Solving Economic Load Dispatch Problem of Power System Based on Differential Evolution Algorithm with Different Mutation Strategies

Wen-Kuo Hao, Yun-Peng Li *, Jie-Sheng Wang, Qi Zhu

Abstract—**The economic load dispatch (ELD) in the power system is to reasonably allocate the output power of each generating unit under the premise of satisfying the operation constraints and the balance of supply and demand, so as to optimize the total cost of power generation as the objective function. Taking the system power balance and the upper limits and lower limits of generator output as constraints in the ELD problem, its mathematical model was established. A differential evolution (DE) algorithm based on different strategies is proposed to solve the ELD problem. Aiming at three ELD examples, the most suitable differential evolution strategy for the ELD problems was found through the results of simulation experiments. Under the same starting conditions, DE algorithm, particle swarm optimization (PSO) algorithm, genetic algorithm (GA) and simulated annealing (SA) algorithm were used to conduct simulation experiments to verify the superiority of DE algorithm. Experimental results show that the proposed DE algorithm has the best performance in solving ELD problems.**

Index Terms—**power system, economic load dispatch, differential evolution algorithm**

I. INTRODUCTION

ELECTRICITY is the lifeblood of national economic development, as well as the energy foundation of industry, production and manufacturing. The safe and stable operation of the power system has become the lifeblood of national economic development. In practice, the fuel cannot be completely converted into electrical energy during the power generation process of a power plant. The process is often accompanied by losses. Part of the electrical energy is lost due to the unreasonable operation of the generator set, and some is lost during the transmission of electrical energy, which will make the power plant have the relatively higher power generation cost and a serious waste of resources. Therefore, under the premise of satisfying the demand for power generation, how to reduce energy consumption, reduce power generation costs, and ensure the quality of power generation have become the top priority of the development of the power system. If the economic load dispatch (ELD) of the power system can be reasonably optimized, the energy structure configuration can be further optimized and the energy utilization efficiency can be improved [1]. ELD problem is a nonlinear, multi-dimensional optimization problem with multiple constraints, which is based on the premise of meeting the energy balance and constraint conditions, reasonably adjusting the output power of each generator set, and the goal of minimizing the cost of power generation is finally realized. The solution of power system ELD problem plays a huge role in improving energy utilization efficiency and rapid social and economic development, and the load dispatch and optimization of multiple generator sets in power plants are regarded as the most important part of power system economic dispatch [2].

Many scholars use mathematical methods to construct economic dispatch models of power systems to explore this high-dimensional, nonlinear, and constrained optimization problem. Traditional economic dispatch methods focus on solving the quadratic function model of the generating unit, but they have extremely strict requirements on the initial value, objective function, and constraint conditions. When the dimension of the problem is too higher, it may cause the convergence to be too slow and fall into the local maximum. Traditional mathematical methods have limitations in dealing with this problem [3]. However, as the scale of the power system continues to expand and the complexity becomes higher and higher, more constraints need to be considered when calculating such problems, and there are higher requirements for the performance of the algorithm to be solved. Therefore, many scholars have adopted evolutionary programming (EP) [4], particle swarm optimization (PSO) [5], genetic algorithm (GA) [6], harmony search (HS) [7], Moth-Flame Algorithm (MFO) [8], simulated annealing (SA) [9] and other heuristic intelligent optimization algorithms to solve such high-dimensional, nonlinear, constrained optimization problems.

Differential Evolution (DE) algorithm is an intelligent optimization algorithm that searches for global optimal solutions. DE algorithm simulates the natural evolution process of organisms [10]. Because DE algorithm is simple and easy to implement, few control parameters and strong search ability, DE algorithm has been extensively studied and

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has been successfully applied to flow shop scheduling [11], uniform amplitude and unequal spacing antenna array synthesis [12], image edge detection [13], reactive power optimization scheduling [14], digital FIR filter design [15] and other fields. In this paper, a DE algorithm based on different strategies is proposed to solve ELD problem. The structure and content of the paper are arranged as follows. The second section introduces the mathematical model of ELD problem, the third section introduces DE, the fourth section is experimental simulation and result analysis, and the last section is the conclusion of the paper.

II. Economic Load Dispatch Problem in Power System

The power system generates electricity through generator sets, transmits and distributes the generated electric energy, and maintains the balance of power supply and demand. Therefore, the power supply in the power system and the distribution of the load of the generator sets restrict the operation of the power system to a certain extent. Through the reasonable dispatch and distribution of power generation resources, it has a great influence on the structural optimization of the power system and the development of social economy.

A. Model of Economic Load Dispatch Problem

The objective of economic load dispatch (ELD) problem in electric power system is to reasonably adjust the output power of each generator and minimize the generation cost under the condition of meeting the load demand during dispatching period. At the same time, constraints such as generator set power constraints, power balance constraints and network transmission loss should be satisfied. In this paper, the total cost of power generation is taken as the objective function to obtain the mathematical model of ELD problem [16] and solve the ELD problem.

B. Objective Function

In the treatment of traditional ELD problems, a second-order polynomial function is used to calculate the fuel cost of a generator set, and the optimization technology of mathematical programming is adopted. The quadratic polynomial function requires that the incremental cost curve be monotonically increasing or piece-wise linear. The specific quadratic polynomial function can be described as:

$$MinF_t = \sum_{i=1}^{n} \alpha_i P_i^2 + \beta_i P_i + \gamma_i \tag{1}$$

where, F_t is used as the total fuel cost of generating electricity by the generator set, P_i is used as the power generation of the *i-th* generator set, $\alpha_i, \beta_i, \gamma_i$ are used as the cost coefficients of the generator set *i*. and *n* is the number of generator sets.

C. Constraints

In actual working state, the generator set is subject to its own limitations and operating constraints, and needs to meet the power balance constraints of the system. When the actual power transmission distance is long, the power loss in the transmission process cannot be ignored. Transmission loss has a great influence on adjusting the output power of the generator set and will increase the generation cost. In this paper, the B coefficient matrix is used to simulate the loss during the transmission process so as to obtain the active network loss of the electric energy during the transmission process. As a simple method for calculating the system network loss, the total output power of all generating sets must be equal to the sum of the total demand for power supply and the loss during transmission, which is specifically expressed as:

$$\sum_{i=1}^{N} P_i = P_D + P_{Loss} \tag{2}$$

$$P_{Loss} = \sum_{i=1}^{N}\sum_{j=1}^{N} P_i B_{ij} P_j + \sum_{i=1}^{N} B_{0i} P_i + B_{00} \tag{3}$$

where, P_D is the total actual power demand; P_{Loss} is the total transmission loss; B_{ij} , B_{0i} , B_{00} are the B coefficients. The output power of the generator set is limited to a certain range to ensure the safe and stable operation of the system, which is described as:

$$P_{i,\min} \le P_i \le P_{i,\max} \tag{4}$$

where, $P_{i,\min}$ and $P_{i,\max}$ are the minimum and maximum allowable output power generation of the *i-th* generator set respectively.

