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Improved Dual-objective Particle Swarm Algorithm Solves the Problems of Raw Coal Blending

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Abstract: The blending process of raw coal's being sold to power plants is a optimization process of pursuing the cost minimization under certain constraints. Among all intelligent algorithms solving those kinds of optimization problems, Particle swarm optimization (PSO) algorithm is relatively a better choice. This paper describes the improvement of the PSO by turning single-objective optimization problems with constrained conditions into a dual-objective optimization problem, of which one is problem original objective function and the other is constraints. Simulation results indicate that the improved dual-objective PSO algorithm is simple and feasible, and has a good global search capability to be able to search for the optimal solution quickly.
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1. Introduction

During the coal mining process, the quality of raw coal, produced in various mines under the same jurisdiction in many mining areas, differs largely and even the same with those in the same mines operated by different coal beds. In order to improve the utilization of coal, reduce energy consumption, the Coal Shipping Station, before transport-ting raw coal to the power station, will conduct coal blending in accordance with a certain proportion of several kinds of raw coal with diverse quality, in the hope of meeting power station's requirements. Take complementary advent-ages of various coal's nature by blending several kinds of raw coal with diverse quality into mixed coal, it can achieve the best overall performance, thus greatly improves thermal efficiency of coal to meet the user's demand [1].

The issue of steam coal blending is a multi-objective optimization problem under certain constraints. Coal blending pursues coal cost minimization, lesser high-quality coal blending ratio, higher low-grade coal blending ratio according to actual situation, but it is restricted to factors including, such as objective ash, volatile matter, sulfur content, calorific value, unit price and freight rates. References [1] and [11] provide models for steam coal blending by employing Matlab's linear programming function and gene-tic algorithm, respectively. When solving such-like multi-objective optimization problems, evolutionary algorithm is a better choice.

Particle Swarm Optimization (PSO) algorithm, put forward by Kennedy and Eberhart in 1995 [2], is a group evolutionary calculation method which could be easily understood and realized. Similar to genetic algorithm, PSO algorithm also starts from the idea of random solutions and searches for optimal solution through iteration, which makes it much simpler than the rules of the genetic algorithm, for it avoids the operation of "crossover" and "mutation" that genetic algorithm needs. Integrating the characteristics of the partial search algorithm and the global search algorithm, PSO balances its algorithm's search capabilities and thus achieves the advantages of simple operation and fast convergence [3]. This essay improves the standard PSO algorithms to have solved multi-objective optimization problems for raw and blending coal under constrained conditions, with effectiveness of the algorithm being verified through simulation. Therefore, satisfactory result is hereby obtained.

2. Dual-objective Particle Swarm Optimization (PSO) Algorithm

2.1. Particle Swarm Optimization

PSO algorithm is a population-based evolutionary algorithm, derived from research on the bird flock foraging behaviour. With each particle in the algorithm representing a solution for optimization problems, multiple particles coexist and cooperate with each other. Each particle granted with a velocity allows itself to fly in the whole feasible solution space and adjust its flight direction according to its and companions' flying experience, during which it continuously records and updates the best position experienced (also known as local best value, P_b) as well as the best position (also known as global best value, P_g) the entire swarm experienced. PSO algorithm seeks the optimal solution in the iterative process based on updated positions and velocities of two particles in extreme positions.

If the i-th particle in the population is denoted as:

$$X_i = \left(x_{i1}, x_{i2}, \ldots, x_{id}\right), \tag{1}$$

the current velocity is:

$$V_i = \left(v_{i1}, v_{i2}, \ldots, v_{id}\right), \tag{2}$$

and the best position it experienced is:

$$P_{bi} = \left(P_{bi1}, P_{bi2}, \ldots, P_{bid}\right), \tag{3}$$

in D-dimensional search space, the updated position and velocity of the particle according to the following formula in the PSO algorithm are as follows:

