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MARKOV HOT BLAST STOVE PREDICTION BASED ON HYBRID INTELLIGENT ALGORITHM

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Hot blast stove air supply is a continuous process, and the working conditions are very complex. The improper data processing of the traditional Markov prediction will easily lead to the deviation of the results. In this paper, a hybrid intelligent optimization algorithm is used to pre-process the data sources and obtain reasonable data. The experimental results show that the algorithm has good convergence and stability. The improved Markov predicted value is close to the actual value and accords with the target.

Keyword: hot blast stove, mathematical model, data preprocessing, Markov prediction, temperature control

INTRODUCTION

The hot blast stove of blast furnace is a complex controlled object. Its work can be divided into two stages: combustion stage and air supply stage. Hot-blast stove is a kind of high energy-consuming equipment. It is an important control target to effectively control the combustion of hot-blast stove, provide stable and continuous heat source to regenerator, regulate gas and air quantity, and achieve the best air-fuel ratio in order to reduce energy consumption [1,2]. Because of the complexity of working conditions, it is difficult to study combustion control by traditional modeling method. In order to solve this problem, Markov prediction method is introduced to predict the air supply temperature, get the coal injection rate, and then evaluate the stability of temperature control [3]. Markov's point of view is that whether in the social field or in the natural science, the process of change of a certain kind of thing is only related to the recent state, and has nothing to do with the past state of the thing. This is the basis for the textual study. For the data needed for prediction, a hybrid algorithm of differential evolution and K-means is proposed to preprocess, which not only avoids the disadvantage of falling into local optimum, but also improves the convergence of the algorithm, makes the data to be measured more reasonable and improves the effectiveness of Markov prediction [4].

MATHEMATICAL MODEL OF VAULT TEMPERATURE

Mathematics model setup

During the combustion period of the hot blast stove, the heat transfer through the vault heating surface per unit time is as follows:

$$\Delta Q_1 = S_1 k_1 \Delta T \Delta \mathrm{t} = S_1 K_1 (T_0 - T_1) \Delta \mathrm{t} \qquad (1)$$

In the formula, S_1 and k_1 are the heat transfer area and coefficient of vault and flue gas respectively, T_0 and T_1 are the temperature of flue gas and vault respectively, ΔT is the temperature difference between smoke and vault, Δt is the unit amount of time.

In the intensified combustion period, the fast burning furnace method is widely used, which requires the optimal air-fuel ratio control, which is the guarantee of the maximum heat of the hot blast stove. However, under no circumstances should the gas be excessive. In other words, when the optimal air-fuel ratio is reached, the air is still excessive. It is generally considered that the combustion state of hot blast stove is good when the volume fraction of residual oxygen in flue gas is kept at 0,2 % ~ 0,8 %. This paper chooses 0,5 % as the control target and 0,2 % as the acceptable fluctuation range. That is to say, no control regulation is carried out in the range of 0,3 % ~ 0,7 %.

When the volume fraction of residual oxygen in flue gas is greater than the maximum value, the following air-fuel ratio regulation model is started:

$$\mathrm{b_k} = \frac{\mathrm{v_k} - \dfrac{(x-0,5)v_y}{0,21}}{v_m} \qquad (2)$$

When the oxygen volume fraction in flue gas is lower than the minimum value, the air-fuel ratio is changed according to the following formula:

$$\mathrm{b_k} = \frac{\mathrm{v_k} + \dfrac{(0,5-x)v_y}{0,21}}{v_m} \qquad (3)$$

In the above formula, b_k is the air-fuel ratio, x is the oxygen content in the exhaust gas(volume fraction/ %). v_y is the amount of flue gas/ m^3/h, v_m is the gas quantity/ m^3/h. v_m is the amount of air/ m^3/h.

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THE BASIS FOR INTRODUCING MARKOV

Basic principles

Markov is the judgment of the future state of the forecasted object, reflecting no aftereffect. It is assumed that the state space $\{X_i|i= 0,1,2,...\}$ is a finite set and its value is a non-negative integer [5]. Setting $X_i=s_i$, where s_i is the state of the object at time i, there exists a probability ρ so that the state of the object at the next time is s_{i+1}, which can be expressed as $\{X_{i+1}= s_{i+1}| X_{i-1}= s_{i-1}, X_i =s_i...\}$. Note the probability that ρ_{ij}^k is a state s_i and then transits to state s_j through k steps, as follows:

$$\rho_{ij}^k=C_{ij} / C_i \tag{4}$$

In the formula, C_i is the total number of occurrences of state s_i, C_{ij} denotes the number of times the state s_i has been converted to s_j through k steps.

It should be pointed out here that any future X_{i+1} state has nothing to do with the past state, it is only related to X_i and X_{i-1}. Then the transition probability matrix of step k in the transformation can be expressed as:

$$M_{ij} = \begin{pmatrix} \rho_{11} & \cdots & \rho_{1j} \\ \vdots & \ddots & \vdots \\ \rho_{i1} & \cdots & \rho_{ij} \end{pmatrix} \tag{5}$$

In the formula, M_{ij} is a probability matrix. ρ_{ij} is the probability in the transformation.