The actual power system ELD has many more constraints, and these constraints will also be coupled with each other, which makes the power system ELD more complicated. In this paper, when studying the ELD problem, the system power balance and the power limit constraint of the generator set are taken as constraints.

III. Differential Evolution Algorithm

Differential evolution (DE) algorithm is an adaptive global search optimization algorithm that iteratively seeks the optimal solution among the target swarm [10]. It originally originated from the solution of Chebyshev polynomial problems. Later, it was discovered that the DE algorithm has advantages in the global search ability when solving complex optimization problems compared with other evolutionary algorithms. Due to its simple principle, fewer required parameters, high stability, and fast speed, the DE algorithm has been widely used to solve problems such as multi-objective optimization and constrained optimization [17]. The main parameters of DE algorithm include scaling factor F, crossover probability CR and population size NP. The values of scaling factor F and crossover probability CR have great influence on experimental results. Moreover, differential evolution algorithm has some shortcomings in local search ability and convergence speed, and may fall into local optimum.

A. Algorithm Initialization

DE algorithm is a population intelligent evolution method. Its initialization requires that the initial population be generated under specific constraints and distributed as completely as possible in the entire search space. Individuals in the population are randomly generated, and each individual is a candidate solution in the entire search space, the principle of which is shown in FIG. 1. Let D be the dimension of the problem and the population size be NP.

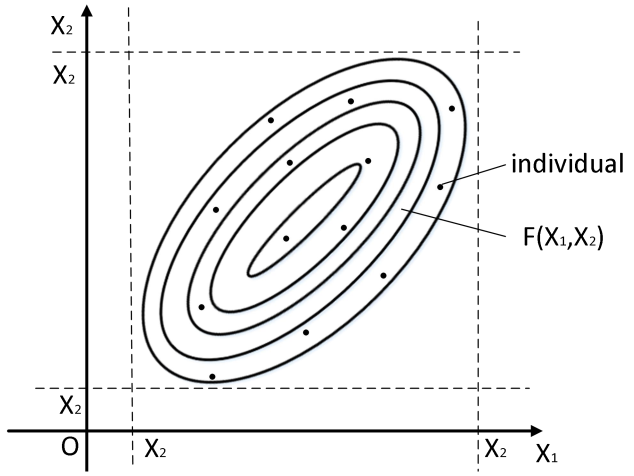

Fig. 1 Example diagram of DE algorithm initialization.

Generally, the population size is usually large, which requires that the minimum $X_{\min} = \{X_{\min}^1, X_{\min}^2, ..., X_{\min}^D\}$ and maximum $X_{\max} = \{X_{\max}^1, X_{\max}^2, ..., X_{\max}^D\}$ of a given individual vector be limited before initializing the population. Finally a target vector of the population composed of NP *D*-dimensional vector individuals is generated.

$$X_{i.G} = \{X_{i,G}^1, X_{\mathrm{i}.G}^2, ..., X_{\mathrm{i.G}}^D\}, \quad \mathrm{i} = 1,2, \ \ldots, \mathrm{NP} \tag{5}$$

where, $X_{i.G}$ is the *i*-th individual vector in the population, and D is the spatial dimension of individual vector.

Due to the large population, it is necessary to search all regions for individual distribution and adopt the random numbers to generate initial values. The position update of each component in the population individual vector is realized by Eq. (6).

$$X_{i,j} = X_{i,j\max} + rand \times \left(X_{i,j\max} - X_{i,j\min}\right) \tag{6}$$

where , $X_{i,j}$ is the *j*-th component of the individual vector X_i, $X_{i,j\max}$ is the maximum value of the *j*-th component of the individual vector X_i, $X_{i,j\min}$ is the minimum value of the *j*-th component of the individual vector X_i, and rand is a random number within [0,1].

B. Mutation Operation

The difference between DE algorithm and other optimization algorithms is mutation operation. Mutation is based on the original population through individual differences to produce new individuals so as to achieve the search for spatial regions. After initializing the population and iteration, the target vector will be mutated to produce a series of mutated vectors $V_{i,G} = \{V_{i,G}^1, V_{i,G}^2, ..., V_{i,G}^D\}$. Suppose the mutation-generating individual is $V_{i,G+1}$, and three different individuals *a*, *b*, and *c* are selected from the population. The mutation operation process shown in Eq. (7) will produce a mutated individual.

$$V_{i,G+1} = X_{a,G} + F \times \left(X_{b,G} - X_{c,G}\right) \tag{7}$$

where, *F* is the scaling factor used to control the differential vector scaling of the variation, and its value range is generally [0, 2]; $a,b,c \in \{1,2,...NP\}$ and $a \neq b \neq b \neq i$;

DE algorithm has many mutation strategies, which have different effects on the performance of DE algorithm, they all have their own mutation characteristics [18]. When facing different problems, they have their own advantages and disadvantages. According to the specific situation, different strategies can be used to analyze the specific model. The common mutation strategies of DE algorithm are listed in Table 1.

Among them, DE/rand/1 strategy is often used in DE algorithm. DE1 strategy mutation vector generation process is shown in Fig. 2. DE1 and DE2 strategies are the two most basic mutation strategies in DE algorithms. The DE1 strategy will produce intermediate individuals when mutating individuals in the population, but this strategy searches in the global space and has defects in operating speed. The DE2 strategy has a strong purpose. It selects the optimal individual from all current individuals, has strong purpose and advantages in local retrieval and convergence speed, but it may fall into the local optimal situation. DE3 strategy is a synthesis of DE1 and DE2 strategies, with better global search and higher stability. The DE4 strategy increases the amount of random disturbance on the basis of the DE2 strategy, where the population diversity is better and the convergence speed is slower than DE2. the DE5 strategy includes random disturbance and optimal disturbance, which balances the global search and local search capabilities.

TABLE 1. MUTATION STRATEGIES OF DE ALGORITHM

	Name	Expression
DE1	DE/rand/1/bin	$V_i = X_{rand1} + F \times \left(X_{rand1} - X_{rand2}\right)$
DE2	DE/best/1/bin	$V_i = X_{best} + F \times \left(X_{rand1} - X_{rand2}\right)$
DE3	DE/rand/2/bin	$V_i = X_i + \lambda \times \left(X_{best} - X_i\right) + F \times \left(X_{rand1} - X_{rand2}\right)$
DE4	DE/best/2/bin	$V_i = X_{rand1} + \lambda \times \left(X_{rand1} - X_{rand2}\right) + F \times \left(X_{rand3} - X_{rand4}\right)$
DE5	DE/rand-to-best/1	$V_i = X_{best} + \lambda \times \left(X_{rand1} - X_{rand2}\right) + F \times \left(X_{rand3} - X_{rand4}\right)$

Note: Where , $\lambda \in [0,1]$; $F \in [0,2]$.