$$\begin{aligned} V_{id}^{n+1} &= \omega * V_{id}^{n} + c_1 * rand() * \left(P_{bid} - X_{id}^{n}\right) + \\ &\quad c_2 * rand() * \left(P_g - X_{id}^{n}\right) \\ X_{id}^{n+1} &= X_{id}^{n} + V_{id}^{n+1} \end{aligned}, \tag{4}$$

where $i = 1, 2,..., N$, in which N represents population size; $d = 1,2, ..., D$; w represents inertia weight coefficient, which in general linearly decreases from 0.8 to 0.4. The larger the inertia weight coefficient is, the stronger the global convergence capability is, while the smaller the inertia weight coefficient is, the stronger the local convergence capability [4]. c_1, c_2 represent learning factor and constant respectively; $rand()$ represents random number in the interval (0, 1).

2.2. Constrained Dual-objective Particle Swarm Optimization Algorithm

Standard PSO algorithm mainly aims at solving unconstrained single-objective optimization problems; however, in social production and scientific practice involved there are mostly constrained multi-objective optimization problems. Generally, a constrained optimization problem can be expressed as follows:

$$\begin{aligned} &\min Y = f\left(x\right) \\ &s.t.\ g_i\left(X\right) \le 0, i = 1, 2, \ldots, l \\ &h_j\left(X\right) = 0, j = 1, 2, \ldots, m \end{aligned}, \tag{5}$$

where $X \in R^m$ represents decision vector; $Y \in R^n$ represents target vector, $g_i(X)$ represents the i-th inequality constraints, and $h_j(X)$ represents the j-th equality constraints. As for equality constraints, it can be converted into inequality constraints through tolerable error, which is:

$$\left|h_j\left(X\right)\right| - \sigma \le 0, \tag{6}$$

with σ represents tolerance and then take the small positive number [5]. Thus, only inequality constrained optimization problem needs to be considered:

$$\begin{aligned} &\min Y = f\left(x\right) \\ &s.t.\ g_i\left(X\right) \le 0, i = 1, 2, \ldots, p \end{aligned}. \tag{7}$$

Here, the concept of constraint violation degree of particle is introduced in order to solve constrained optimization problems. The i-th particle x_i in the Swarm violated the j-th inequality constraints with the degree of:

$$\begin{aligned} &\Phi_j(x_i) = \max(0, g_j(x_i)) \quad , j = 1, 2, \ldots, p \\ &\Phi(X) = \sum_{j=1}^{p} \max(0, g_j(X)) \end{aligned}. \tag{8}$$

Penalty function is a widely used method in terms of constraints, for it could turn constrained optimization problems into unconstrained optimization problems. However, but determination of appropriate penalty factor is rather difficult. This paper puts forward an improved constrained optimization problems method based on the previous studies, namely, the dual-objective Particle Swarm Optimization algorithm, by turning constrained optimization problems (7) into dual-objective optimization problems [6]: the first objective is the original objective function $f(X)$, and the second objective is constraint violation degree of particle function $\Phi(X)$. Among which, $\Phi(X)\geq 0$, when $\Phi(X)=0$, X meets all the constraint conditions.

Minimizing the function $f(X)$ enables original problem (5) objective function to be minimal; minimizing the function $\Phi(X)$ enables to obtain the feasible solution to the original problem. Then the solution to the original problem is turned into the minimization of $f(X), \Phi(X)$. In other words, the constrained optimization problems are turned into unconstrained dual-objective optimization problems. And with the help of weighting method, the dual-objective optimization problems can be turned into the single-objective optimization problems. Make:

$$F(X) = \omega_1 f(X) + \omega_2 \Phi(X), \tag{9}$$

where ω_1, ω_2 represent weights, and then the problem (5) solution is equivalent to:

$$\min Y = F(X) = \omega_1 f(X) + \omega_2 \Phi(X), \tag{10}$$

In the PSO algorithm iterative process, $F(X)$ is regarded as the fitness value function to evaluate the "quality" of particles.

