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OPTIMIZATION ANALYSIS BASED ON INTELLIGENT CONTROL OF THE PROCESS OF THE BLAST FURNACE

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The blast furnace needs to continuously improve of thermal efficiency so as to achieve the goal of energy saving and consumption reduction. By collecting a large amount of field data, the isolated point removal strategy of isolated point is introduced to carry out preprocessing, and the semi-supervised clustering algorithm is adopted to optimize the combustion control process of the blast furnace. This method has been verified by experiments, compared with the traditional data preprocessing strategy, the energy saving effect is obvious.

Key words: blast furnace, thermal efficiency, intelligent control, temperature, gas/air flow

INTRODUCTION

The blast furnace is a complex controlled object, which has the characteristics of nonlinearity, multiple parameters and Time-varying properties. Its own energy consumption is huge, and its function is to provide a continuous and stable heat source for blast furnace production, that is, blast furnace hot air. According to the data analysis, when the hot efficiency of the blast furnace is increased by 1-2 %, the air temperature will increase by 5-8 °C. The air temperature from 900 °C to 1 200 °C, which rises 100 °C, the coke saved is 4 %, 3 % and 2,5 % respectively. It can be seen that high air temperature and thermal efficiency are the key to energy conservation [1,2]. At present, the research on the control of the blast furnace mainly focuses on two aspects: mathematical modeling and artificial intelligence control. In view of the characteristics of multivariate and strong coupling, the analysis method of the mathematical modeling is more difficult. In order to solve the problem of low automation and strong human-dependence in actual production, the ironmaking plant of a steel company is taken as the research object, the air supply mode is cross parallel and the combustion control mode adopts the closed loop double loop of gas and air [3,4]. In this paper, a large number of data generated in the operation of blast furnace are pretreated to obtain a sample training set. Using a semi-supervised clustering intelligent control algorithm to cluster analysis on the sample data, dynamically and accurately adjust the air-fuel ratio, and realize intelligent optimal control of blast furnace under the complex working conditions.

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PUT FORWARD QUESTION

The traditional combustion control methods for blast furnace are mainly the ratio adjustment method and exhaust oxygen content adjustment method. The former is the combustion of air and gas in a fixed proportion, if the situation is complex and unexpected, it will result in the reduction of combustion efficiency. Similarly, although the latter is regulated by the oxygen content of the exhaust gas to the air-fuel ratio, the equipment in the measurement is prone to drift, which has some errors and is not easy to control. It is difficult to control combustion by mathematical modeling. In addition, fuzzy control and neural network method, which are different from traditional control methods, are easy to establish, but the anti-interference ability is poor, that is, the stability is not guaranteed. In this paper, the cluster analysis technology is applied to combustion control in order to obtain a good optimization result through screening a large number of data from the actual operation of the blast furnace [5].

STEADY-STATE-COMBUSTION CONTROL TECHNOLOGY

Treatment of isolated point

The working condition is complex and changeable, and the prior data are not clear or less in the practical problems, which will lead to some abnormal values in the sample data, and the clustering effect is poor. It is the most effective method to remove or replace these anomalous isolated point in clustering [6]. In this paper, a similarity criterion of a shared nearest neighbor is used to analyze it. It follows: two data points are similar to most of the points of the same set, and the two points are similar whether their distance can be measured or not.

It is assumed that the space sample training set is $X = \{x_1, x_2, \cdots, x_n\}$, the nearest neighbor set is S, the relevant definitions are as follows:

Definition 1: The data point is the nearest neighbor. Set $x_i, x_j \in X$, if $d = (x_i, x_j) < \delta$, then $x_i \in S_j$.

Definition 2: Share the nearest neighbor. Set $x_i \in X$, if $x_i \in S_j$ and $x_i \in S_k$, the intersection of S_j and S_k is S_{jk}, then $x_i \in S_{jk}$.

In the formula, S_j is the nearest neighbor set of x_j. S_{jk} is the intersection of the nearest neighbor set of x_j and x_k, $d = (x_i, x_j)$ is the distance between two data points, δ is a distance threshold.

In this paper, the K-means algorithm is used to get the nearest neighbor set of data points, and then remove the isolated point, the specific steps are as follows:

Input: the sample training set X, the value of k, the number of categories c;

Output: The sample training set X', is removed from isolated point。

Step 1: Assuming $k = c$, training X, training m times for each k in iteration, and obtaining nearest neighbor and shared nearest neighbor set of data points based on definition 1 and definition 2;

Step 2: The isolated point detection, after the end of each iteration, to detect the nearest neighbor set of the data point. If there is too few data points in the nearest neighbor of the data point, or the nearest neighbor is an empty set, then the data point is determined to be an isolated point.