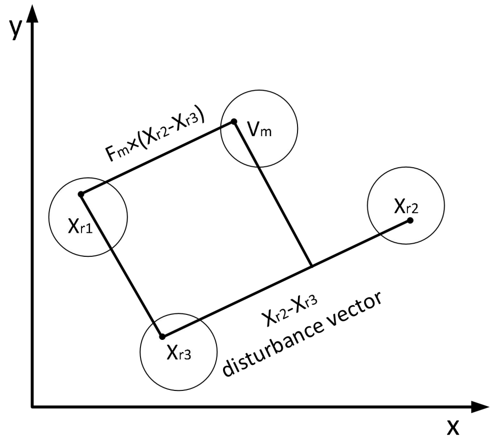

Fig. 2 Variation vector generation diagram based on DE/rand/1 strategy.

C. Crossover Operation

The crossover operation is very important in DE algorithm. The crossover operator determines the ratio of the intermediate individuals to the evolved individuals in the population, which increases the diversity of the population and avoids falling into local optimum. The global search capability and convergence speed can be significantly improved by appropriate crossover operation. This paper adopts the binomial crossover method. When the generated value does not exceed the crossover probability *CR*, the binomial crossover is used for the variant individuals. The crossover operation is shown in Eq. (8).

$$\mathrm{u}_{\mathrm{i,G+1}}^{j} = \begin{cases} v_{i,G+1}^{j} & \mathrm{rand}(0,1) \le \mathrm{CR} \text{ or } \mathrm{j} = \mathrm{j}_{rand} \\ x_{i,G}^{j} & \text{otherwise} \end{cases} \tag{8}$$

Where, *CR* is the crossover probability, The greater the *CR*, the greater the crossover probability, $CR \in (0,1)$; $j_{rand} \in [1, D]$; $v_{i,G}^{j}$ is the vector of the variant individual; $x_{i,G}^{j}$ is the target vector. The binomial crossover is shown in Fig. 3.

D. Selection Operation

The selection operation of DE algorithm adopts the greedy selection method. The optimal individual is selected from the comparison of the individual fitness after the crossover. The smaller the fitness individual, the closer to the target vector, thereby completing the population update. The selection operation is described as follows.

$$x_{\mathrm{m}}^{t+1} = \begin{cases} u_m^t & f(u_m^t) \le f(x_m^t) \\ x_m^t & \text{otherwise} \end{cases} \tag{9}$$

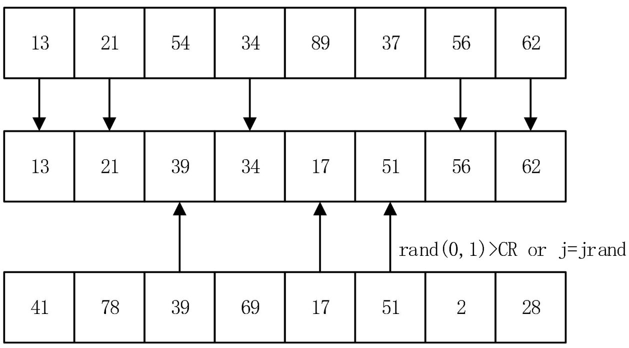

Fig. 3 Schematic diagram of binomial crossover.

where, u_m^t is the experimental vector; *f* is the fitness function; x_m^t is the target vector.

E. Algorithm Flowchart

The DE algorithm is widely used in solving complex optimization problems because of its advantages of simple principle, fewer required parameters, high search accuracy, high stability and fast speed. The DE algorithm mainly includes four links: initialization, mutation, crossover and selection. The DE algorithm is initialized first, and then the algorithm circulates mutation, crossover and selection until the termination condition of the algorithm is satisfied and the global optimal solution is obtained. The initialized population is randomly generated with the search space as the boundary, and changes are made through the differences between individuals in the population. The combination generates mutant individuals. Each mutation in the loop will get a mutation vector.

The mutation vector and the target vector are cross-operated to obtain a new solution. Then find individuals with better fitness and keep them to achieve evolution, and continue to iterate to find the best individuals. When the termination condition is satisfied, the iteration ends and the global optimal solution is obtained. The flowchart of the DE algorithm is shown in Fig. 4.

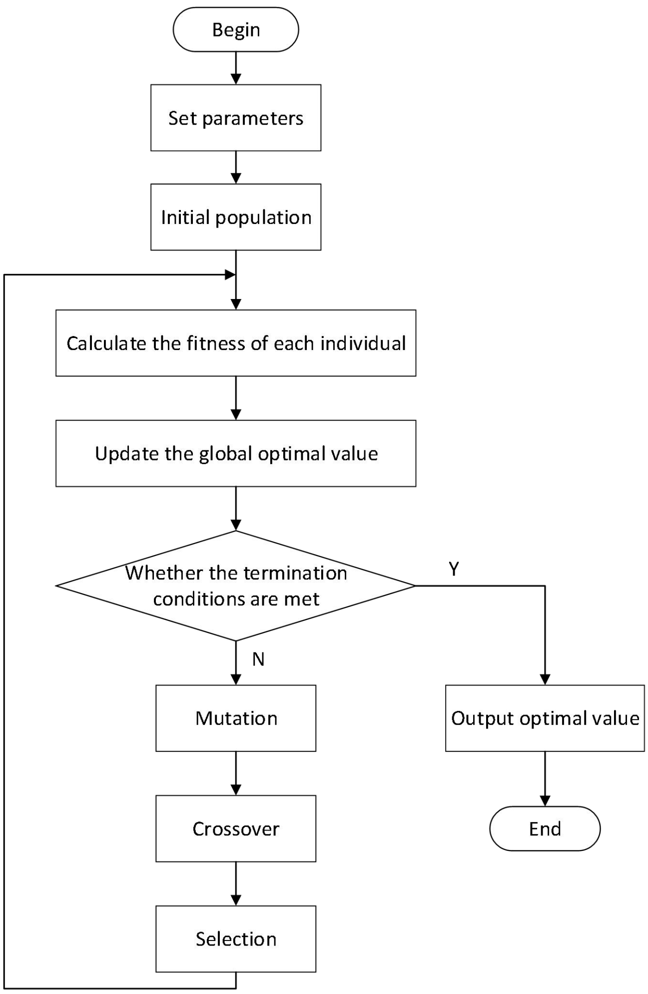

Fig. 4 Flow chart of differential evolution algorithm

IV. Simulation Experiments and Result Analysis

A. Experimental Parameter Setting and Simulation Cases

According to the unit fuel cost coefficient of the ELD problem in the power system and the generator set power limit constraint and power balance constraints in the constraint conditions and the transmission loss simulated by the *B* coefficient matrix, the objective function and constraint conditions of the above-mentioned power system ELD are integrated with the DE algorithm. Through the initialization and setting of the initial value, the total fuel cost of the generator set obtained by the objective function is continuously iterated through mutation, crossover, and selection operations, and the total power generation cost with higher adaptability is updated. When certain conditions are met, the iteration is stopped, and the optimal total fuel cost of the generator set is obtained.