Reference [7] confirmed that mutation operation could enhance the diversity of the population, and then improve the capacity of population to escape from local optima solution, thus avoiding from being trapped in local optimal solution in the single-objective PSO algorithm.

Mutation probability:

$$Rate = 1 - \frac{t}{Maxt}, \tag{11}$$

where t represents current iteration count and Maxt maximum iteration count. Each particle in the swarm is endowed with a random value rand between 0 and 1. If rand is smaller than Rate, it would mutate according to the formula:

$$X_{id}^{n+1} = X_{id}^{n} + V_{id}^{n+1} * \theta * \mu * (1 - rand), \tag{12}$$

when making θ values ± 1 , the flying direction would be changed; when make $\mu > 1$, accelerated particle would escape from the partial optimal speed [8, 9].

2.3. Algorithm Procedures

Procedures for improved PSO algorithm are as follows:

Step1: Initialize particle swarm; make particle scale as N ; position X_i and velocity V_i for each particle would be randomly generated.

Step2: Calculate the fitness value $fitness(x_i)$ of each particle.

Step3: Set local best value P_{bi} for each particle and global best value P_g for swarms.

Step4: Determine whether algorithm termination conditions are met, if so, turn to Step7; otherwise turn to Step5.

Step5: Update the position and velocity of each particle according to the formula (4), while update P_{bi} and P_g according to particle comparison.

Step6: If the particle satisfies variant conditions, mutate the position; otherwise turn to Step7.

Step7: If the iteration ends, output the result and exit; otherwise turn to Step4.

3. Coal Blending Models

Main parameter indexes for coal blending technology follow a linear additive; therefore, linear programming is adaptable when modelling. The principle for power coal blending optimization model design is to pursue the minimum value of objective function, reduce energy consumption and improve economic efficiency [10] under certain conditions.

There are mainly three goals which power coal blending pursues:

1) The pursuit of the lowest overall cost of raw coal, which consists of raw coal costs and freight costs.

Minimization of raw coal costs is preferential. Suppose n kinds of raw coal and single coal conduct coal blending, with the cost price of *i-th* single coal being C_i ;unit freight being C_{uf} ;ratio being X_j ; then the minimized cost blending coast being:

$$Y_{\min} = \sum_{j=1}^{n} \left(C_i + C_{uf} \right) * X_j . \tag{13}$$

2) The pursuit of high-quality coal blending ratio being as little as possible, for high-quality coal is relatively less and the cost is relatively more expensive. Therefore in order to decrease coal blending cost and take fully advantage of the high-quality coal, use of high-quality coal should be minimized.

3) The pursuit of low-grade coal blending ratio as much as possible to make full use of inferior coal, economize high-quality coal.

In the actual blending process, the ratio of the minimum quality coal and inferior coal is impossible to be implemented at the same time, therefore, high-quality coal blending ratio is the way out. Upon comprehensive consideration, objective function should be modified to calculate the weighted overall costs minimization when establishing optimization model, namely:

$$Y_{\min} = \sum_{j=1}^{n} W_j \left(C_i + C_{uf}\right) * X_j \ , \tag{14}$$

where W_j represents the weight of *j-th* single coal.

Coal blending has specific technical requirements on all indexes of coal quality which forms basic constraints. Suppose n kinds of single coal need to be compounded to mix coal with m technical indexes, if *i-th* technical index of *j-th* single coal is T_{ij} ; single coal blending ratio is X_j ; reserve of the single coal is H_j ; upper limit of *i-th* technical indexes of mixed coal is A_i ,lower limit is B_i ,respectively; coal amount of mixed coal is S; then according to the "Guidance for Power Coal Blending" [11], there are:

$$\begin{cases} \sum_{j=1}^{n} T_{ij} * X_j \le A_i \\ \sum_{j=1}^{n} T_{ij} * X_j \ge B \\ X_j \le \dfrac{H_j}{S} \\ X_j \ge 0 \\ \sum_{j=1}^{n} X_j = 1 \\ i = 1,2,...,m, j = 1,2,...,n \end{cases} , \tag{15}$$

equation (14) and (15) constitute the mathematical model for coal blending optimization problems.