Step 3: A set of isolated points, when the K value is fixed, after obtaining an isolated point, detect whether the point around the isolated point is an isolated point. If it is detected that the corresponding point is the nearest neighbor of the isolated point, the point is viewed as an isolated point, and the point is included in the set; if the point is not, it is skipped, go to the next one. Thus, by increasing the k value, all the isolated point in the iteration can be detected, and finally an isolated point set is formed.

Step 4: Determine all shared nearest neighbor sets:

(1) Calculate the nearest neighbor of all points obtained in step 2, and get the number of data point x_i, x_j belonging to one class, mark as *xcount*, at the same time, x_i, x_j analyze and calculate the corresponding probability of the same category, record as $xp(x_i, x_j)$;

(2) In this paper, if $xp(x_i, x_j) > 0{,}5$, it is assumed that x_i, x_j belong to the same category, that is, $x_j \in S_i$, $x_j \in S_i$.

(3) Repeat the above two steps until all the data points are detected, and the shared nearest neighbor sets are all fixed.

For the data points in the core and the border area, based on the shared nearest neighbor principle, Assuming the data points x_i and x_j, their corresponding nearest neighbors are x_j and S_j, and the shared neighbor is S_{ij}. Decision conditions: if $d = (x_i, x_j) < \eta$, then $x_i \in S_i$; about S_{ij}, if $x_i \in S_i$ and $x_i \in S_j$, then $x_i \in S_{ij}$. In the formula, η is the given distance threshold, $d = (x_i, x_j)$ is the distance between points.

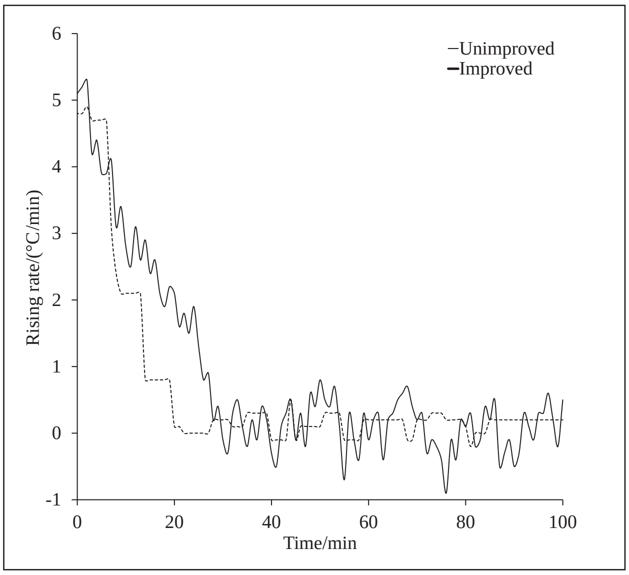


Figure 1 Contrast of vault temperature rise rate

In order to better eliminate the effect of isolated points on clustering results, this paper introduces the concept of closure substitution, that is, using virtual sample points instead of actual sample points, so that the number of sample points is further reduced to achieve a clear distinction.

Definition 1: Same cluster closure, sample point set $\{x_1, x_2, \cdots, x_n\}$, in the formula, $(x_i, x_j) \in S_m$, $i \neq j$, $1 \leq j$, $j \leq n$, the set formed by $\{x_1, x_2, \cdots, x_n\}$ is called the same cluster closure.

Definition 2: Different cluster closure, there are two closure sets $X = \{x_1, x_2, \cdots, x_n\}$ and $Y = \{y_1, y_2, \cdots, y_m\}$, in the formula, $(x_k, y_1) \in S_c$, $1 \leq k \leq n$, $1 \leq l \leq m$, and $x_k \in X$, $y_l \in Y$, then a and b are the closures of each other.

Definition 3: Closure Center, assuming there is the same cluster closure set $\{x_1, x_2, \cdots, x_n\}$, then $\overline{x}$ is defined as the center of the closure set.

In the formula, S_m is constraint of must-link and S_c is constraint of cannot-link. According to the above definition, the points in the sample set are centralized, and the clustering is attempted using the closure center instead of the original sample point. Note: If the sample point has no attribute, the closure center of the point is itself, and the point in the sample set can be considered as an isolated point.

The sample data is processed according to the selected method. The comparison chart of the dome temperature rise rate before and after optimization is shown in Figure 1.

Data preparation

The research objectives of the paper are the change of vault temperature and exhaust gas temperature, the operating parameters are gas volume and air volume, and the measurement index is thermal efficiency.