In the simulation experiment, three actual ELD problem cases of different sizes are selected, namely 6 generator sets (total demand 700MW), 6 generator sets (total demand 800MW) and 13 generator sets (total demand 1800MW), and DE algorithm is used to solve the three cases. In order to test the effect of DE algorithm to solve ELD problem. The DE algorithm is compared with GA, PSO algorithm, SA algorithm. In order to ensure the stability and reliability of the experimental results, each ELD case is independently optimized and run 20 times during the experiments.

(1) Case 1

The ELD case of this power system has a total of 6 generator sets, and the power demand is 800MW [14]. The unit fuel cost coefficients (α_i, β_i, γ_i), the power limit($P_{\max}$ and $P_{\min}$) constraints of the generator set are listed in Table 2. The *B* coefficient matrix is adopted to simulate the network loss so as to obtain the active power loss of the power system in the transmission process. The *B* coefficient matrix is described as follows.

$$B_{ij} = \begin{bmatrix} 0.00014 & 0.000017 & 0.000015 & 0.000019 & 0.000026 & 0.000022 \\ 0.000017 & 0.000060 & 0.000013 & 0.000016 & 0.000015 & 0.000020 \\ 0.000015 & 0.000013 & 0.000065 & 0.000017 & 0.000024 & 0.000019 \\ 0.000019 & 0.000016 & 0.000017 & 0.000071 & 0.000030 & 0.000025 \\ 0.000026 & 0.000015 & 0.000024 & 0.000030 & 0.000069 & 0.000032 \\ 0.000022 & 0.000020 & 0.000019 & 0.000025 & 0.000032 & 0.000085 \end{bmatrix}$$

(2) Case 2

TABLE 2. FUEL COST COEFFICIENT PER UNIT SYSTEM AND POWER LIMIT OF GENERATOR SET (800MW)

Unit	α_i	β_i	γ_i	$P_{\max}$	$P_{\min}$
1	0.15240	38.53973	756.79886	10	125
2	0.10587	46.15916	451.32513	10	150
3	0.02803	40.39655	1049.9977	35	225
4	0.03546	38.30553	1243.5311	35	210
5	0.02111	36.32782	1658.5596	130	325
6	0.01799	38.27041	1356.6592	125	315

The ELD case of this power system has a total of 6 generator sets, and the power demand is 700MW [14]. The unit fuel cost coefficients (α_i, β_i, γ_i), the upper and lower limits $P_{\max}$ and $P_{\min}$) of the active power constraint value of the generator set are listed in Table 3. The *B* coefficient matrix is adopted to simulate the network loss so as to obtain the active power loss of the power system in the transmission process. The *B* coefficient matrix is described as follows.

$$B_{ij} = \begin{bmatrix} 0.14 & 0.17 & 0.15 & 0.19 & 0.26 & 0.22 \\ 0.17 & 0.6 & 0.13 & 0.16 & 0.15 & 0.2 \\ 0.15 & 0.13 & 0.65 & 0.17 & 0.24 & 0.19 \\ 0.19 & 0.16 & 0.17 & 0.71 & 0.3 & 0.25 \\ 0.26 & 0.15 & 0.24 & 0.3 & 0.69 & 0.32 \\ 0.22 & 0.2 & 0.19 & 0.25 & 0.32 & 0.85 \end{bmatrix} * e^{-4}$$

(3) Case 3

The ELD case of this power system has a total of 13 generator sets, and the power demand is 1800MW [15]. The unit fuel cost coefficients (α_i, β_i, γ_i), the power limit($P_{\max}$ and $P_{\min}$) constraints of the generator set are listed in Table 4. The *B* coefficient matrix is adopted to simulate the network loss so as to obtain the active power loss of the power system in the transmission process. The *B* coefficient matrix is described as follow.

TABLE 3. UNIT SYSTEM FUEL COST COEFFICIENT AND POWER LIMIT OF GENERATOR SET (700MW)

Unit	α_i	β_i	γ_i	$P_{\max}$	$P_{\min}$
1	0.007	7	240	100	500
2	0.0095	10	200	50	200
3	0.009	8.5	220	80	300
4	0.009	11	200	50	150
5	0.008	10.5	220	50	200
6	0.0075	12	120	50	120

TABLE 4. FUEL COST COEFFICIENT PER UNIT SYSTEM AND POWER LIMIT OF GENERATOR SET (1800MW)

Unit	α_i	β_i	γ_i	$P_{\max}$	$P_{\min}$
1	0.0028	8.1	550	0	680
2	0.0056	8.1	309	0	360
3	0.0056	8.1	307	0	360
4	0.00324	7.74	240	60	180
5	0.00324	7.74	240	60	180
6	0.00324	7.74	240	60	180
7	0.00324	7.74	240	60	180
8	0.00324	7.74	240	60	180
9	0.00324	7.74	240	60	180
10	0.00284	8.6	126	40	120
11	0.00284	8.6	126	40	120
12	0.00284	8.6	126	55	120
13	0.00284	8.6	126	55	120

$$
B_{ij} = \begin{bmatrix}
0.14 & 0.12 & 0.07 & -0.01 & -0.03 & -0.01 & -0.01 & -0.01 & -0.03 & -0.05 & -0.03 & -0.02 & 0.04 \\
0.12 & 0.15 & 0.13 & 0 & -0.05 & -0.02 & 0 & 0.01 & -0.02 & -0.04 & -0.04 & 0 & .04 \\
0.07 & 0.13 & 0.76 & -0.01 & -0.13 & -0.09 & -0.01 & 0 & -0.08 & -0.12 & -0.71 & 0 & -0.26 \\
-0.01 & 0 & -0.01 & 0.34 & -0.07 & -0.04 & 0.11 & 0.50 & 0.29 & 0.32 & 0.11 & 0 & 0.01 \\
-0.03 & 0.05 & -0.13 & -0.07 & 0.90 & 0.14 & -0.03 & -0.12 & -0.10 & -0.13 & 0.07 & -0.02 & -0.02 \\
-0.01 & -0.02 & -0.09 & -0.04 & 0.14 & 0.16 & 0 & -0.06 & -0.05 & -0.08 & 0.11 & -0.01 & -0.02 \\
-0.01 & 0 & -0.01 & 0.11 & -0.03 & 0 & 0.15 & 0.17 & 0.15 & 0.09 & -0.05 & 0.7 & 0 \\
-0.01 & 0.01 & 0 & 0.50 & -012 & -0.06 & 0.17 & 1.68 & 0.82 & 0.79 & -0.23 & -0.36 & 0.01 \\
-0.03 & -2 & -0.08 & 0.29 & -0.10 & -0.05 & 0.15 & 0.82 & 1.29 & 1.16 & -0.12 & -0.25 & 0.07 \\
-0.05 & -0.04 & -0.12 & 0.32 & -0.13 & -0.08 & 0.09 & 0.79 & 1.16 & 2 & -0.72 & -0.34 & 0.09 \\
-0.03 & -0.04 & -0.17 & -0.11 & 0.07 & 0.11 & -0.05 & -0.23 & -0.21 & -0.27 & 1.4 & 0.01 & 0.04 \\
-0.02 & 0 & 0 & 0 & -0.02 & -0.01 & 0.07 & -0.36 & -0.25 & -0.34 & 0.01 & 0.54 & -.01 \\
0.04 & 0.04 & -0.26 & 0.01 & -0.02 & -0.02 & 0 & 0.01 & 0.07 & 0.09 & 0.40 & -0.01 & 1.03
\end{bmatrix} * e^{-4}
$$

