

Optimal Environmental and Economic Load Dispatch of Power Systems Based on the Pareto Front of Particle Swarm Optimization

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Abstract. Currently, most of multi-objective problems in power systems are changed into a single objective problem by weighting. This paper adopts Pareto front to solve the multi-objective problems in power systems. In order to solve this problem effectively, we present the particle swarm optimization(PSO) algorithm. In addition, we improve PSO with the random black hole strategy, The dynamic update of inertia weight and learning factor, leading particles selection, small probability random mutation. The proposed algorithm can search the Pareto front of the multi-objective functions quickly, and the solutions have the diversity and uniformity. Finally, The algorithm is applied to solve the environmental and economic load dispatch problem of power systems. Considering the environmental impact of CO_2 emissions and the minimum fuel consumption costs of generators, we get the optimal dispatch of generators output depending on the every period load demands.

1. Introduction

The economic load dispatch (ELD) is the optimal load dispatch of the power systems or power plants to minimize the generation costs[1]. Besides, it should meet the load balance and system operation constraints. With the economic development and the realization of sustainable development strategy goals, on the one hand, the electricity demands is increased and energy resources are consumed quickly; on the other hand, people hope to conserve resources and protect the environment. Therefore, the power system optimization problems are not only considered the fuel costs of generators, but also take the environmental impact of harmful gases emissions.

2. Mathematical model of the environmental and economic load dispatch

2.1 Fuel costs of generators

Fuel costs of the generator are the fuel consumption costs during the process of generation. Fuel costs formula of generators are represented as Eq.(1).

$$C(P_{Gi}(t)) = a_i P_{Gi}^2(t) + b_i P_{Gi}(t) + c_i, \quad i = 1, 2, 3, \dots, N. \quad (1)$$

Among them, $C(P_{Gi}(t))$ are the fuel consumption costs of the i -th generator in period t (unit: \$ / h); $P_{Gi}(t)$ is the output active power of the i -th generator; N is the number of generators in the power system; a_i, b_i, c_i is the fuel consumption curve parameters of the i -th generator.

Thus, the total fuel costs of the power system in a scheduling period T can be written as the Eq.(2).

$$f_{fuel} = \sum_{t=1}^T \sum_{i=1}^N C(P_{Gi}(t)). \quad (2)$$

Among them, $i = 1, 2, 3, \dots, N$; $t = 1, 2, 3, \dots, T$. T is the scheduling period.

2.2 environmental damage index of gas emissions

Environmental damage index of gas emissions is the harmful gas emissions masses produced by generators fuel consumption multiplied by the unit punishment ratio of the corresponding gas. The major harmful gases produced by power generation of generators are carbon dioxide(CO_2), sulfur

dioxide(SO_2) and nitrogen oxides(NO_x). The environmental damage index is calculated by the gas emissions masses and a standard of punishment ratio[2]. Three harmful gas emissions per unit time (t / h) are as follows:

$$E_{CO_2i}(P_{Gi}(t)) = \alpha_{Ci}P_{Gi}^2(t) + \beta_{Ci}P_{Gi}(t) + \gamma_{Ci} + k_{Ci} \exp(\lambda_{Ci}P_{Gi}(t)); \quad (3)$$

$$E_{SO_2i}(P_{Gi}(t)) = \alpha_{Si}P_{Gi}^2(t) + \beta_{Si}P_{Gi}(t) + \gamma_{Si} + k_{Si} \exp(\lambda_{Si}P_{Gi}(t)); \quad (4)$$

$$E_{NO_xi}(P_{Gi}(t)) = \alpha_{Ni}P_{Gi}^2(t) + \beta_{Ni}P_{Gi}(t) + \gamma_{Ni} + k_{Ni} \exp(\lambda_{Ni}P_{Gi}(t)). \quad (5)$$

Among them, $E_{CO_2i}(P_{Gi}(t))$, $E_{SO_2i}(P_{Gi}(t))$, $E_{NO_xi}(P_{Gi}(t))$ are the CO_2 , SO_2 and NO_x emissions of the i-th generator generation in period t respectively; $\alpha_{Ci}, \beta_{Ci}, \gamma_{Ci}, k_{Ci}, \lambda_{Ci}$ are the CO_2 emission parameters of the i-th generator; $\alpha_{Si}, \beta_{Si}, \gamma_{Si}, k_{Si}, \lambda_{Si}$ are the SO_2 emission parameters of the i-th generator; $\alpha_{Ni}, \beta_{Ni}, \gamma_{Ni}, k_{Ni}, \lambda_{Ni}$ are the NO_x emission parameters of the i-th generator.