The process of cluster analysis is: collecting data on the spot, forming simulated data space, and obtaining a good set of operation samples according to a given measurement index. The clustering algorithm is used to classify the sample sets, and the similarity between the current working nodes and the sub cluster centers is calculated to get the matching nodes. The field data originates from a ironmaking plant and produces 15 278 sets of data. In the preprocessing, the abnormity values are removed by the shared nearest neighbor detection method and the interpolation method is used to supplement the data, and the normalization is used to facilitate the clustering. The air temperature of the research object in the paper is 1 300 °C. The designed vault temperature is 1 430 °C, a complete air supply period is 240 min, and the combustion time is 120 min. The high temperature zone uses silica bricks, and two small blast furnaces are additionally equipped to preheat the combustion air, and use heat recovery equipment to ensure air temperature. The following is the thermal efficiency formula:

$$\varepsilon = \frac{V_p(T_h C_h - T_c C_c)}{V_t \overline{Q_c}}$$

In the formula, V_t is the gas volume of the air supply period, V_p is the gas volume of the heating period, C_h, C_c is the specific heat capacity of hot air and cold air; $\overline{Q_c}$ is the calorific value of the burning gas. The gas consumption is inversely proportional to the thermal efficiency. The training sample set determines the data that the gas consumption is less than the measured mean and the thermal efficiency is greater than the measured mean.

EXPERIMENTAL ANALYSIS

In this paper, a semi supervised clustering algorithm based on pairwise constraints is applied to implement the clustering. The samples were processed repeatedly to obtain excellent sample set 4 352 groups. The process used K-means algorithm to deal with irregular clusters. The data in the combustion process of the hot stove was monitored. The test was divided into two parts: the optimization ability and the performance of the blast furnace. The simulation results are as follows Figure 2, 3, 4.

