C. N. ZHANG, Y. R. LI

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A COMBUSTION CONTROL STRATEGY OF HOT BLAST STOVE BASED ON KERNEL FUZZY C-MEANS (FCM)

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During the combustion process of hot blast stove, controlling the steady rise of vault temperature and flue gas temperature is an important link. A large amount of data is preprocessed in the field, and the kernel-based clustering algorithm is used to optimize the combustion control process of hot blast stove. The experimental results show that the algorithm has high accuracy and fast convergence. Compared with the traditional combustion control method, the improved method has better optimization effect and better stability.

Keyword: hot blast stove; air-fuel ratio; flue gas; intelligent control

INTRODUCTION

The combustion control of hot blast stove is a very important link in the work of hot blast stove. It not only ensures the outlet hot blast temperature to meet the technological requirements, but also ensures the effectiveness of gas combustion [1]. In the two combustion stages of hot blast stove, whether it is the heating period or the air supply period, the air and gas flow must be adjusted to achieve the optimum ratio and complete the air supply operation on the premise of keeping the vault temperature [2,3]. The most effective way to improve the heating effect of hot-blast stove is to reduce manual intervention and realize the self-control of hot-blast stove combustion. In order to reduce energy consumption, the target temperature needs to be reached quickly, and the temperature difference should be controlled within the allowable range. At the same time, the two-stage switching can be quickly implemented under different working conditions. Practice has proved that the traditional modeling method cannot guarantee the effectiveness of hot blast stove control, which is a multi-variable, non-linear and strong coupling engineering problem. Taking a steel plant as the research object, the introduction of intelligent control technology has achieved good results. A large number of data generated during the operation of hot blast stove are pre-processed, and a clustering analysis based on core C-means algorithm is used to dynamically adjust the air-fuel ratio in order to achieve the purpose of intelligently controlling the supply air temperature [4].

PRESENTATION OF PROBLEMS

The traditional automatic control must be based on an effective and accurate mathematical model, while the mathematical model of hot blast stove mainly calculates the real-time air-fuel ratio, that is, the ratio of gas flow to air flow, which has many problems. For example, it needs a large number of test points, or the accuracy of mathematical model, so relying on mathematical model to control air-fuel ratio is not applicable to the complex controlled object of hot blast stove [5].The intelligent optimal control proposed in this paper is based on a large amount of data collected, and the clustering analysis technology is applied to get the optimal solution in order to obtain good optimization results [6].

C. N. Zhang. e-mail: zcn1979@163.com, Y. R. Li: School of Software, University of Science and Technology Liaoning, Anshan City, China

CLUSTER ANALYSIS

FCM performance evaluation

A large number of field data will be generated during the operation of hot blast stove. These data play an important role, but a considerable part of them is incomplete or missing data. Therefore, this paper intends to adopt a semi-supervised and integrated FCM strategy to control the air-fuel ratio. It is assumed that there is a data set $X = \{x_1, x_2,..., x_n \mid x_i \in S\}$ in the Q dimensional space S. The vector is divided into m classes by using the fuzzy matrix u, $m \in (1, n)$, the initial state clustering center is $Z = \{Z_1, Z_2,..., Z_m\}$, the objective function is defined as follows:

$$J(u,Z) = \sum_j \sum_i u^r_{ji} D^2_{x_i,Z_j} \quad (1)$$

In the formula, u^r_{ji} is the degree of membership, that is, the i data belongs to the degree of membership of the j class. $D^2_{xi,\ Zj}$ is the Euclidean distance, that is, the distance of the i data belongs to the center of the j class. r is the weight factor, and the fuzziness value [1, 3] of the fuzzy matrix is examined.

It can be seen that in the limit case, when $J(u,Z)$ obtains a minimum value, u^r_{ji}, $D^2_{xi,Zj}$ can obtain the optimal value. Here, according to the Lagrange least squares method, the u, Z in $J(u,Z)$ can be adjusted with reference to the following formula:

$$u_{ji}=\frac{1}{\sum_{k=1}^{m}(\frac{D_{x_i,Z_j}}{D_{x_i,Z_i}})2(r-1)^{-1}} \tag{2}$$

$$Z_j=\frac{\sum_{i=1}^{n}(u_{ji})^r x_i}{\sum_{i=1}^{n}(u_{ji})^r} \tag{3}$$

In the formula, if $\| x_i - Z_j \| = 0$, then $u_{ji} = 1$.