B. DE Algorithm to Solve ELD Problem with Quadratic Objective Function

(1) Case 1

The maximum number of iterations is 200, the number of population individuals *NP* is 20, *F*=0.5, *CR*=0.9. Through simulation experiments, the output power, total output power of the generator sets and the loss during the transmission process of the 6 generator sets of each DE strategy under the total demand of 800MW are obtained. The simulation results are listed in Table 5. In order to ensure the reliability and stability of the results, 20 experiments are carried out for this case based on the DE algorithm with different strategies. The statistical results of the total power generation cost data obtained are listed in Table 6. The convergence curves of DE algorithm based on different strategies to solve Case 1 are shown in Fig. 5.

TABLE 5. TOTAL DEMAND OF 800MW AND POWER LOSS

	DE1	DE2	DE3	DE4	DE5
P_1	32.5994	32.5999	32.5981	32.5999	32.6036
P_2	14.4764	14.4831	14.4976	14.4831	14.4912
P_3	141.5449	141.5440	141.5126	141.5440	141.5455
P_4	136.0390	136.0414	136.0366	136.0414	136.0380
P_5	257.6656	257.6588	257.5033	257.6588	257.6557
P_6	243.0058	243.0035	243.1835	243.0035	242.9962
Total generation (MW)	825.3311	825.3307	825.3317	825.3307	825.3302
Power loss	25.3311	25.3307	25.3317	25.3307	25.3302

TABLE 6. COMPARISON TO SOLVE THE 800MW TOTAL DEMAND PROBLEM WITH DIFFERENT DE STRATEGIES

Algorithm	Best	Worst	Ave	Std
DE1	41896.628616	41919.389621	41898.033074	5.07639
DE2	41896.628616	41896.628772	41896.628614	3.48827E-05
DE3	41896.628616	41901.196420	41896.879274	1.01935
DE4	41896.628616	41896.628616	41896.628616	2.23949E-11
DE5	41896.628617	41919.427755	41897.866837	5.08603

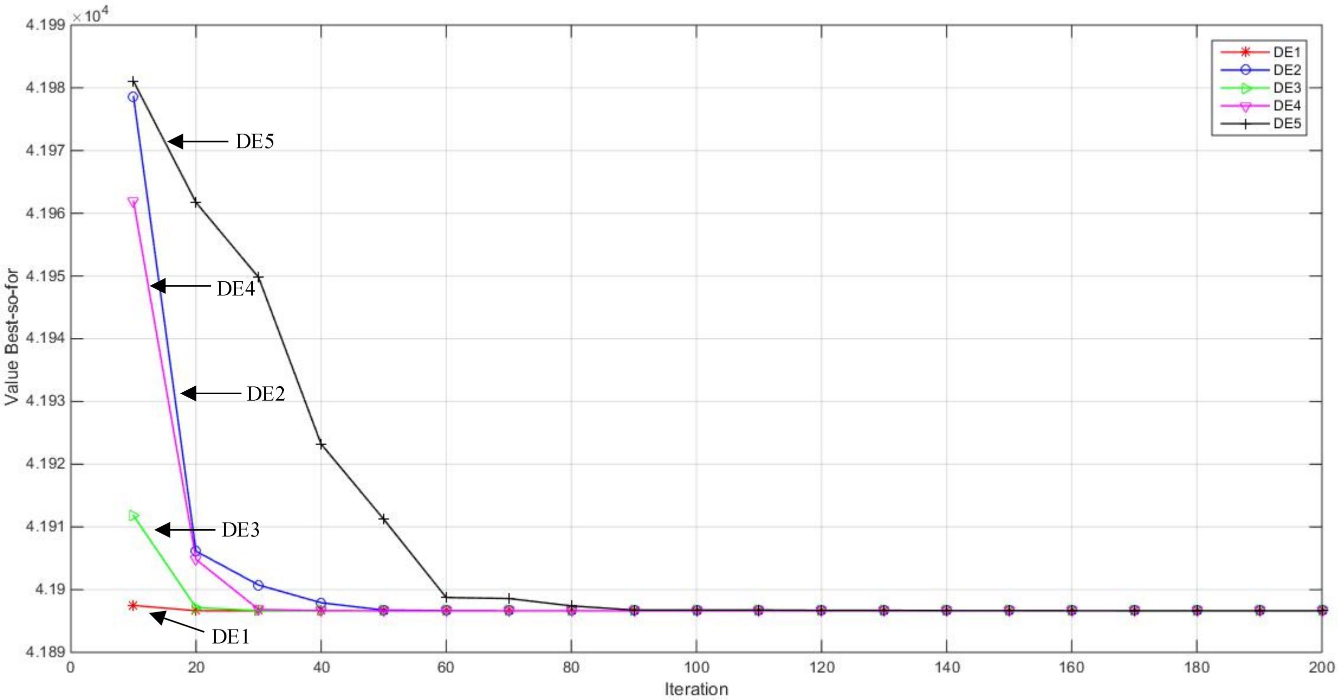

Fig. 5 Convergence curves of DE algorithm with different strategies.

(2) Case 2

The maximum number of iterations is 200, the number of population individuals *NP* is 20, *F*=0.5, *CR*=0.8. Through simulation experiments, the output power, total output power of the generator sets and the loss during the transmission process of the 6 generator sets of each DE strategy under the total demand of 700MW are obtained. The simulation results are listed in Table 7. In order to ensure the reliability and stability of the results, 20 experiments are carried out for this case based on the DE algorithm with different strategies. The statistical results of the total power generation cost data obtained are listed in Table 8; The convergence curves of DE algorithm based on different strategies to solve Case 1 are shown in Fig. 6.

(3) Case 3

The maximum number of iterations is 200, the number of population individuals *NP* is 30, *F*=0.5, *CR*=0.5. Through simulation experiments, the output power, total output power of the generator sets and the loss during the transmission process of the 13 generator sets of each DE strategy under the total demand of 1800MW are obtained. The simulation results are listed in Table 9. In order to ensure the reliability and stability of the results, 20 experiments are carried out for this case based on the DE algorithm with different strategies. The statistical results of the total power generation cost data obtained are listed in Table 10. The convergence curves of DE algorithm based on different strategies to solve Case 1 are shown in Fig. 7.

