Identification of the Optimal Control Center for Blast Furnace Thermal State Based on the Fuzzy C-means Clustering

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It is required to maintain silicon content in hot metal ([Si]) at a stable level to ensure smooth operation of the blast furnace ironmaking process. However, current blast furnace control strategy always leads to frequent fluctuation of silicon content in hot metal. To stabilize blast furnace operation, this article attempts to identify the optimum control centre of silicon content through exploring the operational data of blast furnace ironmaking process. A quantitative analysis of the impact of thermal state on the smelting efficiency and intensity is presented by combining wavelet denoising and fuzzy c-means (FCM) clustering. Simulation results show that the commonly adopted mean value of historical data is not necessarily the optimum state of blast furnace operation. There exists some optimum state lower than the mean value, under which higher smelting efficiency and intensity can be achieved. It is also proved that the "low silica smelting practice" attempt in the steel industry is feasible and meaningful.

KEY WORDS: fuzzy C-means clustering; wavelet denoising; stability; silicon content in hot metal; hourly hot metal output.

1. Introduction

The main control objective of the blast furnace ironmaking is to achieve the high output and low energy consumption on the basis of safe and smooth production. In the blast furnace ironmaking process, due to the close relations among several factors such as the ironmaking stability of blast furnace, the production efficiency, and the ratio of the energy consumption to the quality of hot metal, the silicon content in hot metal ([Si]) is commonly used to represent the thermal state in blast furnace, and accordingly, it is usually regarded as an important quality index in the control of blast furnace ironmaking process.1) During their control of blast furnace ironmaking process, the operators often use the mean value of [Si] (denote as [Si]) from history data as the control objective and try to stabilize [Si] near the control objective, which is also adopted by many online expert systems as their control objective. With the mean value of [Si] as the control objective, the incremental change of next control behavior can then be obtained through optimization or expert knowledge.2) However, the control strategy based on the mean value always leads to frequent fluctuations of production in practice.2–4) The following questions may be asked: Whether or not the control method based on the history data is reasonable? Whether the control objective by the mean value is effective? If not, what’s the effective control objective? Accordingly, the purpose of this paper is to analyze the stability and effectiveness of the control method on the basis of the mean value.

According to the aspect of fixed point theory,5) the nonlinear partial differential equations governing blast furnace ironmaking process may have 2 or more fixed points, or there exists limit cycles on the solution trajectory in the phase plane, as shown in Fig. 1. It is probable that the mean value of silicon content is actually not the stable state of the
system. Thus it is easy to understand the fact that the control of blast furnace by using the mean value as objective leads to frequent fluctuations and instability in the production.

Blast furnace ironmaking process is a complex nonlinear process under high temperature and high pressure, where numerous chemical reactions happen simultaneously with dynamic characteristics affected by both the hydrodynamics and industrial reaction dynamics. Reactions happen in the blast furnace are much different from those simulated in the laboratory, making it difficult to construct an accurate mathematical model to simulate the thermal state. Without an accurate model, it’s difficult to get the stable state (fixed point) in the blast furnace for the mathematical model.\(^{5-9}\)

However, it is possible to identify the stable state where production is smooth, with lower cost and higher production from mining the data collected during the ironmaking process. Considering the huge volume of blast furnace and large quantity of materials involved, this is an important issue both in theory and practice. During the past decades, substantial research efforts have been devoted to stabilizing the production of blast furnace ironmaking near the optimum state using different control strategies.\(^{2,4,6-9}\) The optimum state, however, was seldom explored. Many industrial practices simply set it to be the mean value of historical data \([\text{Si}]\), which may probably be inappropriate since production is not always running near the optimum state. Alternatively, this article tries to identify the optimum control center by exploring the information contained in operational data. Design of control strategy can be useful only when the optimum state is obtained.

Based on the above analysis, two key variables in blast furnace ironmaking process-silicon content in hot metal (\([\text{Si}]\)) and hot metal temperature (FeW), are used to represent the thermal state of blast furnace; and hourly output (Fe/H) is used to represent the efficiency of ironmaking. So sent the thermal state of blast furnace; and hourly output (Fe/H), are used to represent the efficiency of ironmaking. Hence in this paper, we adopt the Mallat algorithm to denoise the original signal, which consists of a decomposition step and a reconstruction step.