When dealing with the model with improved dual-objective particle swarm optimization algorithm, turn the original objective equation (14) into:

$$f\left(X\right) = \sum_{j=1}^{n} W_j \left(C_i + C_{uf}\right) * X_j \ , \tag{16}$$

as the first objective function. Constraint condition equation (15) is converted to the constraint violation degree function $\Phi(X)$, which is used as the second objective function.

4. Simulations

Assume that coal production enterprise A has four production mines, Table 1 shows all technical indexes (all indexes are as received basis) for objective of each single coal and finished coal blending in each coal mine. It requires to find the solution of this optimization problem as follows.

Table 1. All kinds of technical indexes of single coal and coal blending requirements.

Technical indexes					
	A	B	C	D	**Object-tive**
M_t	3.50	10.80	3.15	5.75	≤6.75
A_d	17.5	21.4	32.76	26.10	≤24.00
V_{daf}	20.50	33.53	35.50	23.90	≤27.00
$Q_{gr,ar}$	25009	21660	23400	22300	≥23100
/P	500	420	350	400	-
/F	20	18	10	9	-

In this table, M_t , A_d , V_{daf} represent moisture, ash and volatile matter respectively, all with the unit of percentage. $Q_{gr,ar}$ represents heat with the unit of MJ / kg ; $/P$ represents unit price with the unit of yuan/ton; $/F$ represents unit freight with the unit of yuan / ton.

Make coal blending ratio of coal mine A as X_1 , coal mine B as X_2 , coal mine C as X_3 , coal mine D as X_4 , then objective function and constraint condition of power coal blending are as follows:

$$\begin{aligned} Y_{\min} &= W_1(500+20)X_1 + W_2(420+18)X_2 \\ &+ W_3(350+10)X_3 + W_4(400+9)X_4 \end{aligned} , \tag{17}$$

$$\begin{cases} 3.5X_1 + 10.8X_2 + 3.15X_3 + 5.75X_4 \le 6.75 \\ 17.5X_1 + 21.4X_2 + 32.76X_3 + 26.1X_4 \le 24 \\ 20.5X_1 + 33.53X_2 + 35.5X_3 + 23.9X_4 \le 27 \\ 25009X_1 + 21660X_2 + 23400X_3 + 22300X_4 \\ \qquad \ge 23100 \\ X_1 + X_2 + X_3 + X_4 = 1 \\ X_1, X_2, X_3, X_4 \ge 0 \end{cases} \tag{18}$$

Solve the problem with constrained dual-objective particle swarm algorithm： make the particle scale $N = 100$; dimension D=4 , learning factor c_1=c_2=0.5 , inertia weight coefficient w=0.8; linear decreasing to 0.4; maximal iteration count $Maxt$=100 ; constraint tolerant degree σ=0.0001 . Taking W_1=W_2=W_3=W_4=1 , the original objective function (17) becomes:

$$Y_{\min} = 520X_1 + 438X_2 + 360X_3 + 409X_4 \ . \tag{19}$$

According to the formula (8):