Therefore, in the scheduling period T, the gas emissions environmental damage index of the power system in a scheduling period T can be given as the Eq.(6).

$$f_{emission} = \sum_{t=1}^T \sum_{i=1}^N (\omega_C E_{CO_2i}(P_{Gi}(t)) + \omega_S E_{SO_2i}(P_{Gi}(t)) + \omega_N E_{NO_xi}(P_{Gi}(t))). \quad (6)$$

Among them, $\omega_C, \omega_S, \omega_N$ are the sum of environmental values and punishment ratios, which are the unit emission parameters of CO_2 , SO_2 and NO_x respectively.

2.3 Environmental and economic load dispatch optimization model

2.3.1 The objective function

The true meaning of Multi-objective is based on the pareto front. It is not simply a weighted sum of the multi-objective functions, but the optimal set of feasible solutions which is visually showed by pareto front graphs. The pareto front graphs can show the relationship between each object. Hence, the objective functions are Eq. (2) and Eq.(6).

2.3.2 Constraints

I. The active power constraints of generators:

$$P_{Gi\min} \leq P_{Gi}(t) \leq P_{Gi\max}. \quad (7)$$

Among them, $P_{Gi\min}, P_{Gi\max}$ are the minimum and the maximum output active power of the i-th generator.

II. The active power balance constraints of power systems:

$$\sum_{i=1}^N P_{Gi}(t) = P_{loss}(t) + P_L(t). \quad (8)$$

Among them, P_{loss}, P_L are the grid loss and load of the power system.

III. rotating reserve capacity of generators constraints:

$$\sum_{i=1}^N P_{Gi}^{\max}(t) \geq P_L(t) + S(t), t=1,2,3, \dots, T. \quad (9)$$

Among them, S (t) is the required reserve capacity of the power system.

3 Improved multi-objective particle swarm optimization algorithm

particle swarm optimization(PSO) is a kind of self-improvement, group collaboration and swarm competition algorithm[3]. It is simple in theory, less set parameters, and easy to implement, iterating fast, good in global searching. In this paper, we improve particle swarm optimization algorithm.

3.1 Random black hole strategy

In order to accelerate the PSO iteration speed and strengthen the global searching ability, the speed and position update formula adopt a random black hole strategy. we improve inertia weight, and use the dynamic learning factor. Choose the global optimal particle as a black hole[4]. Within

the range of radius R , the particles have a certain probability drawing in the black hole. Beyond the radius R , the particles update the position and velocity in the original way. In addition, the particles which are in the black hole have a probability escaping from the black hole. Particles not only extend the search range, but also improve the ability of searching the global optimum and greatly accelerate the searching speed.

The Fundamental of IRBPSO algorithm is shown in the following figure.

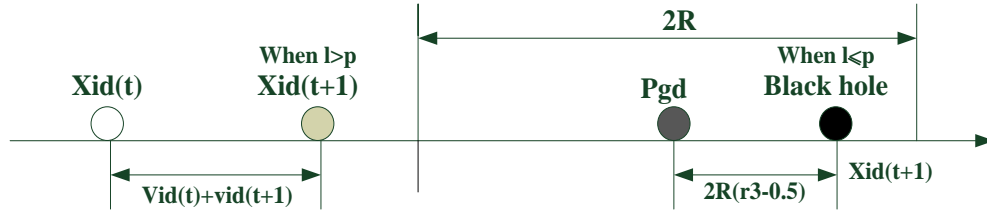


Fig.1: illustration of the IRBH Fundamental

In the each generation and dimension, we randomly propose a particle close to the current optimal particle as a black hole. Set a threshold p which means the magnetism of the black hole, $p \in [0,1]$. In each dimension of every particle, set a value l which is a random number, $l \in [0,1]$. If $l < p$, let the black hole capture the particle. Otherwise, update the position and velocity in the PSO way.

Its position and velocity updating formulas are shown below. And the updating formulas are improved.

$$\text{When } l_{id}^k \geq p, \quad v_{id}^{k+1} = \omega v_{id}^k + c[r1(x_{pid}^k - x_{id}^k) + r2(x_{gid}^k - x_{id}^k)], \quad (10)$$

$$x_{id}^{k+1} = x_{id}^k + v_{id}^{k+1}.$$

(11)

$$\text{When } l_{id}^k < p, \quad x_{id}^{k+1} = x_{gd}^k + 2R(r3 - 0.5). \quad (12)$$

Among them, $r1, r2, r3$ are the random numbers which belong to $[0,1]$. l_{id}^k is the probability of i -th particle on the d -th dimension when it is the k -th iteration. It means the probability that particles escape from the black hole. R is the radius of the black hole.

