

PAPER • OPEN ACCESS

Coal blending optimization for power plants with particle swarm algorithm

To cite this article: Shuci Gao and Bin Li 2019 *IOP Conf. Ser.: Mater. Sci. Eng.* **569** 052059

View the [article online](#) for updates and enhancements.

Coal blending optimization for power plants with particle swarm algorithm

Shuci Gao, Bin Li

Department of Automation, North China Electric Power University, Hebei 071000, China

626538291@qq.com

Abstract. Optimizing coal blending strategy is important for increasing the running efficiency and lowering down the emissions of utility boilers. A model, considering price, calorific value, ash content, volatile matter content, moisture content and sulfur content of the coal, has been established using quantum-behaved particle swarm optimization algorithm. The calculation result showed that, compared with the particle swarm algorithm, the quantum particle swarm had better global search capability and astringency, the optimal coal blending ratio can be quickly searched at reasonable boiler running cost. The blending mode is in line with the actual requirements, and the algorithm has high stability.

1. Introduction

In China's thermal power generation enterprises, the cost of purchasing fuel accounts for more than two-thirds of the total. In addition, the blending of coal blended in thermal power plants has a great impact on the damage of auxiliary equipment in the power plant, soot and sulfur dioxide emissions. Therefore, reducing fuel costs is of great significance for reducing production costs, and is also conducive to energy conservation and emission reduction and promoting the sustainable development of the national economy[1].

In 1980s, a power plant coal blending system COMOSTM was successfully developed by the United States[2,3]. Blending anthracite coal with a certain proportion of other coal types to make combustion more stable has been the main direction of blended coal research in Japan[4]. Domestic scholars have also researched the law of mixed coal burning characteristics[5,6].

In the 1990s, Dr. Kennedy and Dr. Eberhart invented the particle swarm optimization algorithm(PSO). It has been proved that the algorithm is faster and more accurate than the genetic algorithm in many applications. Sun et al. proposed a Quantum-behaved particle swarm optimization (QPSO) model, which proved that the algorithm yielded much better results than PSO.

In this paper, the PSO algorithm is introduced into the multi-objective solving problem of dynamic coal blending. The coal blending model is established from seven coal types in an actual power station, and a specific coal blending scheme is proposed.

2. Particle Swarm Algorithm

In the field of function optimization problems, particle swarm optimization(POS) is a widely used tool. Firstly, we assume that there is a D-dimensional space, where have N non-volume, weightless particles in the beginning. N random particles make up the group $S=\{X_1, X_2, \dots, X_N\}^T$, $X_i=\{X_{i1}, X_{i2}, \dots, X_{iN}\}^T$, $i=1, 2, \dots, N$. Each individual particle represents a solution. When solving the actual value,



simply substitute $P_i=(P_{i1}, P_{i2}, \dots, P_{iD})$ into the corresponding objective function. $P_i=(P_{i1}, P_{i2}, \dots, P_{iD})$ is the best position experienced by the particle flight process, and represents the best point that the i -th particle itself searches for in the group, called the individual extremum, which is denoted as P_{best} . In the group, there is at least one best, we use the symbol g to represent it, then $P_g=(P_{g1}, P_{g2}, \dots, P_{gD})$ is the best value of the group, called the global extremum, expressed in g_{best} . Where g has a value range of $\{1, 2, \dots, N\}$. All particles have their own velocity variables, recorded with $V_i=(v_{i1}, v_{i2}, \dots, v_{iD})$, $i = 1, 2, \dots, N$, indicating the speed of each particle.

