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Coal blending optimization of coal preparation production process based on improved GA

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Abstract

Coal blending optimization of coal preparation production process is one of the most important segments in the schedule of coal preparation production, and the last link of product quality control in coal preparation plant. It can increase the diversity of prepared coal, quality stability and flexibility of production. In the work, a model of coal blending schedule was given with the objective of economic benefits. Relations of optimization parameters were obtained by process analysis, and their model are non-linear. Using adaptive simulated annealing genetic algorithm (ASAGA), coal blending parameters were optimized. Simulation shows that GSAA can obtain better optimization effects and the optimal parameters have instructive significance on production schedule.

Keywords: ASAGA; coal preparation production process; coal blending optimization

1. Introduction

Coal blending optimization of coal preparation production process is one of the most important segments in the schedule of coal preparation production, and the last link of quality control to ensure good products in coal preparation plant. It can increase the diversity of prepared coal, quality stability and the flexibility of production [1].

GA is a way of using the mechanisms of biological evolution to solve the optimization in a larger space of the initial solution through the survival of the fittest. Compared with other methods, it does not only have stronger optimizing ability, but also powerful computing speed [2]. However, the fundamental genetic algorithms have many kinds of bad phenomena such as “premature”. Combined with other optimizing algorithms, it can overcome the shortcomings of the basic genetic algorithm [3]. In this work, the use of adaptive simulated annealing genetic algorithm to optimize coal blending can make the results more satisfactory.

2. Process parameter optimization model

Coal blending optimization of coal preparation production process is that how to find the best blending scheme

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according to the required indexes of customer. In the process of blending optimization, there are commonly some optimizing thoughts as follows [4]:

- To seek the minimum percents of high-quality coal, and the maximum percents of low-quality coal;
- To seek the lowest cost and the largest profit;
- To seek the optimal ratio of cost to performance.

Fig. 1 shows a blending process in a coal preparation plant. Coal blending can effectively solve the two bottleneck problem in the production: transportation capacity and processing capacity of production equipment. In order to increase economic benefits of coal preparation plant, the production schedule needs to consider how to organize the coal blending process plan to balance the production.

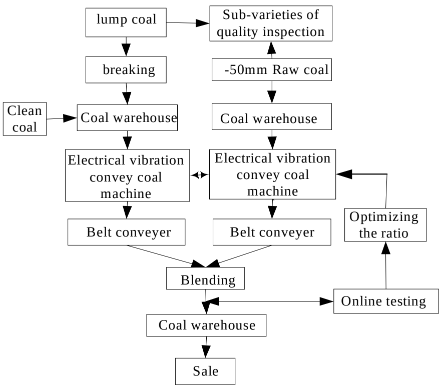

Figure.1 Flow chart of coal blending process

2.1. Coal blending model

Whether to satisfy the requirements of the customers on ash content of product through coal blending and how to organize coal blending schedule production are the chief issues to be considered. In the production, if the ash content of the clean coal in stock is less than that required in contract, the clean coal in stock may be used directly in blending coal production to meet the required clean coal. If the amount of products after blending does not meet the need in the contract, the preparation process of raw coal production need be organized to achieve the target amount of clean coal the client requires in contract.

Two production ways need to be considered. One is to make use of the raw coal to produce the clean coal with ash content below that of the target coal products, and then these products would be involved in coal blending production; the other is to directly use the raw coal to produce the target clean coal products. The costs during the preparation process of all kinds of products in coal preparation plant are basically the same, therefore, the use of the former way may effectively reduce the cost of production, and raise the benefits of coal preparation plant.

We suppose the ash contents of the three blending coals are A_1, A_2, A_3, and their percentages are X_1, X_2, X_3; the coal blending product is A.; the ash contents of the products after blending are required as $A_{\min} < A < A_{\max}$; $A_{\min}$ is the minimum ash content of the target clean coal, and A_{max} is the maximum value. The products whose clean coal ash content surpasses the limit value are regarded as unqualified.

Thus it comes down to the objective function for optimization under certain conditions as follows:

- The objective function

The goal of blending should be to pursue the lowest cost. Supposing the costs of three blending coals are C_1, C_2, C_3., we can the get the objective function as

$$MinF(x) = C_1 * X_1 + C_2 * X_2 + C_3 * X_3 \tag{1}$$

- Constraints:

$$X_i \geq 0, \sum_{i=1}^{n} X_i = 1 \tag{2}$$

$$A_{\min} < A_1 * X_1 + A_2 * X_2 + A_3 * X_3 < A_{\max} \tag{3}$$

- The production constraints of coal enterprise:

The proportion of the scarcity of coal is limited. In the planning period, the amount of blending coal is *S*, but the amount of *i*th raw material coal is only H_i. In order to ensure the completion of the project, it is necessary to guarantee that the blending ratio X_i of the *i*th raw coal is not more than that its resource H_i accounts for in blending plan, that is ,

$$X_i \leq H_i / S \tag{4}$$

That is to say, in coal blending planning time, the blending ratio of raw coal insufficient in resource should not be more than the ratio it accounts for in coal blending plan.