The Mallat decomposition can be described as follows:

\[
c_{j,1,m} = \sum_{k} b(m-2k)c_{j-1,m} \quad \text{(1)}
\]

\[
d_{j,1,m} = \sum_{k} g(m-2k)c_{j-1,m} \quad \text{(2)}
\]

where \(c_{j,k}, d_{j,k}\) are the corresponding decomposition coefficient, and \(h(n), g(n)\) are the impulse responses of the wavelet low-pass filter and high-pass filter. The Mallat reconstruction is given as:

\[
c_{j-1,m} = \hat{c}_{j-1,m} + \hat{d}_{j-1,m} \quad \text{(3)}
\]

\[
\hat{c}_{j-1,m} = \sum_{k} c_{j,k}h(m-2k) \quad \text{(4)}
\]

\[
\hat{d}_{j-1,m} = \sum_{k} d_{j,k}g(m-2k)
\]

where \(\hat{c}_{j-1,m}, \hat{d}_{j-1,m}\) are reconstructed coefficients and \(m = 2k + n, k, n \in \mathbb{Z}\).

Denote \(c_0\) as the original signal X. Via the method in (1) and (2), we can decompose \(c_0\) into \(d_1, d_2, \ldots, d_J\) and \(c_J\), where \(J\) is the maximum resolution number, \(c_j\) and \(d_j\) are the smooth term and detail term at the resolution of \(2^j\) respectively. At each step, the number of terms decreases 50%, which implies that the time resolution ratio decreases 100%; that is, the frequency resolution increases 100%. Commonly, the Mallat algorithm can be divided into three steps.\(^{9}\)

(1) **Signal decomposition**: Choose an appropriate mother wavelet and decomposition scale \(N\), then decompose the original signal into \(N\) scale. Note that the selection of \(N\) is crucial to the correction of unnormal data.

(2) **Threshold quantification**: For the high frequency coefficient \(d_j^i (i = 1, \ldots, N)\), we handle them with the soft-threshold method and get the high frequency component after denoising.

(3) **Signal Reconstruction**: Reconstruct signal by the wavelet method according to the modified high frequency coefficients from scale 1 to \(N\) and the low frequency coefficients of scale \(N\).

2.2. **Fuzzy C-Means Clustering**

Clustering analysis is a common technique for statistical data analysis and has been widely used in many fields
including the machine learning, data mining etc. Perhaps the most well known clustering methods are the c-means clustering (also called hard c-means clustering, HCM) and fuzzy c-means clustering (FCM). In the HCM, the degree of membership has only two values, i.e. 0 and 1; that is, each sample is a member of one and only one cluster. Since the HCM restricts each sample to exactly one cluster and the clusters are not overlapped, some similar individuals cannot be assigned to the same cluster. In contrast, the degree of membership in the FCM is a value between the closed interval [0, 1]. Moreover, a sample belongs to all clusters with different degree of membership. By using the fuzzy membership function, FCM can better cluster dataset with overlapping clusters. It is obvious that HCM is a special case of FCM.\(^{10,18}\)

Let \(X = \{x_1, x_2, \ldots, x_p\}\) denote the object set that need to be clustered and each object has \(m\) characteristics indexes \(U = \{u_{ij}\}_{ij}\) and the corresponding matrix is \(U = \{u_{ij}\}_{ij}\). We first classify the objects set \(X\) into \(c\) types. Denote the centers of \(c\) clustering vectors as a matrix \(V = \{v_{ik}\}_{ik}\). We find the suitable fuzzy classification matrix \(R = \{r_{ik}\}_{ik}\) and clustering centers matrix to minimize the following objective function

\[
J_q(R, V) = \sum_{k=1}^{c} \sum_{i=1}^{n} (r_{ik}^q) \left[ u_{ki} - V_i \right]^2 \quad (5)
\]

where \(q\) is the weighted or smoothing index that can be any real number greater than 1, but it is commonly set as \(q = 2\). \(r_{ij} \in [0,1]\) is the degree of membership of \(u_{ki}\) in the cluster \(j\) (Obviously, \(r_{ij} \in [0,1]\) for the case of HCM), \(u_{ki}\) is the \(k\)th of \(m\)-dimensional data, \(V_i\) is the \(m\)-dimensional center of the cluster and \(u_{ki} - V_i\) denote the distance between object \(u_{ki}\) and the centers vector \(V_i\). Fuzzy partitioning is carried out through an iterative optimization\(^{19}\) of the objective function in Eq. (5), with the update of membership \(r_{ij}\) and the cluster centers \(V_i\) by

\[
r_{ij} = \frac{1}{\sum_{k=1}^{c} \left( \left| u_{ki} - V_i \right| \right)^q} \quad (6)
\]

\[
V_i = \frac{\sum_{k=1}^{p} r_{ik}^2 u_{ki}}{\sum_{k=1}^{p} r_{ik}^2} \quad (7)
\]

The iteration will terminate when the membership converges to a local minimum or a saddle point of \(J_q\). With the membership and cluster center computed, the cluster of each data sample can be easily obtained. After obtaining the optimal fuzzy classified matrix and clustering centers matrix that are consistent with the requirement, we are able to complete the clustering for each object according to the principle of optimal clustering center.