3.2 The dynamic update of inertia weight and learning factor

Inertia weight ω and learning factor c update themselves dynamically. The following formulas Eq.(13) and Eq. (14) are given.

$$\omega = \omega_0 + r4(1 - \omega_0). \quad (13)$$

$$c = c_0 + \frac{t}{Mt}. \quad (14)$$

Among them, $r4$ is a random number, $r4 \in [0,1]$; ω_0 is a constant, $\omega_0 \in [0, 0.5]$; c_0 is a constant, $c_0 \in [0.5, 1]$; t is the number of iterations; Mt is the maximum number of iterations. Large inertia weight enhances global searching capability, and small inertia weight strengthen the capacity of local searching. The update method of learning factor improve the capacity of the global searching in the later searching period[5].

3.3 NSGA-II non-dominated sorting

This paper makes use of NSGA-II non-dominated sorting. The idea of NSGA-II non-dominated sorting has become the mainstream method of solving the multi-objective optimization problem to get the pareto optimal solution set. The specific operation is shown in Fig.2.

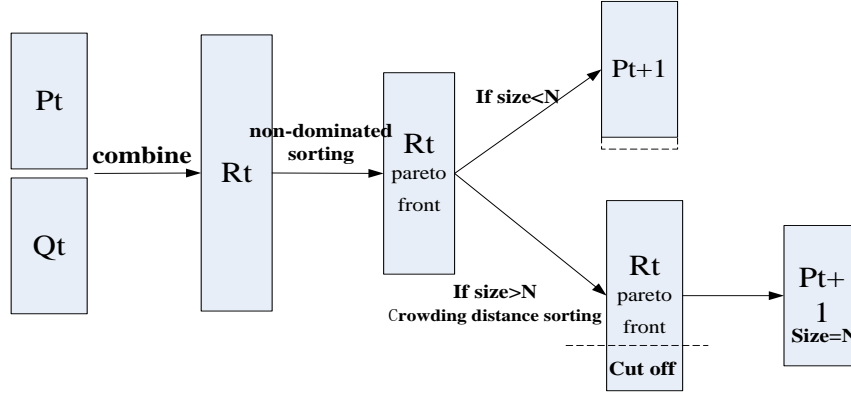


Fig.2: The specific operation of non-dominated sorting

If the population of particle swarm is N , to be the diversity of the population, first of all, we combine the dominated solution set P_t and the offspring solution set Q_t . It forms a new particle swarm R_t (population is $2N$). Calculate the fitness values of the new particle swarm R and do its non-dominated sorting. Then, we get the Pareto optimal front solution set of R_t . If the number of R_t 's Pareto optimal front solutions is equal or less than N , we elect R_t 's Pareto optimal front solutions as the next generation particle swarm P_{t+1} . In addition, if the number of R_t 's Pareto optimal front solutions is greater than N , we do the crowding distance sorting of its optimal front solutions. In order to ensure the uniformity of Pareto optimal front solutions distribution, we delete the small crowding distance solutions. Finally, we choose the remaining N large crowding distance solutions as the next generation particle swarm P_{t+1} .

3.4 Crowding distance sorting

We should avoid the ordinary crowding distance sorting which is deleting the smallest crowding distance solutions. It doesn't take the crowding distance change to other solutions after each solution is deleted into account. Therefore, this paper proposes a method that we eliminate the current minimum crowding distance solution at every turn. It can obtain the distribution uniformity of solutions.

3.5 Leading particles selection

Leading particles are including global best particles and personal best particles. For the sake of ensuring that the particles try to move closer to the true Pareto front, we choose a set of Pareto optimal front solutions randomly as the global best particles. Make the lower non-dominated front particles and the lowest non-dominated front particles have the same probability to be the global best particles[6]. Personal best particles are decided by the relationship of domination and non-domination. When the current particles dominate the personal best particles, the current particles are updated as the the personal best particles. Or do not update the personal best particles.

3.6 Small probability random mutation

To keep the diversity of solutions and global searching capabilities of the algorithm, this paper introduces a small probability random mutation. In the evolutionary process of PSO, we add a random mutation mechanism. It can produce a small range disturbance of particles positions to enhance the global searching ability of the algorithm[3]. Positions of the particles adopt polynomial mutation rules[7], and the mutation probability P_m is a small constant which belongs $[0,1]$.