- Solving variables

For the linear programming model above, we calculated the percentages according to the objective function X_1, X_2 and X_3 and its constraints.

2.2. Scheduling model

Taking the maximum economic benefits of coal preparation plant as a target, we established the mathematical model of the scheduling process. Supposing the unit time cost of preparation of each kind of coal in coal preparation plant is almost the same, the scheduling model can be translated into solving a set of appropriate K_m, X_1, X_2 and X_3 to pursue the maximum economic benefits. There is the following mathematical programming.

The objective function:

$$MaxZ = W_e P - (W_0 + \frac{W_m}{\Phi(K_0, K_m)})P_0 - \frac{W_m}{\Phi(K_0, K_m)V(K_0, K_m)} C_m + \frac{W_m}{\Phi(K_0, K_m)} \Gamma(K_0, K_m) P_b \tag{5}$$

Constraints for the objective function:

- The relationship among K_e, K_0, K_k and K_m should meet the blending formulae:

$$X_1 + X_2 + X_3 = 1 \tag{6}$$

$$K_e \leq X_1 K_o + X_2 K_m + X_3 K_k \tag{7}$$

- According to the actual situation, there are also the following boundary conditions:

$$W_k \geq W_e X_3 \tag{8}$$

$$W_0 = W_e X_1 \tag{9}$$

$$W_m = W_e X_2 \tag{10}$$

$$0 \leq X_i \leq 1, i = 1,2,3 \tag{11}$$

$$K_o \geq K_e, K_m, K_k \tag{12}$$

where,

K_m: The clean coal ash content of actual production;
K_e: The clean coal ash content required in one-day program (contract);
K_k: The ash content of the clean coal in stock;
K_0: The raw coal ash content;
W_e: Coal output of the targets in one-day program (contract)
W_k: The amount of clean coal in stock;
W_0: The raw coal quantity used to blend with the clean coal of actual production;
W_m: The amount of clean coal (ash is K_m) of actual production;
P: The prices of clean coal in the contract;
P_0: The prices of raw coal;
P_b: The weighted price of coal products except clean coal;
C_m: The unit time cost of preparation coal;
X_1, X_2, X_3: The proportion of each kind of coal before blending;

Function $V(K_0, K_m)$ is the speed function of preparation coal in the preparation plant while the raw coal with ash content K_0 is processed into clean coal with ash content K_m.

Function $\Gamma(K_0, K_m)$ is the productivity function as the raw coal with ash content K_0 is washed into clean coal with ash content K_m except the clean coal and coal gangue.

Function $\Phi(K_0, K_m)$ is the productivity function of clean coal while the raw coal with ash content K_0 is washed into clean coal with ash content K_m.

Taking some coal preparation plant as an example, we studied the process of rough-jigging, dense-medium separation and coal flotation. Jigging selection gives three products, and so does the dense-medium separation. In order to facilitate the research, assume that only one raw coal is selected in the choices, and the raw coal is divided into two groups measuring greater than 0.5 mm and less than 0.5 mm in diameter and with weight percentages of 78.2% and 21.8%, respectively. From the experiment of preparation ability of raw coal greater than 0.5 mm in diameter and the ups and downs of coal sludge less than 0.5 mm in diameter, as well as the actual data of the distribution curve of jigging and dense-medium separation, the model of optimization parameters can be obtained ,shown in Table 1.

Here, the separation effect of flotation process is predicted by the experimental results with small ups and downs, so the productivity formulae are nonlinear.

Table 1. Model names, fitting errors and parameter values

Curve name		Model name	Fitting error (%)	Parameter value
50-0.5 mm Raw coal	Density curve	Compound hyperbolic tangent	0.01	k=7.48353, x=1.27402, a=1.41714, c=-0.7480, b=-0.22835
	Floating object cumulative curve	Compound hyperbolic tangent	0.02	k=7.97188, x=0.29989, a=1.01663, c=-0.59657, b=-0.13742
<0.5 mm Raw coal	Density curve	Hyperbolic tangent	0.67	k=7.22282, x=1.44558, a=0.60939, c=-0.38974
	Floating object cumulative curve	Compound hyperbolic tangent	0.86	k=4.14494, x=1.13683, a=0.75112, c=-0.2457, b=-0.19136
Jigging distribution curve	First section	Compound hyperbolic tangent	0.5	k=7.28171, x=1.33559, a=2.62995, c=0.18549, b=-1.22987
	Second section	Hyperbolic tangent	1.39	k=7.11761, x=1.60846, a=0.52361, c=-0.41200
Dense medium distribution curve	First section	Compound hyperbolic tangent	0.41	k=7.18649, x=1.31527, a=2.16273, c=0.21537, b=-1.32075