Table 5-10 and Fig. 5-7 show the comparison of the total cost of power generation by the DE algorithm with different strategies for different ELD problems. Under the same initial conditions for Case 1, it can be seen form Table 5-6 and Fig. 5 that the DE algorithm with DE1 and DE3 strategies have a better convergence speed compared with other strategies. Transmission loss and stability are within the normal range, and the total cost of power generation is similar. In Case 2, it can be seen from Table 7-8 and Fig. 6 that DE algorithm with DE1 and DE3 strategies have better convergence speed and stability than other strategies, and the transmission loss is within the normal range. The total cost of power generation is similar. In Case 3, it can be seen from Table 9-10 and Fig. 7 that DE algorithm with DE1 strategy has a faster convergence speed, DE algorithm with DE1 and DE3 strategies have better stability, the transmission loss is within the normal range and the total cost of power generation is similar. Therefore, in the DE algorithm, compared with other strategies, DE1 strategy and DE3 strategy have better optimization performance in solving the above-mentioned ELD problem of power system.

TABLE 7. TOTAL DEMAND OF 700MW AND POWER LOSS

	DE1	DE2	DE3	DE4	DE5
P_1	323.6373	323.6387	323.6374	322.81790	323.8248
P_2	76.6857	76.6833	76.6857	76.1018	78.1014
P_3	158.4359	158.4411	158.4359	160.1730	158.7900
P_4	50.0000	50.0000	50.0000	50.0000	50.0000
P_5	51.9765	51.9723	51.9765	51.6606	50.0000
P_6	50.0000	50.0000	50.0000	50.0000	50.0000
Total generation (MW)	710.7354	710.7354	710.7355	710.7533	710.7162
Power loss	10.7354	10.7354	10.7354	10.7533	10.7161

TABLE 8. COMPARISON OF DIFFERENT STRATEGIES TO SOLVE THE 700MW TOTAL DEMAND PROBLEM

Algorithm	Best	Worst	Ave	Std
DE1	8422.610918	8422.610918	8422.610918	0
DE2	8422.610918	8422.615789	8422.611558	0.00123225
DE3	8422.610918	8422.610918	8422.610918	0
DE4	8422.610921	8422.649343	8422.614546	0.008973683
DE5	8422.616863	8422.882278	8422.682071	0.05335483

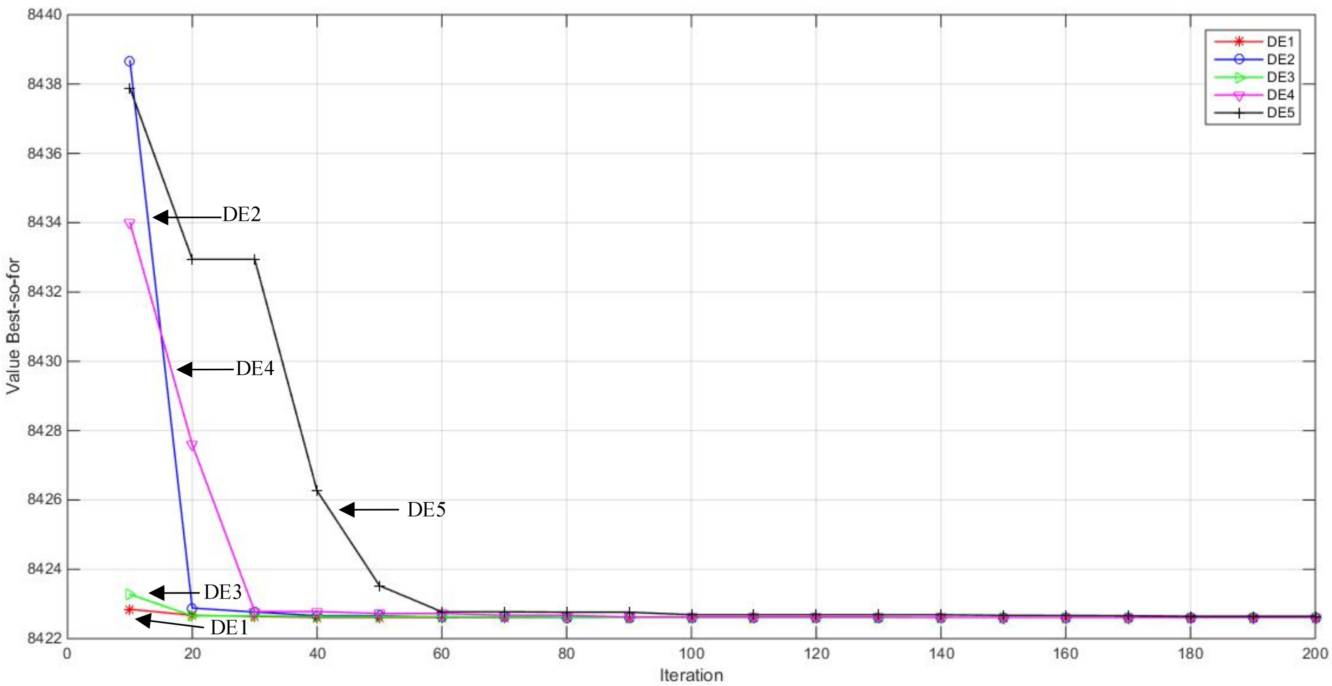

Fig. 6 Convergence curves of DE algorithm with different strategies.

TABLE 9. TOTAL DEMAND OF 1800MW AND POWER LOSS

	DE1	DE2	DE3	DE4	DE5
P_1	551.0771	551.0787	551.077	551.0773	555.8795
P_2	250.7343	250.7411	250.7343	250.7345	251.8332
P_3	197.7811	197.7833	197.7812	197.7808	199.4951
P_4	105.471	105.4778	105.471	105.4709	106.3021
P_5	118.521	118.5191	118.521	118.5209	119.4199
P_6	132.9236	132.9153	132.9237	132.9235	132.4069
P_7	119.2334	119.2269	119.2334	119.2334	117.754
P_8	69.4721	69.4729	69.4721	69.4721	64.5276
P_9	82.9984	82.9973	82.9984	82.9985	80.4736
P_{10}	40	40	40	40	40
P_{11}	40	40	40	40	40
P_{12}	55	55	55	55	55
P_{13}	55	55	55	55	55
Total generation (MW)	1818.212	1818.212	1818.212	1818.212	1818.092
Power loss	18.2120	18.2120	18.2120	18.2120	18.0919