Formulas (2) and (3) iterate continuously, and adjust the values of U and Z. When J converges to a certain extent, that is, the agreement is satisfied, the final result of clustering are obtained.

According to the complex and variable situation of the industrial field, the evaluation indicators of dataset fuzzy division are adopted, as follows:

$$V_{KB}=\sum_{i=1}^{c}\left(\frac{\sum_{j=1}^{n}u_{ij}\left(1-K\left(V_i,X_j\right)\right)}{n\sum_{i=1}^{c}\left(1-K\left(V_i,V_j\right)\right)}\right) \tag{4}$$

In the formula, u_{ji} is the membership degree from the j data point to the cluster center of the i class. The minimum value obtained by the function is the optimum number of clusters. The kernel V_{KB} is a validity function, which not only solves the problem of setting the optimal number of clusters, but also because the upper part of the index examines the compactness within the class, so that the algorithm not sensitive to the isolated points of the data.

Kernel-based FCM

The elements in clustering are defined as a triple $M(P, E, C)$. The three elements in the formula are vertex set, edge set and weighted matrix, and expressed by Gauss kernel function. The following is the definition of Gauss kernel:

$$\overline{k_{ij}}=\begin{cases}\exp(-\frac{\| x_i - x_j \|^2}{\sigma^2}) & i \neq j \\ 0 & i = j\end{cases} \tag{5}$$

In the formula, σ is a regulatory factor, that is used to control the decay of the kernel. The row vectors of $\overline{k_{ij}}$ will be distributed on the hypersphere in the K dimensional space, and the corresponding diagonal matrix is:

$$A_{ij}=\sum_{j=1}^{n}\overline{K}_{ij} \tag{6}$$

Then, $\overline{k_{ij}}$ is converted to:

$$K_{ij}=\frac{\overline{K}_{ij}}{\sqrt{A_i A_j}} \tag{7}$$

Processing the matrix K, extracting the eigenvectors corresponding to the k maximum eigenvalues, and transforming to obtain the matrix N:

$$N_{ij}=\frac{K'}{\sqrt{\sum_j K_{ij}'^2}} \tag{8}$$

Each row vector in matrix N can be regarded as data points in sample space to implement clustering using FCM.

Sample x_k in Q dimensional space is mapped to high-dimensional space Q' by using the kernel function, while the topological structure of the original spatial data remains unchanged. If the clustering center is expressed by function $\psi(x_k)$, the corresponding clustering function can be expressed as follows:

$$\begin{aligned} J &= \sum_j \sum_i u_{ji}^r \| \psi(x_i) - \psi(Z_k) \|^2 \\ &= \sum_j \sum_i u_{ji}^r (K(x_i,x_j) - 2K(x_i,Z_j) + K(Z_j,Z_i)) \end{aligned} \tag{9}$$

In the formula, Z_k is the clustering center of the K class, $\psi(Z_k)$ is its image in kernel space, which can be expressed as:

$$\psi(Z_i)=\frac{\sum_{i=1}^{n}u_{ji}^r\psi(x_k)}{\sum_{i=1}^{n}u_{ji}^r} \tag{10}$$

Assuming that the Must-link constraint set is S_m, that is, $S_m = \{x_i, x_j\}$, the sample data x_i and x_j are in the same category. The Cannot-link constraint set is S_c, which is denoted as $\{x_m, x_n\}$, the sample data x_m and x_n are in different classes. After the pairwise constraints are introduced, the kernel-based FCM objective function is adjusted to:

$$\begin{aligned} J &= \sum_j \sum_i u_{ij}^r \left\| \psi(x_i) - \psi(z_k) \right\|^2 + \\ &\beta\left(\sum_{i=1}^{n}\left(\sum_{(x_i,x_j)\in S_m}\sum_{k=1}^{c}u_{ik}u_{jk} + \sum_{(x_i,x_j)\in S_c}\sum_{k=1}^{c}u_{ik}u_{jk}\right)\right) \end{aligned} \tag{11}$$

$$\beta=\frac{n}{m}\frac{\sum_{k=1}^{c}\sum_{i=1}^{n}u_{ik}^2 d^2(x_i,Z_k)}{\sum_{k=1}^{c}\sum_{i=1}^{n}u_{ik}^2} \tag{12}$$

In the formula, the latter item is the penalty item for violating the restriction. This indicates the extent to which Must-link and Cannot-link are violated. The membership degree is used to adjust the objective function, and less constraint violations are maintained to minimize the value of the objective function. The constraint information plays an important role in clustering process. β is the adjustment factor, which reflects the impact of violation of constraints in clustering. That is, the importance of constraints in the objective function is mainly adjusted by means of normalized performance indicators. When the degree of normalization is good, the value of β is small. On the contrary, when the degree of normalization is poor, the value of β is larger, usually the value is (0,1).