3. Adaptive simulated annealing genetic algorithm

3.1. Coding and initialize population

The ash contents of clean coal and raw coal are given. The parameter to optimize is the allocated proportion of raw coal, clean coal in stock and the clean coal in actual production as well as the ash content of clean coal production. Here, we assume that the amount of raw coal in the coal preparation plant is enough to meet the production and blending; in actual process of blending coal, it also needs to meet the actual restrictions of the clean coal inventory. For this coal blending problem, we adopted the real value in coding.

We use figures to represent the ash content of clean coal in the production, and give some percentages to show the blending ratio of every kind of coal. According to this way, an individual is randomly generated, such as 8.90, 66.0, 32.1 and 1.9. This kind of coding represents a coal blending program: the ash content of clean coal product is 8.9%; the blending ratio of raw coal, clean coal product and clean coal in stock is 66.0%, 32.1%, 1.9%.That may generate an initial population. The size of the *N* population can be gained from the experiment.

3.2. Fitness function

In the optimizing question of coal blending, the given aim is to achieve the maximum value of economic benefits Z in the coal preparation plant. Because the values of fitness need to be sequenced, their selecting probability is calculated, and it should be positive. Therefore we adopt the following as the fitness function:

$$f(x) = Z(x) \tag{13}$$

There are several constraints, while introducing penalty function into the fitness function. Once surpassing the constraints, it would be punished, and thus be transformed into a non-constrained optimization problem.

Through the penalty function, the problem above can be transformed into a non-binding one:

$$Max: \ f(x) + \sum_{i=1}^{N} r_i \Phi_i [b(x)] \tag{14}$$

where, Φ_i is the penalty function of restrictive condition i; r_i is the punishment factor; *b(x)* is the function of optimizing parameters.

In the practical application, r_i is usually set different value according to different restrictive conditions to make the punishment of surpassing the constraints be appropriate.

3.3. Calculation of genetic operator

- Selecting operator

Adaptive genetic algorithm improves the selection operator. First of all, linear transformation is used to stretch individual fitness:

$$f_i = \begin{cases} af_i + b & f_i \geq 0 \\ 0 & f_i < 0 \end{cases} \tag{15}$$

The parameters a, b above may ensure that the average fitness of the stretched populations keeps the same. The optimal fitness is a times the average. Stretching is to avoid the problems of stagnation and premature.

In this paper, the choice of operators is a kind of fitness proportional method with the optimal preservation strategy. The optimal preservation strategy is:

- To find out the lowest individual fitness and the highest individual fitness in the current group;
- If the best individual fitness in the current group is even higher than the one by far, the best individual fitness in the current group is considered as a new best one by far.
- The best individual fitness by far is used to replace the worst one in the current group.

The optimal preservation strategy can be seen as part of the selection operation. The implementation of the strategy may ensure that the optimal individual by far is not destructed by genetic operation such as selection, cross and genetic variation. It is an important guarantee condition for the convergence of genetic algorithms. Here, the roulette wheel method is usually chosen. Obviously, the greater the individual fitness is, the higher the probability of being chosen is, and vice versa.

- Cross operator

During the coal blending model, we use the single point crossover method. It should be noted that since the total ratio of the three should be equal to 100, after the completion of the cross, they should be normalized, and their total ratio should be guaranteed to be equal to 100.

- Mutation operator

According to the mutation probability P_m, mutation operator is a randomly selected individual from individual code string in groups, and one of the individuals is chosen to make the change stochastically. If the last three bits in this gene value are changed, it also needs to be normalized.

- Cross probability Pc and mutation probability Pm

According to the evolution situation of the population, we dynamically adjust the probability of cross and mutation so as to achieve the aim to overcome the premature convergence and quicken the search speed. The expression can be set up as follows:

$$P_c = \begin{cases} k_{c1}(f_{\max} - f')/(f_{\max} - f_{acg}) & f' \geq f_{avg} \\ k_{c2} & f' < f_{avg} \end{cases} \tag{16}$$

$$P_m = \begin{cases} k_{m1}(f_{\max} - f'')/(f_{\max} - f_{acg}) & f'' \geq f_{avg} \\ k_{m2} & f'' < f_{avg} \end{cases} \tag{17}$$

where k_{c1}, k_{c2} are the coefficients of cross-operation; k_{m1}, k_{m2} are coefficients of variation-operation, which are determined on the specific circumstance; f_{avg} is average fitness value of the current group; f' is the larger fitness value of the two cross-individuals; f'' is fitness value of the variation individual;. Once $|f_{max} - f_{avg}| < \varepsilon$, fix P_c and P_m, to prevent the original solution space from being completely destroyed; $\varepsilon = 0.05 f_{max}$ is given in this paper.