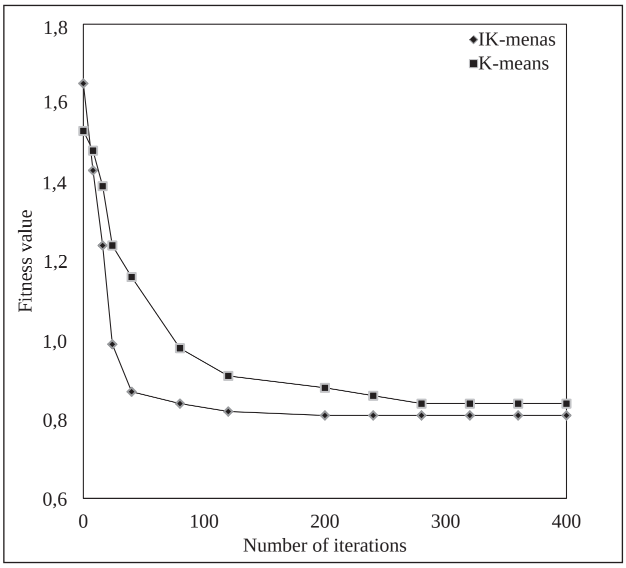


Figure 2 Convergence Analysis

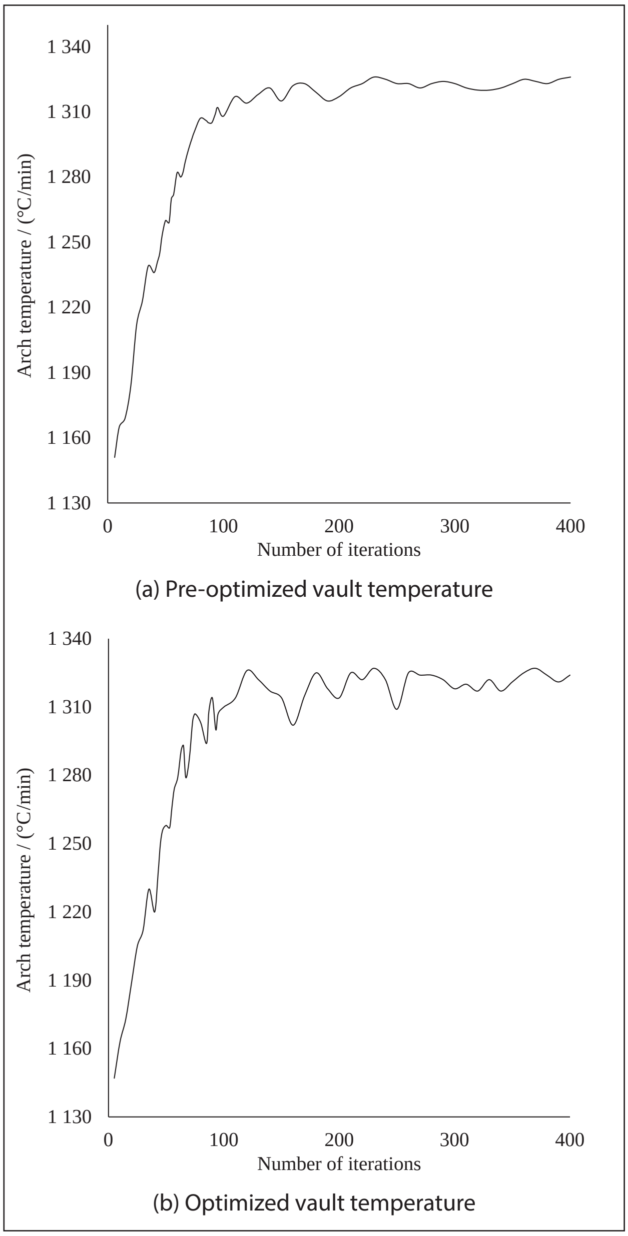


Figure 3 Vault temperature

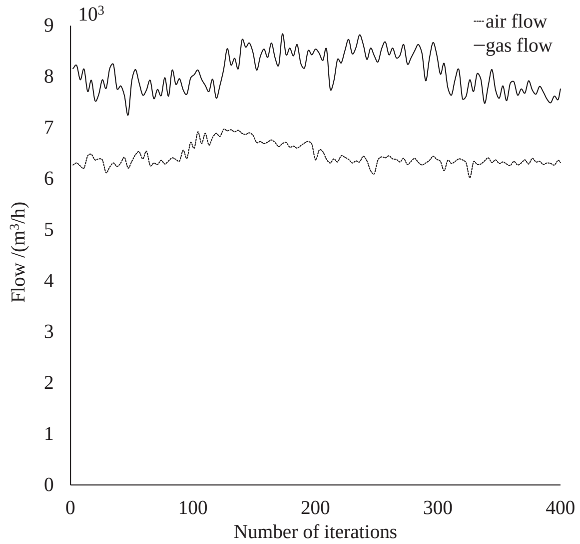
Figure 2 is a comparison of the convergence of the algorithm. It is known from the graph that the improved algorithm has better convergence than traditional algorithm.

Figure 3 is a change curve of the vault temperature in a combustion cycle. It is known from the graph that the optimized vault temperature is more in line with the ideal output value, rising rapidly and steadily, and the stability of the management period is good.

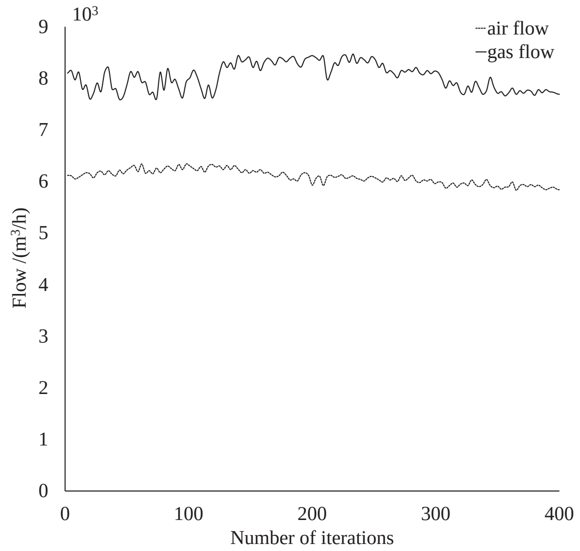
As can be seen from Figure 4, under the same conditions, the consumption of gas and air is reduced, and the thermal efficiency is effectively improved.

CONCLUSIONS

Different from the traditional control technology of hot blast furnace, the data preprocessing strategy of the



(a) Pre-optimized gas and air flow



(b) Optimized gas and air flow

Figure 4 Comparison of optimized gas and air flow

outlier anomaly removal has provided the substitution of missing data points, thus, the integrity of the data is guaranteed, the operation sample set is better optimized, and the optimal solution is obtained quickly. In the experiment, the accuracy of operation is enhanced, and the energy saving effect is very obvious.

Acknowledgments

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REFERENCES

[1] Špička I, Zimný O, Špičková D, Sikorová A. Measuring and recording of temperature on pedagogical model of hot-blast stoves[C]. Anniversary International Conference on Metallurgy and Materials 25(2016),1732-1735,

[2] Simkin A, Kobysh E. Control model of the heating hot blast stove regenerative chamber based on fuzzy knowledge with training set[J]. Metallurgical and Mining Industry 7(2015) 6, 96-101.

[3] Zetterholm J, Ji X.Y, Sundelin B, Martin P M, Wang Chuan. Model Development of a Blast Furnace Stove[C]. International Conference on Applied Energy 7(2015),1758-1765.

[4] Zhang Q, Li H.L, Zhao X.Y, Jia H. Dynamic prediction model of blast furnace gas generation and consumption and its application[J]. Journal of Harbin Institute of Technology 48 (2016) 1, 101-106.

[5] Sinha A, Jana P K. A hybrid MapReduce-based k-means clustering using genetic algorithm for distributed datasets[J]. Journal of Supercomputing 74(2018)4,1562-1579.

[6] Wiklund C.M, Helle M, Saxén H. Economic assessment of options for biomass pretreatment and use in the blast furnace[J]. Biomass and Bioenergy 91(2016), 259-270.

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