4 Example calculation results and analysis

4.1 Simulation parameters setting

In this paper, we do a environmental and economic load dispatch simulation on IEEE30 system. The detailed parameters of IEEE30 system can refer to the literature[8]. The parameters of 6 generators are shown in Table 1. Set the number of improved PSO iterations is 100; the population of particles is 100; the initial inertia weight $w_0 = 0.3$; initial learning factor $c_0 = 0.9$; black hole radius $R = 8$; black hole magnetism probability $p = 0.3$.

because of the Different efficiency of each generators' desulfurization and denitration equipments, we use the average values to calculate the gas emissions. It is that the absorption rate of SO_2 is 98%, the absorption rate of NO_x is 85%[9]. There is no absorber to absorb the CO_2 emissions. The consumption of 1 ton coal in power plants will release 2.62 tons CO_2 , 8.5kg SO_2 and 7.4kg NO_x . Besides, IEEE30 system only has the CO_2 emission parameters. Therefore, this paper only considers the emission influence of CO_2 .

The emission parameters of CO_2 is given in Table 2; the load needs of IEEE30 system are according to a typical summer day which is written in Table 3. According to the power industry emission standards[10], the environmental values and punishment index of unit CO_2 emission are represented in Table 4.

Table 1: Basic parameters of generators

Generator	a	b	c	P_{Gmax} /MW	P_{Gmin} /MW
G1	0.0079	1.9	25	50	5
G2	0.0016	1.9	40	60	5
G3	0.0020	1.9	60	100	5
G4	0.0011	2.2	95	120	5
G5	0.0030	2.1	120	100	5
G6	0.0020	2.0	75	60	5

Table 2: CO_2 emissions parameters

Generator	α_c	β_c	γ_c	k_c	λ_c
G1	0.017	-0.810	80	2.00×10^{-6}	0.0285
G2	0.011	-0.554	30	5.00×10^{-6}	0.0333
G3	0.016	-0.554	50	0.01×10^{-6}	0.0800
G4	0.011	-0.954	70	2.00×10^{-6}	0.0200
G5	0.009	-0.610	45	0.01×10^{-6}	0.0800
G6	0.010	-0.600	37	0.10×10^{-6}	0.0667

Table 3: Each period load demand

Time period	Load/MW	Time period	Load/MW
0	125.8	12	283.4
1	118.9	13	320.8
2	100.5	14	360.4
3	85.6	15	358.5
4	67.4	16	346.3
5	76.6	17	312.6
6	82.9	18	265.3
7	104.1	19	242.7
8	135.2	20	213.4
9	168.5	21	204.1
10	184.2	22	189.4
11	205.2	23	165.2

Table 4: Pollution emission standards of electric industry

Index	CO_2
Environmental value	0.002875
Punishment ratio	0.00125

4.2 Simulation results analysis

The load of the 12-th time interval is 283.4MW. Its Simulation results can be seen in Fig.3.