$$f(x_i) = 520x_{i1} + 438x_{i2} + 360x_{i3} + 409x_{i4} \ , \tag{20-1}$$

$$\begin{cases} g_1(x_i) = 3.5x_{i1} + 10.8x_{i2} + 3.15x_{i3} + \\ \qquad 5.75x_{i4} - 6.75 \\ g_2(x_i) = 17.5x_{i1} + 21.4x_{i2} + 32.76x_{i3} \\ \qquad + 26.1x_{i4} - 24 \\ g_3(x_i) = 20.5x_{i1} + 33.53x_{i2} + 35.5x_{i3} \\ \qquad + 23.9x_{i4} - 27 \\ g_4(x_i) = -25009x_{i1} - 21660x_{i2} - \\ \qquad 23400x_{i3} - 22300x_{i4} - 23100 \\ g_5(x_i) = x_{i1} + x_{i2} + x_{i3} + x_{i4} - 1 - \sigma \\ \Phi(x_i) = \sum_{j=1}^{5} \max(0, g_j(x_i)) \\ \Phi(X) = \sum_{j=1}^{5} \max(0, g_j(X)) \\ 1 \le i \le N \end{cases} \quad (20\text{-}2)$$

then comes the fitness function $fitness(X)=f(X)+\Phi(X)$.

Use the software simulation of Matlab, here comes the simulation results (Figs. 1, 2):

1) The first objective function optimization process.

2) The second objective function optimization process.

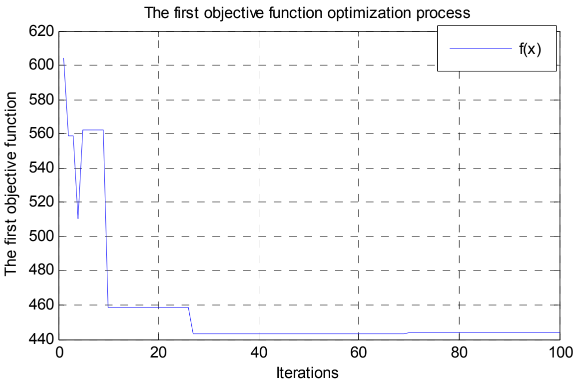

Fig. 1. The first objective function optimization results.

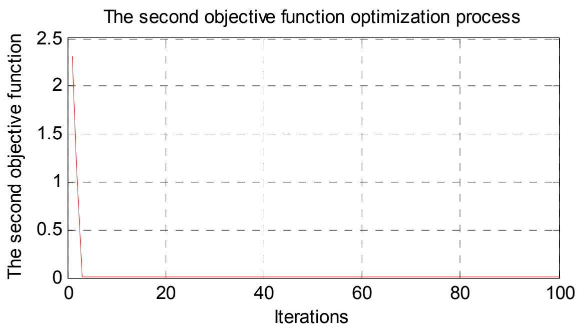

Fig. 2. The second objective function optimization results.

3) Simulation results

Select other better algorithms including Micro-PSO [12], RY [13] and FSA [14] for comparison, with the results as shown in Table 2.

Table 2. All kinds of algorithm optimization results.

Algorithm / mine	Coal blending ratio X / %			
	DPSO	RY	FSA	Micro-PSO
A	34.8	35.88	48.6	42.42
B	21.56	24.43	16.45	17.22
C	22.98	4.83	18.80	17.78
D	20.66	34.81	16.07	22.58
cost Y_{min}	442.62	487.16	495.73	483.73

Where DPSO is improved dual-objective particle swarm algorithm.

Comparison of simulation results shows that the improved particle swarm algorithm reduces the ratio of high-quality coal and enhances the ratio of inferior coal, thus the cost of raw coal is reduced. The optimal solution is satisfactory, and this is very valuable reference for policy-makers.

In the actual blending process, the goal of less ratio of high quality coal and more low-quality coal can be achieved by setting different weight coefficient in the objective function.

5. Conclusions

Provides the improvement of the particle swarm algorithm and puts forward a new algorithm, which turns the original problem into dual-objective unconstrained optimization problems and works out the solution by using constraint violation degree of particle function. Besides, mutation of the particle would be conducted in the process of algorithm iteration to avoid the algorithm from being trapped in partial optimum. The improved algorithm has better balancing and local search capabilities, with convergence rate being accelerated as well as the problem of raw and blending coal efficiently solved, thus greatly improving the thermal efficiency of coal and the economic efficiency of enterprises.

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