Markov prediction

The air temperature of hot blast stove is recorded as thing s, the initial state is s_0, and it undergoes a process of change: s_1, s_2, s_3..., s_n. When the air supply temperature is embedded before and after, the termination state s_n is only related to the previous state s_{n-1}, that is, the influence of a change depends only on the last change, that is, the invalidity of Markov. The current supply air temperature state is set to s_i, the transition probability matrix is analyzed, and the predicted value is obtained after the state is determined. ρ_{ij}^k describes the possibility of the current state transferring to any state, and arranges the transfer probability matrix in order of size to obtain the maximum possible predicted value of the air supply temperature, which can obtain the most possible air supply temperature of the regenerative air supply after the transformation at the end of the air supply. Source data need to be analyzed and processed. Because of the complex and changeable environment, in order to improve the accuracy of prediction, the data should be preprocessed. In this paper, a hybrid clustering algorithm is introduced to solve this problem.

HYBRID ALGORITHM AND IMPLEMENTATION

Algorithm analysis

The basic idea of Differential Evolution (DE) is similar to that of genetic algorithm. It uses mutation operation to generate new individuals, then carries out crossover and selection operation, and searches for global optimal solution through continuous iterative evolution[6]. In the optimization problem, the solution of the nonlinear minimization problem is taken as an example, the basic mathematical formulas are as follows:

$$\begin{cases} \min f(x_1, x_2, \cdots x_Q) \\ x_j^L \le x_j \le x_j^U, j = 1,2,\cdots,Q \end{cases} \tag{6}$$

In the formula, Q is the dimension of solution space. $U{\cdot}L$ is the upper and lower limit of component x_j respectively.

The algorithm includes three important parameters: population size N_p, scaling factor F and cross probability CR. According to experience, the population size should be moderate, too much computing time should be spent; too small will reduce the diversity of the population, convergence can't be guaranteed, usually set to 5-10 times the dimension, that is $N_p \in [5Q, 10Q]$. The scaling factor is used to control the scaling of the difference vector, taking the value $F \in [0{,}5, 1]$. The crossover probability is used to adjust the diversity of the population. It should be noted that if the crossover probability is too large, the algorithm will easily become a stochastic algorithm, and the permissible range $CR \in [0, 1]$ is usually used.

Reasonable setting of F and CR can effectively adjust the convergence of the algorithm. Because of the premature nature of DE algorithm, global search ability should be strengthened in the initial stage of the algorithm, and population diversity should be improved. In the later stage, local search ability should be controlled to improve the accuracy of the algorithm. In this way, the values of F and CR are slightly higher in the early stage, but lower in the later stage. The following parameters are improved:

$$\begin{cases} F(k+1) = F(k) - \dfrac{F(0) - F_{\max}}{k_{\max}} \\ CR(k+1) = CR(k) - \dfrac{CR(0) - CR_{\min}}{k_{\max}} \end{cases} \tag{7}$$

In the formula, $F(0)$ and $CR(0)$ are primary scaling factors and crossover probability, $F_{\max}$ and $CR_{\min}$ are respectively the maximum of scaling factor and the minimum of crossover probability in iteration, $k_{\max}$ is the maximum number of iterations.

Data preprocessing

The original data needs to be pre-processed before the prediction. The method of combining K-means with differential evolution algorithm is adopted. The specific analysis steps of the algorithm are as follows:

Step 1: Determine the population size N_p. the number of clusters is K, the maximum number of iterations is k, the data set is X, the scaling factor is F and the crossover probability is CR.

Step 2: Initialize the population. According to the nearest neighbor rule, classes are classified, and the clustering centers are calculated based on $f=\sum_{j=1}^{N_p}\sum_{i=1}^{K}\| x_i - c_j \|$. Among them, f is the dispersion degree, and the smaller the number value, the better the clustering effect, and c_j is the clustering center of the current cluster.

Step 3: The results are mutated to produce new individuals.

Step 4: Performing a cross-over operations to generate the individual to be tested.

Step 5: Selection operations are performed to obtain new individuals.

Step 6: Determine the threshold value, to judge whether individual replacement is implemented or not.

Step 7: Determine whether the current number of iteration exceeds the limit, if not, return to step 3, otherwise the algorithm terminates.