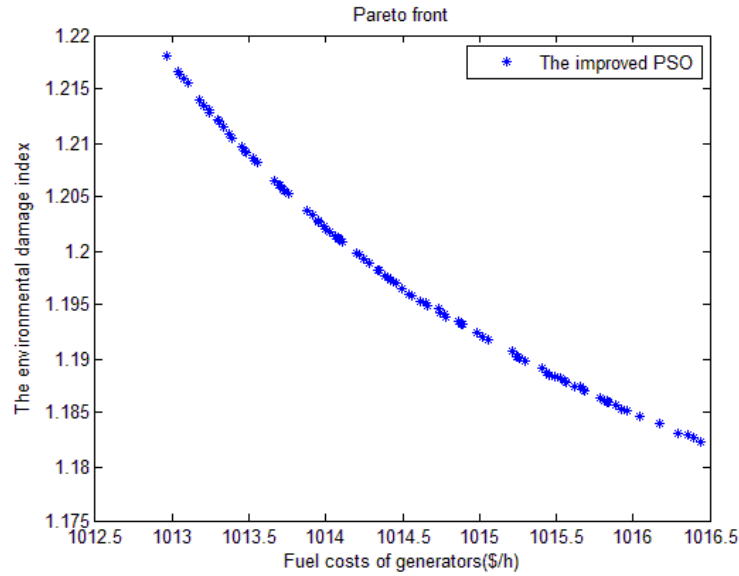


Fig.3: The optimal dispatch pareto front of 283.4MW

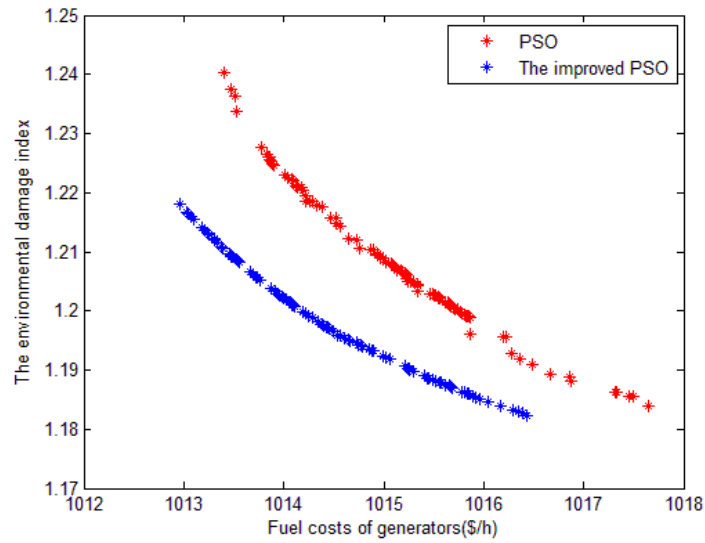


Fig.4: The pareto front comparison of algorithms

As we can see from the above Fig.3, the proposed algorithm in this paper can calculate the Pareto optimal solution set of multi-objective functions. The relationship of the two-objective functions can be illuminated directly. The number of its optimal front solutions is 100. According to a certain preference, we can choose the appropriate optimal solutions.

Comparing standard PSO algorithm with improved PSO algorithm, and its comparison results are shown in Fig.4. It can be seen that the improved PSO has a better global searching capability which can get closer to the true Pareto front. What's more, it can obtain the diversity and distribution uniformity of solutions .

Depending on the load demands of each period, choose the compromised solutions considering the fuel costs and environmental damage index. Its each period environmental and economic load dispatch results are given as Fig.5 and Fig.6.