EXPERIMENTAL ANALYSIS

The data uses the shared neighbor algorithm to remove the isolated points, and completes the normalization process. A total of 4 255 sets of sample data are generated for correlation analysis, in which gas flow and air flow are selected as input parameters. According to the current working condition, the semi-supervised clustering algorithm is used to get the matching value. In this paper, the air supply temperature is 1 300 °C, the vault temperature is 1 420 °C, a complete air supply cycle is 240 min, and combustion time is 120 min. Silicon brick is used in high temperature zone, two small hot stoves are added to preheat combustion supporting air, and waste heat recovery equipment is used to ensure air temperature. The concrete steps of clustering algorithm are as follows:

The dataset is $X = \{x_1, x_2,..., x_n\}$, the clustering number is c, the regulatory factor is β, the nuclear regulatory factor is b, the termination threshold is ϕ, the maximum number of iterations is max*count*, the counter is *icount* = 0.

Step 1: Adding constraint information and constructing similarity matrix $\overline{k_{ij}}$, the feature vectors corresponding to the k maximum eigenvalues are obtained;

Step 2: Initialize the membership degree and calculate the clustering center;

Step 3: Calculate the objective function according to formula (11);

Step 4: Recalculate the membership degree;

Step 5: Update the kernel parameters;

Step 6: Determine whether the current iteration reaches the maximum number of iterations or meets the termination threshold condition, and if so, it terminates, otherwise recalculates the cluster center and returns to step3.