To quantify the effect of clustering, the following clustering validity index is introduced.\(^{11,20,21}\)

\[
FP(R; c) = F(U; c) - P(U; c) \quad (8)
\]

\[
F(U; c) = \frac{1}{c} \sum_{i=1}^{c} \left( \sum_{j=i}^{c} r_{ij}^2 \right) / \left( \sum_{j=1}^{c} r_{ij}^2 \right) \quad (9)
\]

\[
P(U; c) = \frac{1}{c} \sum_{i=1}^{c} \left( \sum_{j=1}^{c} r_{ij}^2 \right) / \left( \sum_{j=1}^{c} r_{ij}^2 \right) \quad (10)
\]

where \(F(U; c)\) and \(P(U; c)\) are partition coefficient and possible partition coefficient. For set number of cluster \(c\), the smaller \(FP(R; c)\) is, the better the clustering is. It is easy to see that for HCM, the cluster validity index is 0. Hence if the validity index of FCM is negative, then the clustering result is better than HCM and vice versa.

In this article, Mallat algorithm is firstly used to denoise the raw data, followed by Fuzzy c-means clustering to analyze the denoised data. Using the denoised data, cluster analysis results by FCM will be closer to the true state of the system classifications.

3. Simulation on Blast Furnace Data

3.1. Data Preprocessing

In practice, due to numerous reasons, the time intervals between the previous and later blast furnace tapping is generally different, making it difficult to characterize the ironmaking efficiency using average output of unit volume (Fe/L). In order to eliminate the negative impact of this disparity, we first use the SQL and Matlab to transform the average output of unit volume (Fe/L) into the sequence of average hourly output (Fe/H), according to the following formula:

\[
Fe/H = (Fe/L)/(T_n - T_{n-1}) \quad (11)
\]

where \(T_n\) represents the end time of current tapping and \(T_{n-1}\) denotes that of last tapping. In this paper, we consider two datasets collected from No. 7 blast furnace of Handan Steel Group of China respectively. Each dataset includes 600 samples and each dataset contains a total of 3 variables, i.e. [Si], FeW and Fe/H. The time series graph of the original data is shown in Fig. 2.

3.2. Wavelet Denoising

Due to the strong mean reversion of the control of blast furnace ironmaking process\(^{22}\) the time series of [Si], FeW and Fe/H may contain much high frequency components. To ensure the quality of data by de-noising while still retain the high frequency components of the original data, we apply the Db3 wavelets to decompose the original time series at the 2nd scale fast Mallat decomposition; then use the maximum-minimum rule to determine the threshold and perform the soft thresholding procedure for the wavelet coefficients\(^{23}\) and in the end, we conduct the Mallat reconstruction for these wavelet coefficients after soft thresholding, which result in the denoised time series for [Si], FeW and Fe/H (see, Fig. 3).

Comparing Fig. 2 with Fig. 3 it is easy to find that by appropriately control the wavelets de-noising process and suitable selection of wavelet parameters, satisfying de-noising results can be obtained while still retaining the high frequency part of the original data.

3.3. Optimal Control Center Extraction by FCM

The two datasets after de-noising are classified into two object sets to be clustered, which are denoted as:

\[
X_n = \{x_{1,n}, x_{2,n}, \ldots, x_{500,n}\} \quad n = 1, 2, \ldots (12)
\]
Each subject $x_{in}$ in the data set corresponds to a 3-dimensional vector $u_{i,n}$:

$$u_{i,n} = ([Si]_{i,n}, FeW_{i,n}, Fe/H_{i,n}) \quad i = 1, 2, \cdots, 600, \ n = 1, 2, \cdots$$

(13)

Since the data of [Si], FeW and Fe/H have different magnitudes, it is difficult to reveal the relationship between variables using FCM directly. Thus a normalization procedure is applied to the de-noised signal:

$$[Si]_{i,n} = \frac{[Si]_{i,n}}{\text{mean}([Si]_{i,n})} \quad i = 1, 2, \cdots, 600, \ n = 1, 2, \cdots$$

(14)

$$FeW_{i,n} = \frac{FeW_{i,n}}{\text{mean}(FeW_{i,n})} \quad i = 1, 2, \cdots, 600, \ n = 1, 2, \cdots$$

(15)

$$Fe/H_{i,n} = \frac{Fe/H_{i,n}}{\text{mean}(Fe/H_{i,n})} \quad i = 1, 2, \cdots, 600, \ n = 1, 2, \cdots$$

(16)

Where mean$([Si]_{i,n})$, mean$((FeW)_{i,n})$ and mean$((Fe/H)_{i,n})$ are the mean values of [Si], FeW and Fe/H in the nth data sets.