TABLE 10. COMPARISON OF DIFFERENT STRATEGIES TO SOLVE THE 1800MW TOTAL DEMAND PROBLEM

Algorithm	Best	Worst	Ave	Std
DE1	18097.448206	18097.862123	18097.489598	0.127400964
DE2	18097.448206	18097.448355	18097.448224	3.71074E-05
DE3	18097.448206	18097.862123	18097.468902	0.092554655
DE4	18097.448206	18097.448206	18097.448206	7.46498E-12
DE5	18097.454523	18098.887884	18097.745853	0.409139974

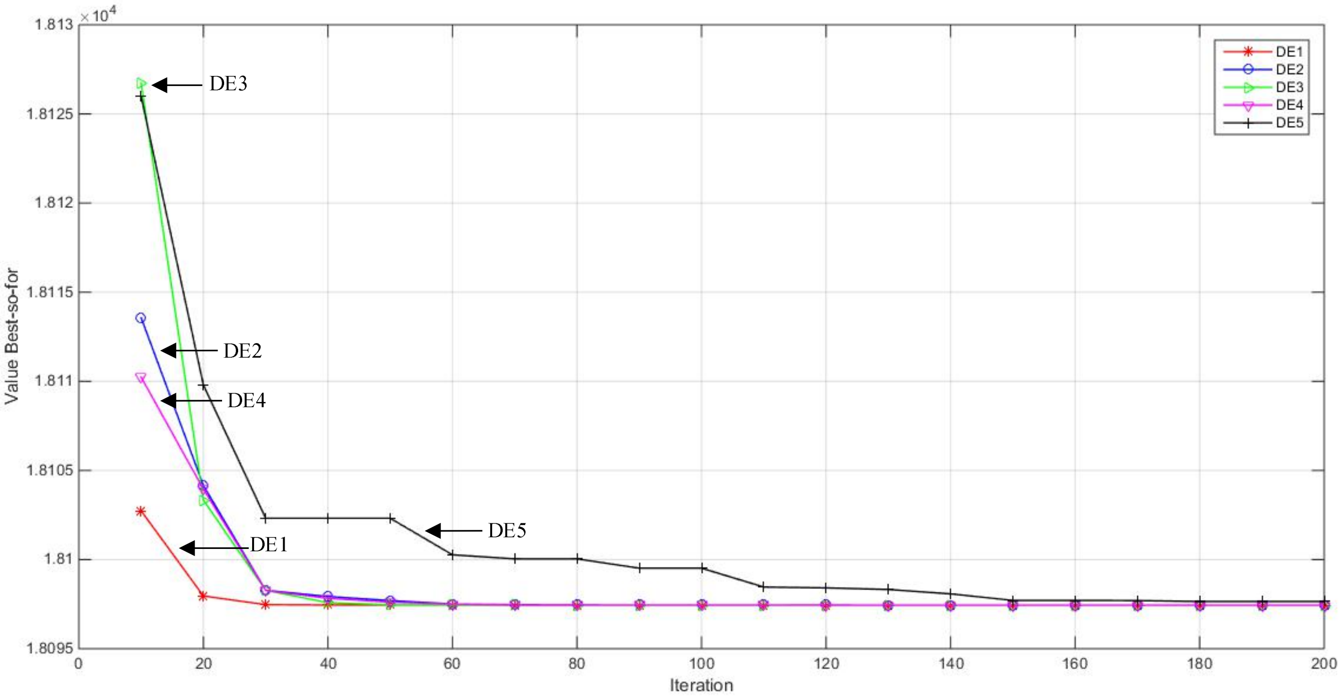

Fig. 7 Convergence curves of DE algorithm with different strategies.

C. Different Algorithms to Solve ELD Problem with Quadratic Objective Function

Based on the Table 2-4 and the B coefficient matrix used to simulate the active loss in the transmission process, the MATLAB 2015 software was used to simulate the above three cases. The DE algorithm with DE1 strategy and other intelligent optimization algorithms are used to carry out simulation experiments and optimization performance comparison on three cases.

(1) Case 1

Through simulation experiments, the output power of the 6 generator sets of DE1 and other optimization algorithms under the total demand of 800MW, the total output power of the generator sets and the loss during transmission are obtained. The results of the simulation data are listed Table 11. In order to ensure the reliability and stability of the results, different algorithms have been tested for this case 20 times, and the statistics of the total power generation cost data obtained are shown in Table 12, and the average value is shown in Fig. 8.

TABLE 11. TOTAL DEMAND OF 800MW AND POWER LOSS

	DE1	PSO	GA	SA
P_1	32.5994	32.5788	26.8541	32.5987
P_2	14.4764	14.447	43.1880	14.4819
P_3	141.5449	141.5283	148.8517	141.5453
P_4	136.03900	136.0693	210	136.0371
P_5	257.6656	257.6379	257.6379	257.6622
P_6	243.0058	243.0717	212.0031	243.0055
Total generation (MW)	825.3311	825.3330	898.534776	825.3307
Power loss	25.3311	25.3330	98.5348	25.3307

TABLE 12. COMPARISON OF DIFFERENT METHODS TO SOLVE THE 800MW TOTAL DEMAND PROBLEM

Algorithm	Best	Worst	Ave	Std
DE1	41896.628616	41896.628772	41896.628624	3.4883E-05
PSO	41896.628617	41971.851656	41908.766405	19.2617
GA	42149.360207	44294.158430	42587.589435	458.3791
SA	41896.628617	41919.427755	41897.866837	2.2349E-06

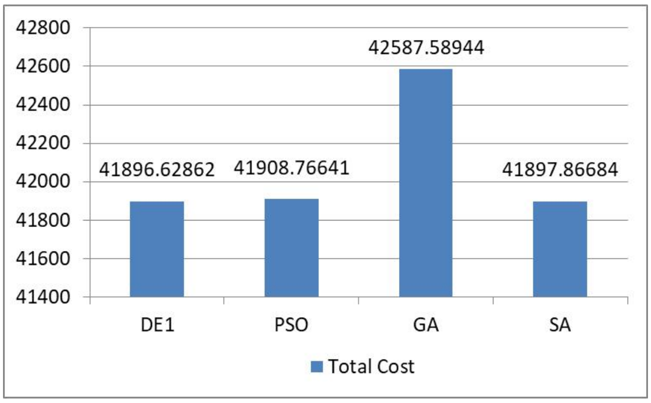

Fig. 8 Comparison of average values of different algorithms.

(2) Case 2

Through simulation experiments, the output power of the 6 generator sets of DE1 and other optimization algorithms under the total demand of 700MW, the total output power of the generator sets and the loss during transmission are obtained. The results of the simulation data are listed Table 13. In order to ensure the reliability and stability of the results, different algorithms have been tested for this case 20 times, and the statistics of the total power generation cost data obtained are shown in Table 14, and the average value is shown in Fig. 9.