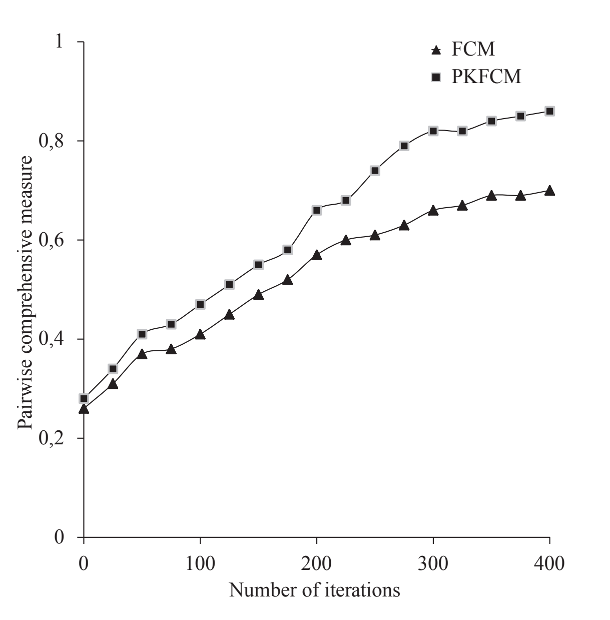


Figure 1 Clustering performance analysis

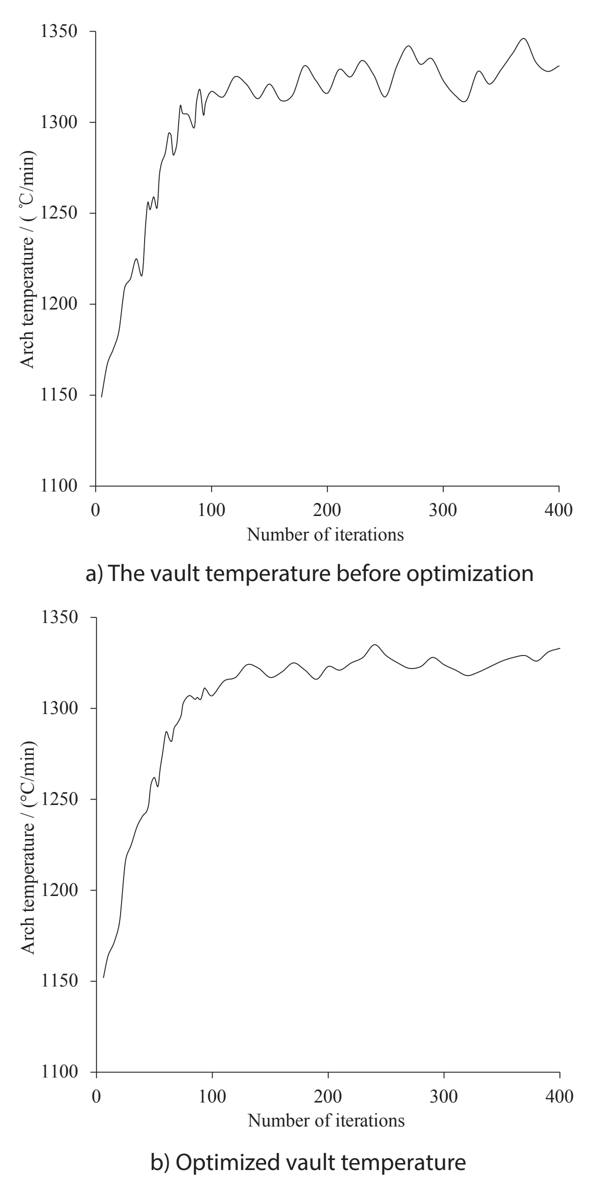
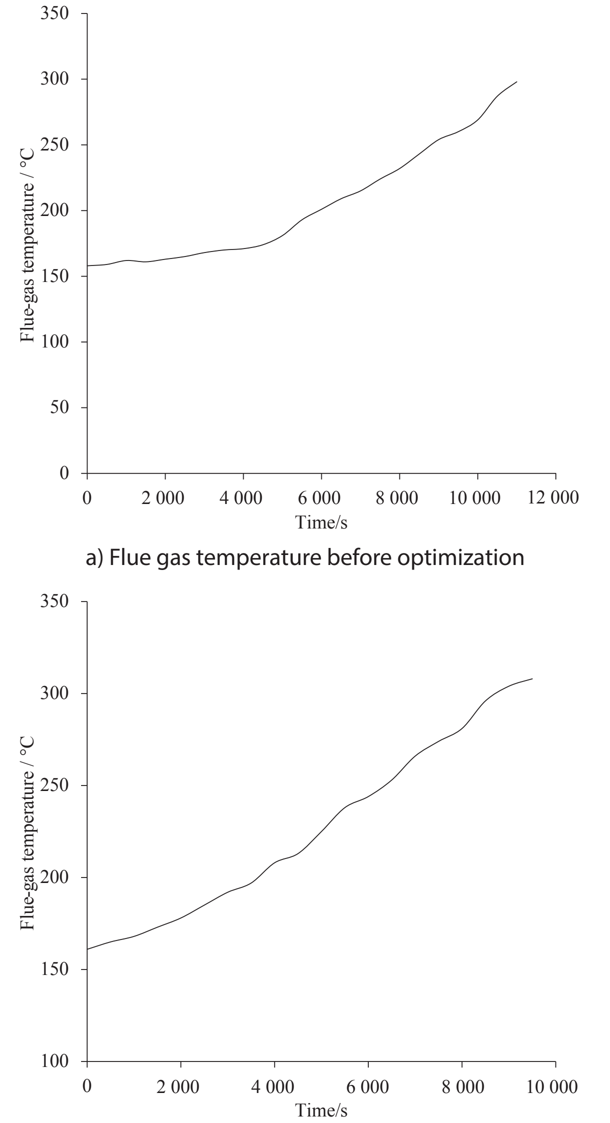


Figure 2 Vault temperature

The experimental tests are divided into two parts: the performance analysis of the algorithm and the performance analysis of the hot blast stove. It is planned to select the data set Balance. Balance is a low-dimensional data set with 4-dimensions, which can be divided into three categories, each of which has 625 samples. The simulation results are as follows:

Figure 1 is an analysis of the accuracy of the algorithm. According to the graph, the improved algorithm has obvious advantages in accuracy. In Figure 2, the optimized vault temperature has a stable rising trend and fewer jumps, which meets the requirements of temperature control during the management period. As can be seen from Figure 3, the temperature of flue gas before optimization accelerates suddenly after a period of operation, while the temperature after optimization reaches the expected value smoothly and ahead of time, and the efficiency is higher.



a) Flue gas temperature before optimization

b) Optimized flue gas temperature

Figure 3 Contrast map of flue gas temperature

CONCLUSIONS

The traditional control method of hot blast stove has some limitations. In this paper, the pre-processing strategy is adopted for the large amount of data generated by the hot blast stove operation, and the kernel-based clustering algorithm is used for cluster analysis, so that the operation sample data can be optimized to obtain the optimal solution quickly. The experiment show that the indexes of the improved hot blast stove are in line with expectations.

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