EXPERIMENTAL ANALYSIS

The experiment is divided into two parts, the algorithm performance index analysis and Markov prediction results analysis. The former mainly analyses the convergence of the algorithm. In the comparative analysis, the population size is set at 50 and the maximum iteration number is 800. $F(0)=0{,}75$, $CR(0)=0{,}8$, as the iteration proceeds, the smoother the value is, the better. For the latter, the historical data of the average temperature of the regenerator at the end of 16 air supply predictions before the next forecast of a factory are selected in order to obtain the predicted value of the average temperature of the regenerator at the end of the next air supply. In the analysis of pre-processing data algorithm, two algorithms are used, one is the traditional fuzzy differential evolution algorithm, which is denoted as DE; the other is the improved hybrid K-means algorithm, which is denoted as KDE. Two benchmark functions are selected to complete the test. Considering the randomness of the algorithm, the two algorithms run 20 times to get the mean value. The following is a description of the benchmark function:

(1) *Schwefel* function formula is as follows:

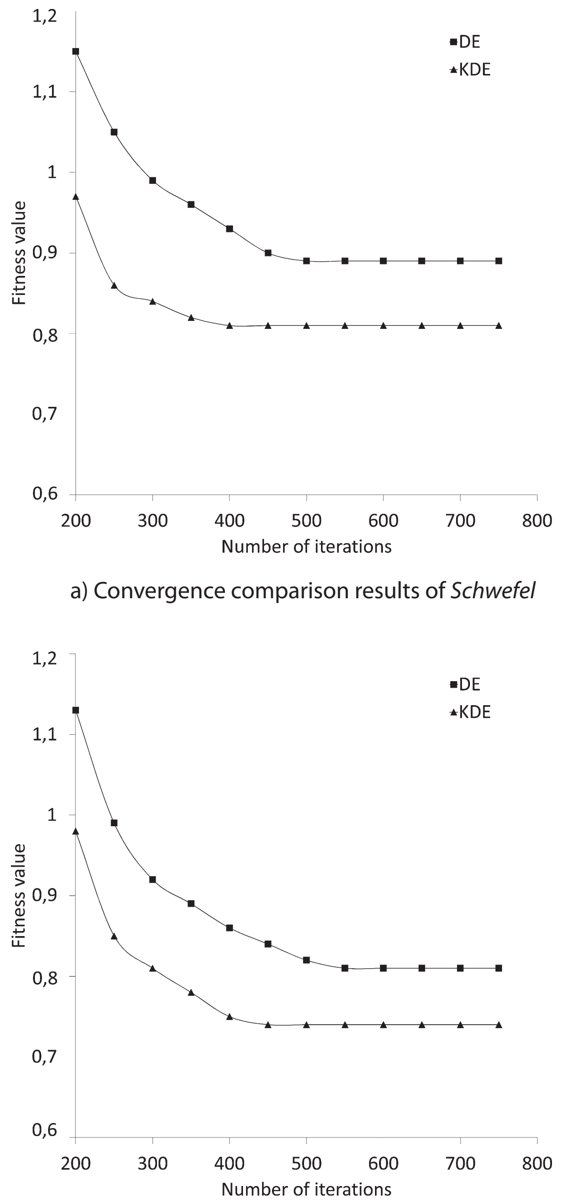
$$Schwefel(x)=\sum_{i=1}^{D}(x_i \sin\sqrt{|x_i|})$$

(2) *Rosenbrock* function formula is as follows:

$$Rosenbrock(x)=\sum_{i=1}^{D}(100(x_{i+1}-x_i^2)^2+(1-x_i)^2)$$

In the Table, $R1$, $R2$, $R3$ respectively indicate lower, normal and higher.

Figure 1 is the convergence analysis of the algorithm. The improved KDE algorithm has faster convergence speed and smoother later period, which shows that the hybrid algorithm has stronger global search ability. Table 1 shows the comparison between the predicted value and the actual value of air supply temperature. It can be seen from the Table that the ratio of the predicted value to the actual value is close, indicating that the predicted effect is better. Table 2 is the distribution of predicted supply air temperature. The distribu-



a) Convergence comparison results of *Schwefel*

b) Convergence comparison results of *Rosenbrock*

Figure 1 Convergence comparison

Table 1 **Comparison tables of actual and predictive**

time	actual value/°C	predicted value/°C	Actual/predicted/%
3:00	1 135	1 156	98
7:00	1 141	1 164	98
10:00	1 149	1 112	97
13:00	1 143	1 178	97

Table 2 **Predicted temperature distribution table**

state	Temperature value/%	Section
R1	1 112, 1 132	(1 112,1 132)
R2	1 144, 1 143, 1 148, 1 144, 1 150, 1 142, 1 147, 1 143, 1 148	(1 142,1 150)
R3	1 152, 1 164, 1 178, 1 181	(1 152,1 181)

tion of normal values in the table is more than expected. There are many normal values in the table, which shows that the improved algorithm is in line with expectations.

CONCLUSION

Aiming at the complex working conditions of hot blast stove, the data sources are analyzed, and the data are pre-processed by intelligent hybrid algorithm to get clustered data in order to obtain reasonable prediction results. Through experimental analysis, the predicted value obtained by Markov prediction is not far from the actual value, and the predicted temperature distribution is in line with expectations, so as to guide production.

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Note: The responsible for English is Zhang Yue Ru Liaoning, China