TABLE 13. TOTAL DEMAND OF 700MW AND POWER LOSS

	DE1	PSO	GA	SA
P_1	323.6373	323.637335	308.859105	323.630597
P_2	76.6857	76.685680	81.676399	76.684846
P_3	158.4359	158.435869	144.463235	158.434590
P_4	50.0000	50.000000	54.641698	50.000252
P_5	51.9765	51.976536	68.244275	51.985223
P_6	50.0000	50.000000	53.058370	50.000040
Total generation (MW)	710.7354	710.735419	710.943082	710.735547
Power loss	10.7354	10.7355	10.9431	10.7355

TABLE 14. COMPARISON OF DIFFERENT METHODS TO SOLVE THE 700MW TOTAL DEMAND PROBLEM

Algorithm	Best	Worst	Ave	Std
DE1	8422.610918	8422.610918	8422.610918	0
PSO	8352.610922	8352.687698	8352.615199	0.017091678
GA	8365.241933	8796.624687	8538.900494	143.88403
SA	8422.610928	8422.611161	8422.610983	6.07079E-05

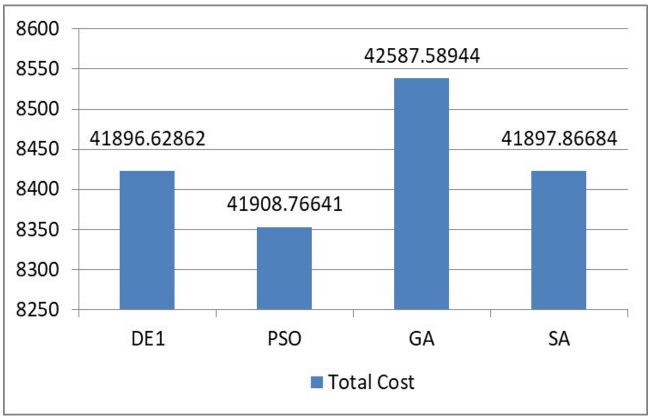

Fig. 9 Comparison of average values of different algorithms.

(3) Case 3

Through simulation experiments, the output power of the 13 generator sets of DE1 and other optimization algorithms under the total demand of 1800MW, the total output power of the generator sets and the loss during transmission are obtained. The results of the simulation data are listed Table 15. In order to ensure the reliability and stability of the results, different algorithms have been tested for this case 20 times, and the statistics of the total power generation cost data obtained are shown in Table 16, and the average value is shown in Fig. 10.

TABLE 15. TOTAL DEMAND OF 1800MW AND POWER LOSS

	DE1	PSO	GA	SA
P_1	551.0771	581.7161944	452.4684	551.0513
P_2	250.7343	266.0899011	272.5888	250.7431
P_3	197.7811	111.8574303	145.3423	197.7875
P_4	105.471	110.346984	82.98931	105.4714
P_5	118.521	123.0967603	119.668	118.5205
P_6	132.9236	138.3928127	142.5267	132.9464
P_7	119.2334	123.7906827	99.31256	119.2206
P_8	69.4721	80.10255253	62.69935	69.46761
P_9	82.9984	94.30118514	86.35865	83.00267
P_{10}	40	40	120	40.00007
P_{11}	40	40	58.73861	40.00011
P_{12}	55	55	120	55.00012
P_{13}	55	55	55.05186	55.00024
Total generation (MW)	1818.212	1819.694503	1817.745	1818.212
Power loss	18.2120	19.6945	17.7446	18.2120

TABLE 16. COMPARISON OF DIFFERENT METHODS TO SOLVE THE 1800MW TOTAL DEMAND PROBLEM

Algorithm	Best	Worst	Ave	Std
DE1	18097.448206	18097.862123	18097.489598	0.127400964
PSO	18127.064356	18194.621148	18156.466157	19.84730303
GA	18136.937192	18324.170586	18211.419914	52.89982023
SA	18097.448263	18097.448526	18097.448343	6.63778E-05

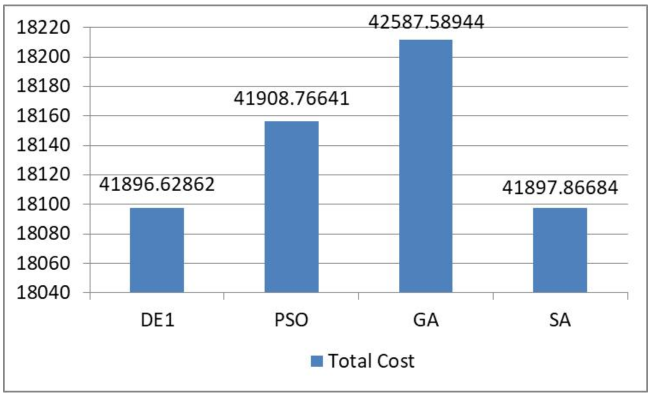

Fig. 10 Comparison of average values of different algorithms.

The Table 11-16 and Fig. 8-10 show the comparison of the total cost of power generation with different intelligent optimization algorithms for different requirements. All algorithms run under the same initial conditions. In Case 1, the Table 11-12 and Figure 8 clearly indicate that the total cost of power generation obtained by using DE1 algorithm to solve this case is 41896.628624$/h, which is lower than the total cost of power generation obtained by PSO, GA and SA algorithms. The transmission loss of DE1, PSO and SA are small. It can be seen from the standard deviation that DE1 and SA have the best stability. The running time of DE1 algorithm is 0.307s, which is faster than other algorithms. In Case 2, the Table 13-14 and Figure 9 clearly indicate that that the cost of solving this case obtained by PSO algorithm is the least, which is 8352.615199$/h. The cost obtained by DE1 and SA algorithm is close, only 0.83% higher than that of PSO. All algorithms have relatively small transmission losses. It can be seen from the standard deviation that DE1 has the best stability, and the running time of DE1 algorithm is 0.425s, which is faster than other algorithms. In Case 3, the Table 15-16 and Figure 10 clearly indicate that the cost obtained by SA algorithm to solve this case is the least, which is 18097.448343$/h. The cost obtained by DE1 algorithm is 18097.489598$/h, and there is little difference between the cost obtained by DE1 and SA. All algorithms have relatively small transmission losses. It can be seen from the standard deviation that SA has the best stability, and DE1 algorithm also has good stability. However, the running time of SA algorithm is the longest, and the running time of DE1 algorithm is 0.307s, which is faster than other algorithms. In general, DE1 algorithm performs best in solving ELD problems compared with other intelligent optimization algorithms.

V. Conclusion

In this paper, the DE algorithm based on different strategies are applied to solve the ELD problem. According to the simulation experiments results, the DE strategy that is most suitable to deal with the ELD problem of the power system is found. The results can clearly show that under the same initial conditions, the DE1 strategy used in the DE algorithm has a faster convergence speed and better stability. Then the DE algorithm is compared with PSO algorithm, GA algorithm and SA algorithm under the same starting conditions. Experimental results show that DE algorithm is better than other intelligent optimization algorithms in solving ELD problems.

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