We use the FCM function and relative module in Matlab 7.6, the iteration is ended until $\varepsilon = 0.0001$ or the step of iterative process reaches 200. In our implementation, the smoothing index is set as $q = 2$ and the number of cluster is $c = 5$.

To test the validity of clustering methods, cluster analysis is performed on set 1 and set 2 using both HCM and FCM. For HCM, the number of cluster is also set as 5. The clustering validity index $FP(R; c)$ are computed and compared in Table 1.

Table 1. The value of $FP(R; c)$ by HCM and FCM respectively.

| No. | The Value of $FP(R; c = 5)$ |
|-----|----------------------------|
|     | HCM | FCM |
| Set 1 | 0   | 0   |
| Set 2 | 0   | 0.0441 |

From Table 1 it can be seen that for both set 1 and set 2, the validity index are negative, i.e., 0.0314 and 0.0441, hence FCM achieves better clustering than HCM.

To analyze the results of FCM, Fig. 4 describes the clus-
ter space graph of set 1 and set 2. \(\text{Tables}\ 2\) and \(\text{3}\) show the cluster centers, number of data samples and the mean value of output Fe/H for both sets, respectively. Furthermore, we include the mean value of characteristics index for the Fe/H in each type.

From Table 2, we can find the following interesting insights of set 1:

(1) Why volatility: Most of the 600 objects in set 1 are not near the mean value of 0.4504, and the cluster whose center is near the mean value (cluster 4) contains only 17 objects. Although the average hourly output Fe/H reaches 330.6, this is not a stable state since it contains too few objects;

(2) Which state is more stable: The clustering center [Si] of cluster 1 is the greatest among all clusters, it contains 203 samples; and the clustering center [Si] of cluster 2 is the lowest, and it contains 173 samples. The hot metal temperatures under these two states appear to be relatively stable, which implies that the blast furnace ironmakings under these two states have the remarkable “fixed point” attractive property;

(3) Comparing efficiency: Comparing the ironmaking efficiency under the two states it can be seen that, the average hourly output (Fe/H) of cluster 2 under the lower [Si] state is higher than the average hourly output of the cluster 1 under the higher [Si] state (229.63 vs. 222.33). Furthermore, it is also higher than the average hourly output of set 1, which is 228.22. These facts suggest that the ironmaking in the appropriate lower [Si] state does not decrease the global ironmaking capacity of the blast furnace ironmaking. What is more important, ironmaking under lower [Si] state has many advantages such as less energy consumption and emission.

Analyzing the results in \(\text{Table}\ 3\) similar concludings can be obtained:

(1) Stable state: The mean value of [Si] in set 2 is 0.4490 (close to 0.45), however, this is far from the centers of all clusters. We also notice that there are 221 (52+169=221) samples in the 4th and 5th cluster, whose center has lower [Si], and there are 212 (168+44=212) samples in the 2nd and 3rd cluster with higher [Si]. These results show that the blast furnace ironmakings under these two states also have the remarkable “fixed point” attractive property;

(2) Comparing efficiency: Similar to analysis of set 1, we can see that the clusters (cluster 4 and cluster 5) corresponding to low [Si] state contain many objects. Moreover, the weighted average hourly output in the 4th and 5th clusters is 237.89 ((312.85×52+214.83×169)/(52+169)=237.89). It is higher than those of 2nd and 3rd clusters, and also higher than the average hourly output of the whole dataset, which is 228.33. These results also imply that the ironmaking in the appropriate lower [Si] state does not decrease the overall ironmaking capacity of the blast furnace ironmaking.

For both set 1 and set 2, cluster centers of hot metal temperature (FeW) are much closer. This indicates that the temperature at the lower part of blast furnace is relatively stable. Although FeW is closely related to [Si], the later is more sensitive to the change of thermal status in hot metal. That’s one of the main reasons to consider [Si] as the main indicator of thermal state in blast furnace.

4. Conclusions

In this paper, the fuzzy c-means clustering method is used to identify the optimal control center of blast furnace ironmaking process. Three key variables in blast furnace ironmaking process, \(i.e.\) silicon content in hot metal, hot metal temperature and hourly output, are considered. The data is first filtered and de-noised by wavelet method. Simulation results show that the commonly adopted control objective, \(i.e.\) mean value of historical data is not a good choice since it may be an instable state. Cluster results show that the blast furnace operation is stable with [Si] near 0.41 and is identi-
fied as the optimal control center with respect to high output and low cost. It further proves that the appropriate lower [Si] ironmaking practice can not only lower the cost, but also maintain the high efficiency. The proposed method can be applied online to seek the optimal control center to stabilize the fluctuation of [Si].

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