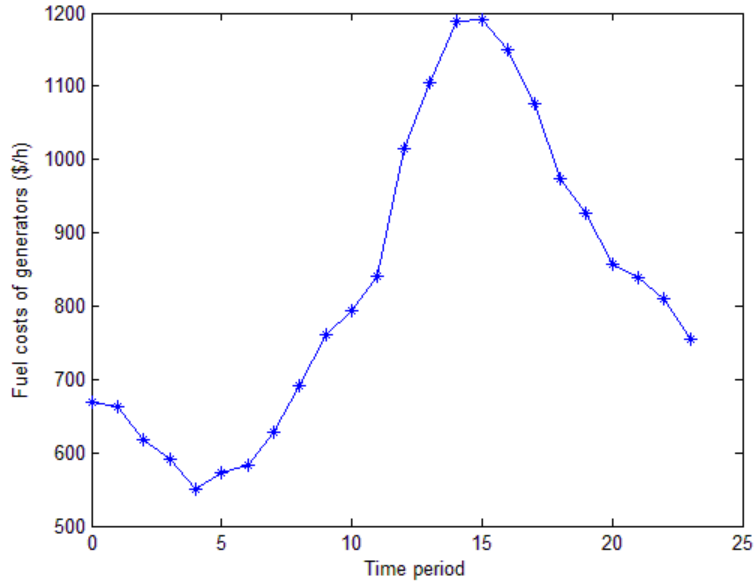


Fig.5: Fuel costs curve of each period

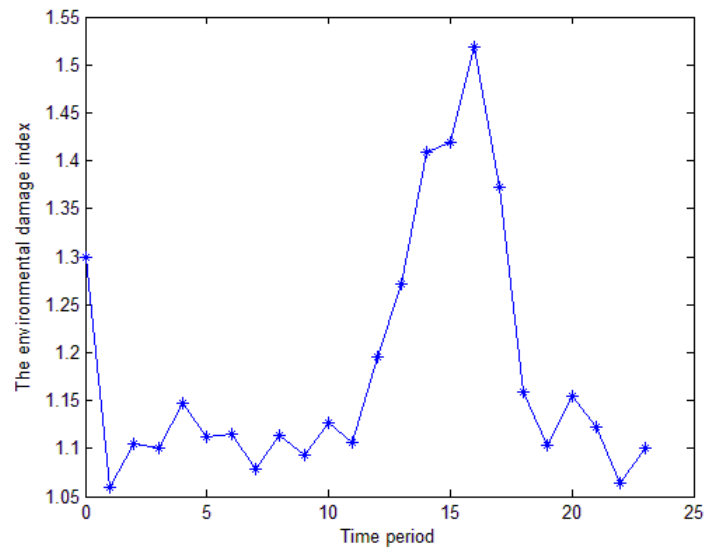


Fig.6: The environmental damage index of each period

As we can see from Fig.5 and Fig.6, the different load demands, the different fuel costs and CO_2 environmental damage index. Fig.7 is the output active power optimal dispatch of generators each period.

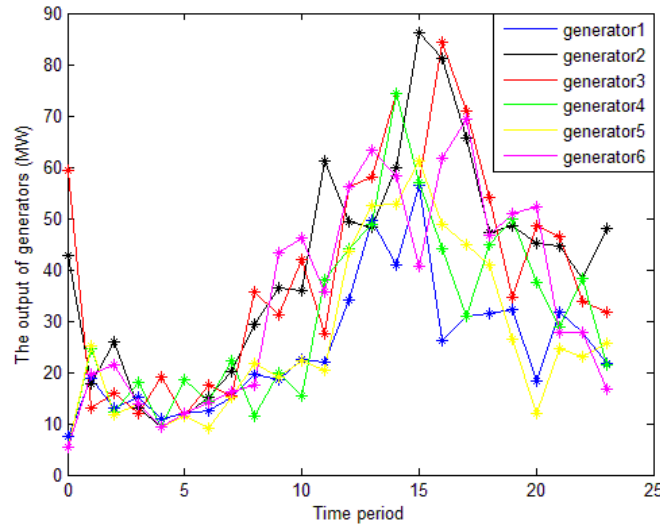


Fig.7: The generators output of each period

5. Summary

For the defect of the standard PSO algorithm, this paper presents an improved particle swarm optimization algorithm. We apply it to search the Pareto optimal front solution sets. For specific, we use it to solve the environmental and economic load dispatch problem of power systems and get the satisfied results. The simulation results show that the proposed algorithm can search Pareto front effectively, and the solutions have the diversity and uniformity. Considering the environmental impact of CO_2 emissions and the minimum fuel consumption costs of generators, we get the optimal dispatch of generators output depending on the every period load needs.

References

- [1] Qian Ke-jun, Yuan yue, Shi Xiao-dan, etc. Environmental benefits analysis of distributed generation. *Proceedings of the CSEE*, 28(29), pp. 11-15,2008.
- [2] Zhou Ren-jun, Ran Xiao-hong, Mao Fa-long, etc. Energy-saving coordinated optimal disptch of distributed combined cool, heat and power supply. *Power System Technolgy*, 36(6), pp. 8-14,2012.
- [3] Li Zhong-kai, Tan Jian-rong, Feng Yi-xiong, etc. Multi-objective particle swarm optimization algorithm based on crowding distance sorting and its application. *Computer Integrated Manufacturing Systems*, 14(7), pp. 1329-1336,2008.
- [4] Zhang Jun-qi, Liu Kun, etc. Random black hole particle swarm optimization and its application. *Proceedings of IEEE Conference on Neural & Signal Processing*. Zhenjiang(China)2008: 359-365.
- [5] Cheng Shan. *The multi-objective optimization of the distributed generators on the Distribution network*. Chongqin:Chongqi University,2013.
- [6] Chen Min-you, Zhang Cong-yu, Luo Ci-yong. Adaptive evolutionary multi-objective particle swarm optimization algorithm. *Control and Decision*, 24(12), pp. 1851-1864,2009.
- [7] Debk, Jains. Multi-speed gearbox design using multi-objective evolutionary algorithms. *Journal of Mechanical Design*, 125(3), pp. 609-619,2003.
- [8] ABIDO M A. Multi-objective particle swarm optimization for environmental / economic dispatch problem. *Electric Power Systems Research*, 79(7), pp. 1105-1113,2003.
- [9] Zhao Jian-wei. *Economicemission load dispatch in power systems based on improved particle swarm optimization algorithm*. Shandong:Qing dao University,2002.

- [10] Zhou Ren-jun, Li Shao-jin, etc. Space particle swarm optimization algorithm and its application in environmental & economic load distribution of power system. *Electric Power Automation Equipment*, 34(9), pp. 7-12,2014.