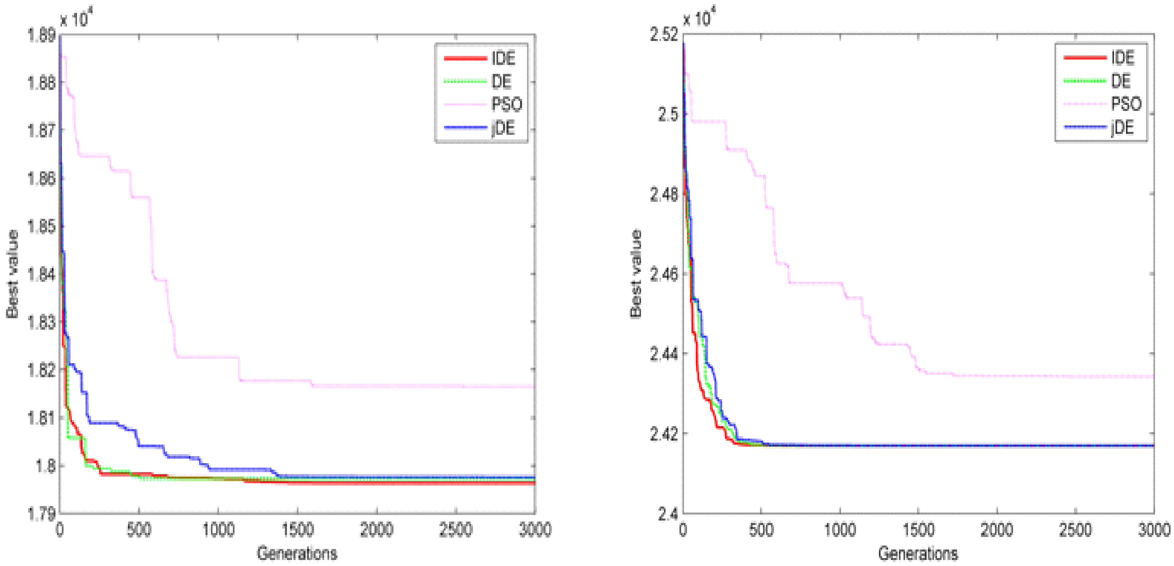
Algorithm	Best	Mean	Wost	Std
PSO[19]	24297.07	24394.08	24575.61	1.12e+02
DE [20]	24169.92	24169.92	24169.92	9.43e-03
JDE[17]	24169.91	24169.91	24169.91	2.51e-07
IDE	24167.92	24167.92	24167.92	4.81E-12

Table 10. Statistical results with PSO, DE, jDE, IDE for the ELD problem with valve point effect (2520MW)

$\Sigma P_i = 1800$		$\Sigma P_i = 2520$	
Algorithm	Best	Algorithm	Best
PSO [19]	18440.47	PSO[19]	24297.07
DE [20]	17972.81	DE[20]	24169.92
JDE [17]	17972.81	JDE[17]	24169.91
IFEP[24]	17994.07	IFEP[24]	24169.9
CDE[25]	17963.94	CDE[25]	24169.9
IDE	17968.91	IDE	24167.92

Table 11. Comparison with other reported algorithms for the best value

Compared with the basic ELD problem, this problem is much harder due to the consideration of valve point effect and two load demands. Table 8 and Table 9 reveals that IDE is again superior to others three algorithms in terms of all comparison aspects. Due to the double mutation operators, the exploration and exploitation ability of IDE is balanced, which make the population locate in a more reasonable area and to perform effectively in exploring the global optimal working condition. Meanwhile, by contrast



(a) (b)

Figure 3. The convergence curve of the ELD problem with valve point effect. (a) 1800MW (b) 2529MW

with the implementation of Classical DE and jDE, it is apparent that the double mutation is able to further improve the search of DE. Moreover, from Fig.2, we know that IDE again outperforms all other compared algorithms in terms of the convergence rate. It can be seen from Table 10 that the best solution obtained by IDE is better than other reported algorithms found. Therefore, it can be concluded that the proposed algorithm is suitable approach for such kinds of complex problems.

6. Conclusions

Economic load dispatch (ELD) is an important and difficult optimization problem in power system planning. So an improved differential evolution algorithm was proposed to solve it in this paper. The classical double mutation was introduced to maintain the diversity and speed up the convergence rate. To improve the quality of the solution, an adaptive updating method of parameter and a chaotic local search was employed. So the IDE can further stress the balance the global exploration and local exploitation. We use two types of ELD problems to test the efficiency of the proposed algorithm. The computational results were shown that IDE provides robust and good performance for ELD problems. In the further, the proposed IDE algorithms can be extended to solve other ELD problems, such as ELD with forbidden zone restrain, ELD with load variation and so on.

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