Using the searched P_{best} and g_{best} , the particle uses the following formula to change its position and speed.

$$v_{iD}^{t+1} = v_{iD}^t + R_1 c_1 (P_{iD} - \chi_{iD}^t) + R_2 c_2 (P_{gD} - \chi_{gD}^t) \quad (1)$$

$$\chi_{iD}^{t+1} = \chi_{iD}^t + v_{iD}^{t+1} \quad (2)$$

In formula (8), (9) $i = 1, 2, \dots, N$ (N represents the number of particles in the group)

t : The number of the current iteration of the algorithm;

v_{iD} : The component of the velocity vector of the particle i after the t -th iteration in the D -th dimension;

χ_{iD}^t : The component of the position vector of the particle i after the t -th iteration in the D -th dimension;

P_{iD} : The component of the best position in history of particle i in the D -th dimension;

P_{gD} : The component of currently best position of the group in the D -th dimension;

R_1, R_2 : Independent random numbers obeying $U(0,1)$ distribution;

c_1, c_2 : Learning factor, usually a constant^[8];

Formula (8) and formula (9) are called standard particle swarm optimization.

3. Construction Model of Quantum Particle Swarm Optimization

3.1. Description of specimens

Static Compared with the classical particle swarm optimization algorithm, the quantum particle swarm optimization algorithm (QPSO) can converge to the value 1 at a faster speed, and the search ability is stronger, and the corresponding control parameters are less, which greatly improves the defects of the classical particle swarm optimization algorithm^[9]. The quantum particle swarm algorithm has only one displacement update formula, and there is no speed update formula^[10]. Its displacement update equation is:

$$x_{ij}(t+1) = q_{ij}(t) \pm b |C_j(t) - x_{ij}(t)| \ln \left[\frac{1}{u_{ij}(t)} \right] \quad (3)$$

$$q_{ij}(t) = \varphi_j(t) \times p_{beset_{ij}} + |1 - \varphi_j(t)| g_{beset_j} \quad (4)$$

$$C(t) = (C_1(t), C_2(t), \dots, C_N(t)) = \frac{1}{N} \sum_{i=1}^N p_{beset_{ij}} = \left(\frac{1}{N} \sum_{i=1}^N p_{beset_{i1}}, \dots, \frac{1}{N} \sum_{i=1}^N p_{beset_{iD}} \right) \quad (5)$$

i : ($=1, 2, \dots, M$) Represents the i -th particle;

N : Whole size;

D : The dimension of the search space;

j : ($=1, 2, \dots, N$) Represents the j -th dimension of the particle;

t : Iterative algebra;

$u_{ij}(t), \varphi_j(t)$: Uniformly distributed random numbers in the interval $[0,1]$;

$x_{ij}(t)$: The location of particle when the evolutionary generation is t ;

$p_{beset_{ij}}$: The best place for particle individuals to date;

g_{bestj} : The current best position for the entire particle swarm;

$q_{ij}(t)$: Attractor location;

$C(t)$: The average of the best positions of all the individual particles, when the evolutionary generation is t ;

β : Expansion-contraction coefficient.

In the quantum particle swarm algorithm, the value of β affects the convergence of individual particles. The necessary and sufficient condition for a single particle to converge to an attractor is $\beta < 1.782$. β is the only parameter in the algorithm other than the size of the group and the number of iterations. It usually uses a linear descent strategy of 1.0~0.5.:

$$\beta = \beta_{\max} - t \times (\beta_{\max} - \beta_{\min}) / t_{\max} \quad (6)$$

4. Application of Particle Swarm Optimization in Coal Blending Optimization

This paper takes a power plant as an example to carry out the practical application of the coal blending optimization model. Using the technical indicators and coal quality characteristics of the power plant, the coal blending optimization model is improved to make it more suitable for the actual situation of the power plant.

4.1 Coal characters

Table 1 shows the coal characters of the seven types of coal used in the power plant.