3.4. Metropolis criterion strategy

The groups passing through reproduction, crossover and mutation operation is considered as the initial. Then we may use the criteria based on the metropolis replication strategy to produce the next generation groups. The criteria based on the Metropolis replication strategy are as follows:

The implement of Metropolis is used to differentiate replication strategy of the criterion, that is, produce the new individual j stochastically in the neighborhood of chromosome i, and i and j enter the criterion of the next generation group by competition. And using the metropolis criteria, assume that: $\Delta f = f(X_j) - f(X_i)$. If $\Delta f \le 0$, X_j is copied into the next-generation groups, or given a random number r in $[0,1]$; If $r \le \exp(\Delta f / t_k)$, similarly X_i is copied into the next-generation groups, otherwise X_j is copied.

The duplication strategy based on Metropolis criterion ensures that the optimal individual groups in the middle community can enter the next generation. At the same time, the next generation should accept limitedly the inferior solution to ensure the diversity of groups and avoid falling into the partial optimal solution.

3.5. Determine simulated annealing parameter

- Initial temperature t_0

Determining the initial temperature is as follows: Set p_0 as the initial reception probability; set f_{avg} and f_{min} as group's average and the smallest adaptation value.

$$t_0 = (f_{avg} - f_{min}) / \ln(p_0) \qquad (18)$$

Here, the initial temperature $t_0 = 1000$.

- Temperature update function *T(t)*

Annealing temperature formula: $t_{k+1} = a t_k \ (k = 0,1,2,\cdots)$, $a = 0.95$.

- Markov chain length L_k

According to the scale of the problem and the experience, select a fixed value.

4. Simulation example

Taking a coal preparation plant as an example, the customer's needs and current production situation are as shown in Table 2. Here, the probability of the initial is checked for $P_c = 0.25$, $P_m = 0.05$; $\text{pop\_size} = 100$.

Simulation of the productivity calculation model is shown in Table 1. Adaptive simulated annealing genetic algorithm is compared with simulated annealing genetic algorithm by simulation, as shown in Fig. 2. The ASAGA in this paper has faster convergence speed and greater value than the basic genetic algorithm (GA) and simulated annealing genetic algorithm (SAGA).

The maximum profit of 1.773×10^6 Yuan is shown from the simulation results. Optimization parameters $K_m = 9.50\%$, $X_1 = 0.1318$, $X_2 = 0.7765$, and $X_3 = 0.0923$.Therefore, the optimal blending scheme is gotten as Table 3.

Table 2. Input of simulation data

	Variety	Amount(t)	Ash (%)	Price(Yuan/t)
Contract requirements	Clean Coal	12000	12.5	320
Current situation	Clean coal in stock	1200	10	330
	Raw coal	12000	32	190
	Other coal price	210 Yuan/t		
	Time cost	40 Yuan/t		
	Processing speed	500t/h		

Table 3. Optimal scheme of coal blending

	Variety	Amount(t)	Ash(%)	Price(Yuan/t)
Contract requirements	Clean Coal	12000	12.5	320
Coal blending scheme	Clean coal in Stock	1107.6	10	320
	Raw coal in blending	1575.4	32	190
	Clean coal of production	9317.6	9.5	
	Maximum profits	1.773×10^6		

5. Conclusions

This paper has studied the optimizing parameter problems of coal blending in the coal preparation plant. Coal blending is one of the most important links in the process of coal preparation production. It takes the economic benefits as the goal, and establishes coal blending optimization model of the production. Through the process analysis, we find out the relations among the optimization parameters. And we use the auto-adapted simulation annealing algorithm to optimize the coal blending parameter. The simulation shows that ASAGA can get a better optimization result. These optimization parameters have the guide significance in the actual production schedule.

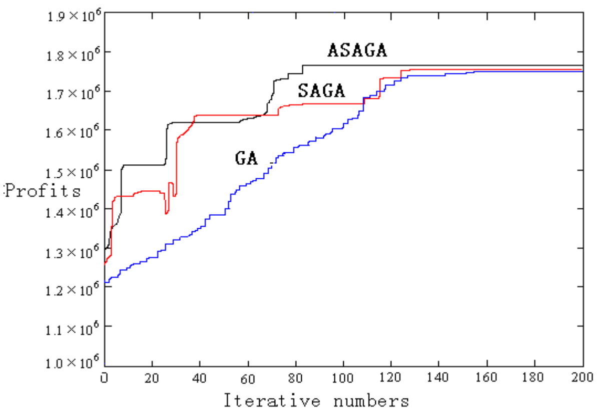

Fig. 2. Simulation comparison of three algorithms

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