Table 1 Table of coal characters of each coal type

Type number of coal	Coal unit price (yuan/ton)	Q_{net} (KJ/kg)	V_{ar} (%)	A_{ar} (%)	M_{ar} (%)	S_{ar} (%)
No.1	310	14.935	40.95	29.03	25.5	1.21
No.2	320	15.030	40.40	36.11	14.6	0.79
No.3	150	9.473	45.80	51.73	16.5	1.09
No.4	335	15.611	38.32	26.50	25.18	1.36
No.5	410	19.599	38.22	16.63	21.31	0.83
No.6	350	15.885	40.05	28.35	20.51	1.68
No.7	130	6.885	47.40	42.71	21.24	2.82

4.2 Restrictions

Refer to the conditions that the power plant needs to meet the coal characters under the 70% load stable operation condition, and determine the Restrictions of Q_{net} , V_{ar} , A_{ar} , M_{ar} and S_{ar} :

$$Q_{net,i} \geq 15.903、37 \leq V_{ar,i} \leq 42.5、A_{ar,i} \leq 35、M_{ar,i} \leq 20、S_{ar,i} \leq 1.5$$

5. Establishment of Optimization Model for Coal Blending in Power Plants

Based on the above chapters, the objective function of the coal blending optimization model is:

$$Y_{\min} = \sum_{j=1}^6 \omega_j \times y_j \quad (7)$$

$$y_j = 0.01 \times \sum_{i=1}^n k_{ji} \times x_i \quad (j=1,2,3,4,5,6) \quad (8)$$

Where x_i represents the percentage(0~100) of the i -th coal in the blended coal blending; k_{ji} represents the calorific value, volatile component, ash, moisture, sulfur and Coal unit price of the i -th coal from $j=1\sim 6$, respectively.

6. Simulation Results

6.1 Setting of Initialization Parameters

In view of the above summary, the PSO algorithm with inertia weight is used to solve the problem, and the mathematical model is established. The simulation experiment is carried out by using MATLAB 7.1 software. In the simulation experiment, the parameters that need to be set are:

Number of particles: $N=20$, Number of iterations: $t=100$, In a total of 20 simulation experiments, under the premise that the coal blending meets the constraints, the key point is to minimize the cost price.;

$\omega_1, \omega_2 \dots \omega_6$ are weight values of sub-objective functions, and their value assignment directly affects the optimal solution set of the objective function. If ω_1 is larger, the entire optimization process tends to make the low calorific value of the blended coal close to the target calorific value.; If ω_2 is larger, the entire optimization process tends to make the volatiles of the blended coal close to the target volatiles and so on. On the other hand, the assignment of $\omega_1, \omega_2 \dots \omega_6$ should satisfy the normalization condition, namely: $\omega_1 + \omega_2 + \omega_3 + \omega_4 + \omega_5 + \omega_6 = 1$. Through multiple simulation experiment, the weighted value assignment is selected as: : $\omega_1=0.1, \omega_2=0.1, \omega_3=0.1, \omega_4=0.3, \omega_5=0.1, \omega_6=0.5$.

6.2 Simulation data

Since the constraint is not a direct constraint on the primary variable x_i , but a constraint on the quadratic variable y_i obtained after the x_i processing, when the program is written, the "space-for-time" method commonly used in computers is introduced. In addition, since the low calorific value of these types of coals are generally low, in order to meet the constraint condition that the calorific value is greater than 15.903 MJ/kg, the No. 5 coal must occupy a large weight, otherwise the program initialization is difficult to succeed and consumes a lot of time. After solving the above two main difficulties affecting the performance of the algorithm, the programming can be completed smoothly, so that the program can run accurately and efficiently. Table 2 shows the results of 20 simulations.

Table 2 Simulation experiment data sheet

Global target value	No.1 coal	No.2 coal	No.3 coal	No.4 coal	No.5 coal	No.6 coal	No.7 coal	calorific value (MJ/kg)	V_{ar} (%)	A_{ar} (%)	M_{ar} (%)	S_{ar} (%)	Coal Unit price (yuan/t)
169.2246	0.0012	0.0031	0.3598	0.0028	0.6319	0.0005	0.0006	15.9147	40.9644	29.3848	19.5739	0.9270	315.6325
169.3952	0.0060	0.0007	0.3536	0.0115	0.6235	0.0033	0.0015	15.9106	40.9388	29.3196	19.6713	0.9360	315.9308
169.3984	0.0073	0.0146	0.3496	0.0024	0.6197	0.0040	0.0023	15.9038	40.9509	29.4080	19.5674	0.9325	315.9788
169.4084	0.0074	0.0013	0.3536	0.0115	0.6233	0.0019	0.0009	15.9127	40.9370	29.3202	19.6742	0.9343	315.9566
169.2577	0.0048	0.0012	0.3566	0.0052	0.6262	0.0048	0.0012	15.9059	40.9595	29.3695	19.6232	0.9338	315.6701
169.2639	0.0006	0.0013	0.3567	0.0024	0.6300	0.0059	0.0030	15.9084	40.9669	29.3545	19.5925	0.9353	315.7026
169.1569	0.0014	0.0003	0.3595	0.0006	0.6332	0.0026	0.0024	15.9081	40.9764	29.3710	19.5846	0.9313	315.4890
169.1382	0.0012	0.0029	0.3601	0.0007	0.6291	0.0055	0.0006	15.9035	40.9744	29.4266	19.5619	0.9301	315.4537

169.1385	0.0016	0.0086	0.3591	0.0007	0.6292	0.0001	0.0006	15.9050	40.9709	29.4466	19.5341	0.9253	315.4689
169.2700	0.0063	0.0064	0.3548	0.0050	0.6255	0.0004	0.0016	15.9061	40.9563	29.3817	19.6059	0.9305	315.7040
169.1592	0.0019	0.0040	0.3600	0.0022	0.6309	0.0004	0.0005	15.9089	40.9689	29.4096	19.5671	0.9268	315.4989
169.3157	0.0007	0.0010	0.3559	0.0035	0.6243	0.0129	0.0017	15.9040	40.9613	29.3801	19.5975	0.9389	315.7976
169.2195	0.0005	0.0060	0.3553	0.0034	0.6291	0.0020	0.0037	15.9034	40.9656	29.3769	19.5747	0.9333	315.6196
169.1254	0.0010	0.0018	0.3611	0.0003	0.6334	0.0012	0.0012	15.9092	40.9766	29.3993	19.5654	0.9277	315.4326
169.2410	0.0050	0.0053	0.3567	0.0003	0.6274	0.0041	0.0013	15.9071	40.9683	29.3989	19.5776	0.9306	315.6573
169.3922	0.0009	0.0013	0.3552	0.0081	0.6285	0.0036	0.0024	15.9162	40.9469	29.3182	19.6245	0.9348	315.9530
169.2204	0.0034	0.0056	0.3569	0.0019	0.6259	0.0053	0.0011	15.9032	40.9661	29.4160	19.5728	0.9315	315.6150
169.1094	0.0005	0.0012	0.3601	0.0016	0.6336	0.0006	0.0024	15.9060	40.9767	29.3834	19.5777	0.9299	315.3955
169.2988	0.0044	0.0058	0.3558	0.0050	0.6252	0.0032	0.0007	15.9086	40.9545	29.3908	19.5948	0.9307	315.7672
169.4477	0.0008	0.0248	0.3470	0.0034	0.6186	0.0018	0.0036	15.9031	40.9425	29.4494	19.4891	0.9299	316.1181

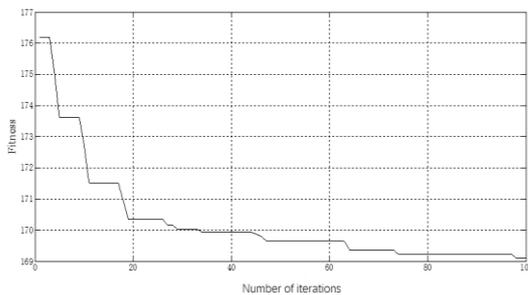


Figure 1 Global optimal fitness curve

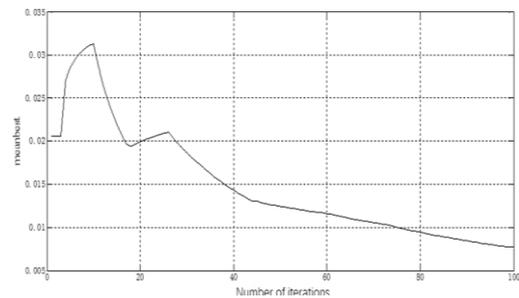


Figure 2 Average optimal value curve

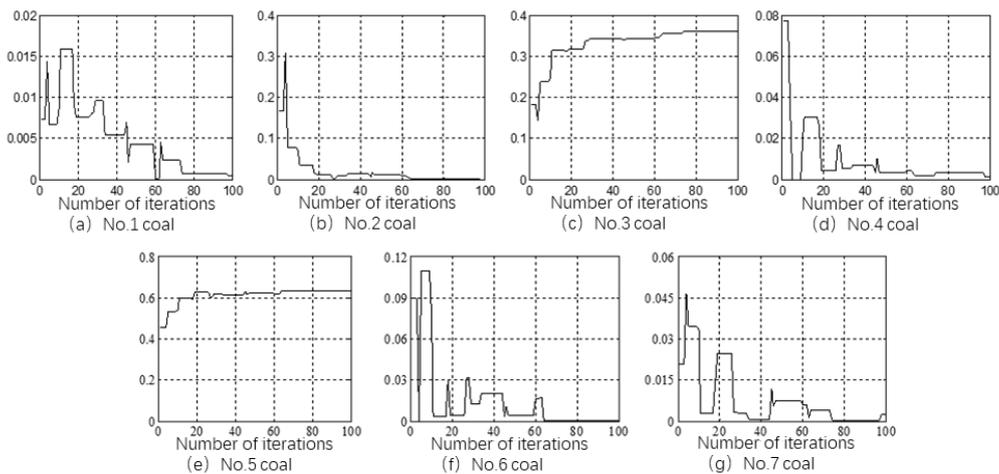


Figure 3 Proportion curve of global optimal values of each particle

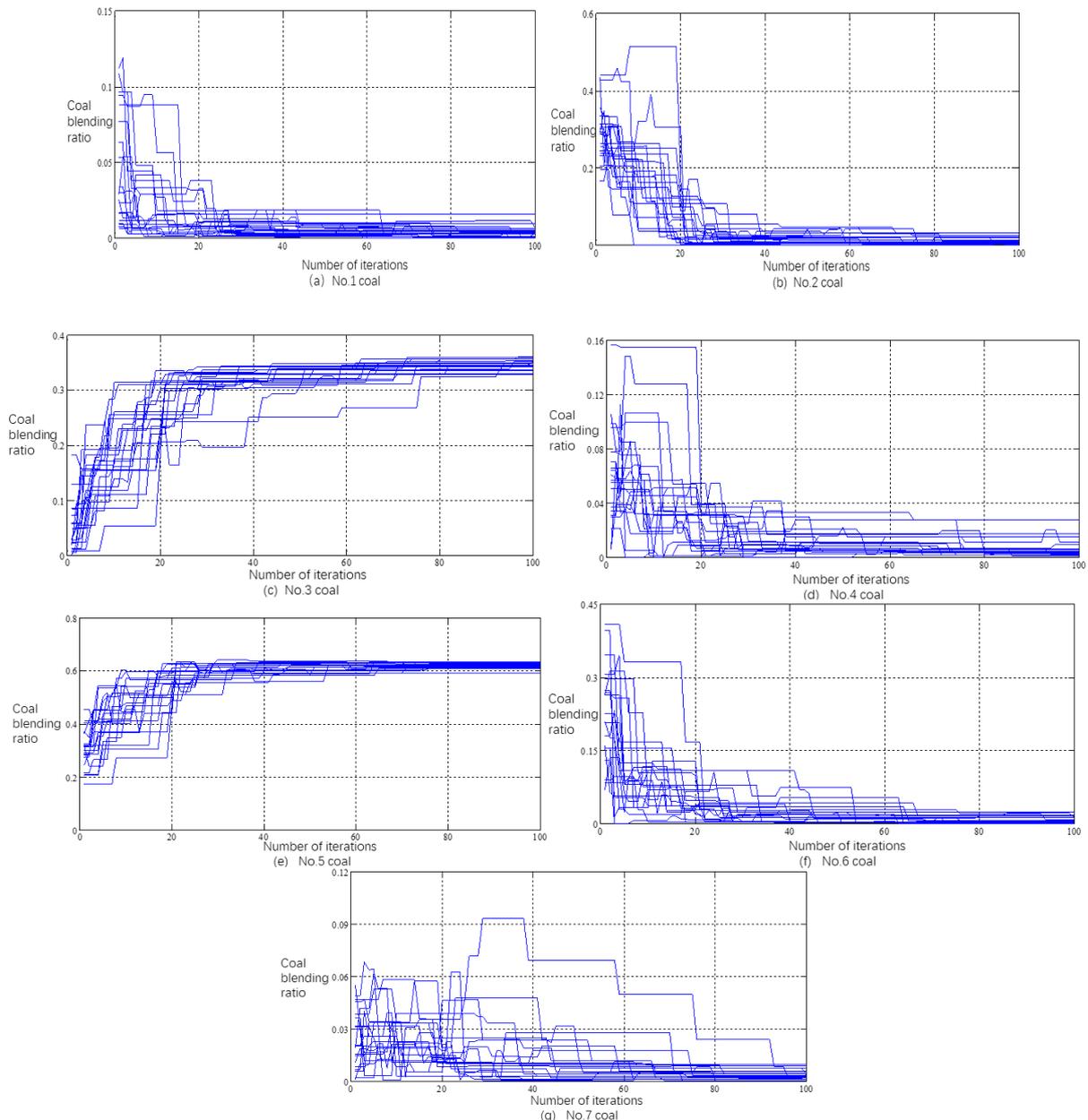


Figure 4 Proportion curve of local optimal values of each particle

7. Results and Discussion

According to the coal data analysis in Table 4-1, the price of No. 3 coal and No. 7 coal is relatively cheap, but the low calorific value is also very low. The calorific value of No. 7 coal is even the lowest of the seven kinds of coal listed. Since it is necessary to ensure that the low calorific value is at least 15.903 MJ / kg, when mixing coal blending, if mixing No. 3 coal and No. 7 coal, it is necessary to blend more coal to increase the calorific value, which will undoubtedly make the overall coal blending price soar. Therefore, in the optimal coal blending scheme, the proportion of No. 7 coal is very low, as shown in Figure 4-3 (g). In addition, the ratio of calorific value to price of No. 3 coal is higher than that of No. 7 coal. If it is mixed with No. 4 coal and No. 5 coal, it can make up for the deficiency of higher volatile and ash content. Because the lowest coal blending price is the objective function, the proportion of No. 3 coal and No. 5 coal increases step by step under the constraint condition that the ash content is less than 35% and the sulfur content is less than 1.5%, as shown in Figure 4-3. And Figure 4-3 (e), while the

proportion of No. 2 coal and No. 6 coal gradually decreased, as shown in Figure 4-3 (b) and Figure 4-3 (f). In addition, with the increase of the number of iterations, in order to meet the water constraints, the ratio of coal blending of No. 1 coal and No. 4 coal with higher moisture decreased rapidly, as shown in Figure 4-3(a) and Figure 4-3(d).

Based on all the above graphs, at the beginning, the particles have different coal quality characteristics and cannot fully satisfy the six constraints listed, but there are always one or more particles that can satisfy all the conditions. As the number of iterations increases, each particle flies to the location of p_{best} and g_{best} , so that the overall constraints can be reached. Finally, the global optimal coal blending ratio was searched.

The optimal coal blending percentage obtained through simulation experiments is: 0.05% for No. 1 coal, 0.12% for No. 2 coal, 36.01% for No. 3 coal, 0.16% for No. 4 coal, 63.36% for No. 5 coal, 0.06% for No. 6 coal, No. 7 Coal is 0.24%.

At this ratio, the coal quality of coal blended coal has a low calorific value of 15.9060 MJ/kg (greater than the lowest value of 15.903 MJ/kg), a volatile content of 40.9757% (according to 37% to 42.5%), and an ash content of 29.2824% (less than the highest value of 35%). The moisture is 19.5777% (less than the highest value of 20%) and the sulfur content is 0.9299% (less than the highest value of 1.5%). Fitness = 169.1094. The price of coal blending is 315.1 yuan / ton.

8. Conclusion

In this paper, according to the coal quality conditions of a power plant in Inner Mongolia power grid, a series of studies have been carried out. Based on the theory of quantum particle swarm optimization, a coal blending optimization model has been established and the objective function has been selected. The global target value Fitness is adopted to establish the model, which emphasizes the minimum coal blending price on the premise of safe and stable operation of the boiler.

(1) The constraints are determined. After the objective function is established, the low calorific value, ash, sulfur, volatile matter, moisture and coal price are used as constraints.

(2) The research of particle swarm optimization. This paper elaborates the concept, steps and flow of PSO algorithm in detail, and introduces the design principles and parameters, which lays a good foundation for future programming work.

(3) The design of the particle swarm algorithm. In order to get better global search ability and convergence performance, this paper decided to use the quantum particle swarm optimization (QPSO) algorithm to optimize the coal blending scheme, and use MATLAB 7.1 to write the program. In order to improve the performance of the algorithm when writing the program, the "space-for-time" algorithm was added. Experiments show that the QPSO algorithm can search for the optimal each coal ratio relationship more accurately and quickly, and also compensates for the defect that the particle swarm algorithm is easy to fall into local optimum.

(4) The choice of the optimal solution. The optimal coal blending percentage obtained through 20 simulation experiments is: 0.05% for No. 1 coal, 0.12% for No. 2 coal, 36.01% for No. 3 coal, 0.16% for No. 4 coal, 63.36% for No. 5 coal, and 0.06% for No. 6 coal. The No. 7 coal is 0.24%, and the price of the coal blended under this scheme is 315.1 yuan/ton.

References

- [1] Jianwen Li, Hongliang Wang. Analysis on Optimized Operation Technology of Boiler Blending Coal [J]. Shanghai University of Electric Power, 2008,21(6): 558 -562.
- [2] A.Bogot,R.P.Hensel.Combustion in Blending Coals to Meet SO₂.mission Requirement Combustion. 1978(7):934-939.
- [3] D.G.Xiang.Current Status of Coal Combustion Technology in the United States-- Report to the United States.1988 (4):3-12.
- [4] P.A.He,Y.P.Dong.A Study of Coal Combustion Technology in Japan.1988(4):37-66.
- [5] Y.G.Xu. "Study on Combustion Characteristics and Proportion of Blended Coal,"Ph.D.thesis,Kun Ming: Kunming University of Science and Technology,2007.

- [6] K. Zhu. "Experimental study of burnout characteristics and optimization of coal mix ratio," Ph.D. thesis, Wu Han: Huazhong University of Science and Technology, 2007.
- [7] Jingpeng Gao, Danfeng Zhao, Xiangsong Huang. Signal detection for MIMO-OFDM system based on improved particle swarm optimization [J]. Journal of Harbin Engineering University 2015, 36(2).
- [8] Vibration, testing and diagnosis. Adaptive filtering optimization algorithm based on hybrid particle swarm [J]. Chinese Society For Vibration Engineering, Zhejiang University: 2006: 108.
- [9] Zhenjiang Zhao. PID Parameter Control Based on Quantum Particle Swarm Optimization Algorithm [J]. Science technology and engineering, 2012,20(22): 5489 -5492.
- [10] Bergh F V D. An analysis of particle swarm optimizers[D]. Pretoria: Faculty of Natural and Agricultural Science, University of Pretoria, 2001.