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Long term prediction for generation amount of Converter gas based on steelmaking production status estimation

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***Abstract*—Long term prediction for generation amount of Converter gas is very important for the optimal scheduling of energy system in iron and steel making enterprises. In this paper, a long term prediction approach based on steelmaking production status estimation is proposed to address this issue. Steelmaking production status estimation has two stages, namely feature extraction and feature fusion. At the first stage, the generation time series of Converter gas is divided into some data segments with the same length, and then a method based on template matching is used to extract the time and frequency domain characteristics of steelmaking production status. At the second stage, an improved version of fuzzy C-mean clustering method is developed for feature fusion, which integrates the characteristics from different data segments to obtain a universal feature of steelmaking production status. Finally, the universal feature is used to reconstruct the generation time series of Converter gas. To verify the effectiveness of the proposed method for long term generation amount prediction of Converter gas, a set of experiments is conducted based on the real world data from an iron and steel enterprise. The experimental results demonstrate that the proposed method exhibits high accuracy and can provide an effective guidance for balancing and scheduling the byproduct Converter gas.**

Keywords—steelmaking production; feature extraction; feature fusion; fuzzy C-mean clustering; long term prediction

I. INTRODUCTION

The iron and steel manufacturing is a pollutant emission and energy-intensive process, whose energy cost constitutes about 20% of the total operation cost [1].With primary energy shortage, efficient use of byproduct energy is very important in reducing the total operation cost and waste emissions. Converter gas generated from steel making process is a kind of significant byproduct energy, which can be further used as secondary fuel for several production processes, such as hot rolling, cold rolling and power generation. However, balancing and scheduling of the Converter gas system is a difficult problem since its generation amount exhibits frequent and significant fluctuations corresponding to the production status. Thus, long-term accurate prediction for generation amount of Converter gas that can provide effective guidance and save plenty of time plays a central role in reducing energy cost and waste emission.

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Since the generation amount of Converter gas is related to the steelmaking production status that is a complex process, it is difficult to establish a mechanism model for prediction. Recently, data-driven prediction techniques is the most commonly used research methods, such as neural networks (NNs) based methods and support vector machine (SVM) based methods [2]-[4] [6]-[8].Improved versions of echo state networks (ESNs) based time series prediction was proposed in [2] [3] for generation amount of byproduct gas, which exhibits good performance for the data in addition to noise. Based on the fact that the industrial data is noisy, another ESN based model considering the uncertainties results from noises is reported in [4] to predict the generation amount of byproduct gas and the nonlinear Kalman filters based dual estimation is also developed to estimate the parameters of the proposed model. Compared to NNs based methods, SVM based techniques with small number of training samples can also get a good performance. The least squares support vector machine (LSSVM) proposed in [5] was applied for forecasting the generation amount of byproduct gas and a gradient descent method was used for parameters optimization [6].Considering the computational efficiency, an LSSVM based prediction model combined with the parallel strategies that largely reduce the computational cost was proposed in [7], in which parameters optimization is realized online by a parallel particle swarm optimization being implemented with the use of a graphic processing unit (GPU) [9].However, both the studies in [6] and [7] offered few considerations on the impact of the industrial noise. A LSSVM model based on online hyper-parameters optimization was proposed in [8] where the variance of effective noise of the sample was estimated. A series of comparative experiments based on a real-time prediction of gas flow in steel industry were conducted to verify its rapidity and accuracy.

Time series prediction that mine the dynamic characteristics of historical data stated above is not suitable for long term prediction due to three reasons. First, accumulation of error cannot be avoided for time series prediction, which is destructive for long time period prediction. Second, continuity of data sample is necessary for time series prediction since data incompleteness may lead to an inaccurate prediction. However, the data missing in energy system of iron and steel making enterprises is very common because of equipment failures. Third, the prediction accuracy has a close relationship with the consensus between the training data and the testing data. When the dynamic characteristics of the testing data are consistent with those of the training data, an expected forecast can be obtained. However, the consensus cannot be guaranteed because the steelmaking production status has a strong impact on the generation amount of Converter gas.

In this paper, a long term prediction approach for the generation amount of Converter gas based on steelmaking production status estimation is proposed. Steelmaking production status estimation has two stages, namely feature extraction and feature fusion. At the first stage, the generation time series of Converter gas is divided into some data segments with the same length, and then template matching is used to extract the time and frequency domain characteristics of steelmaking production status. At the second stage, an improved version of fuzzy C-mean clustering method which integrates the prior industrial process knowledge into the clustering objective function is developed for feature fusion. Specifically, the characteristics extracted from different data segments are assembled to obtain a universal feature of steelmaking production status. Finally, the universal feature is used to reconstruct the generation time series of Converter gas. To verify the effectiveness of the proposed method for long term generation amount prediction of Converter gas, a set of comparative experiments is conducted based on the real-world data from an iron and steel enterprise. The experimental results demonstrate that the proposed method exhibits high accuracy and can provide an effective guidance for balancing and scheduling the byproduct Converter gas.

II. PROBLEM STATEMENTS

The Converter gas system consists of LD converters for gas generation, a series of gas users for consumption, pipeline networks for gas transportation and gas holders for temporary storage. Taking a steelmaking plant as an example, the Converter gas system is presented in Fig. 1, where 6 LD converters supply the Converter gas into the pipeline networks. The generated gas is firstly stored in the gas holders, and then transported to other consumption units, such as hot blast stove, hot rolling process, cold rolling plant, and low pressure boiler. If the generation amount of Converter gas in a period is larger than the consumption amount of the users, the gas holder will accumulate the surplus Converter gas. However, the cushion for the gas holder is sometimes very limited; the useful gas energy has to be diffused into the environment for safety reasons. On the other hand, if the accumulative generation of Converter gas is less than the consumption demand, much more fossil energy such as coal or natural gas will have to be used as the alternative energy for sustaining the overall production. Obviously, the balance of Converter gas system has a strong relationship with the generation amount. Long term accurate prediction of Converter gas generation can provide effective guidance and plenty of time for scheduling and balancing the Converter gas system.

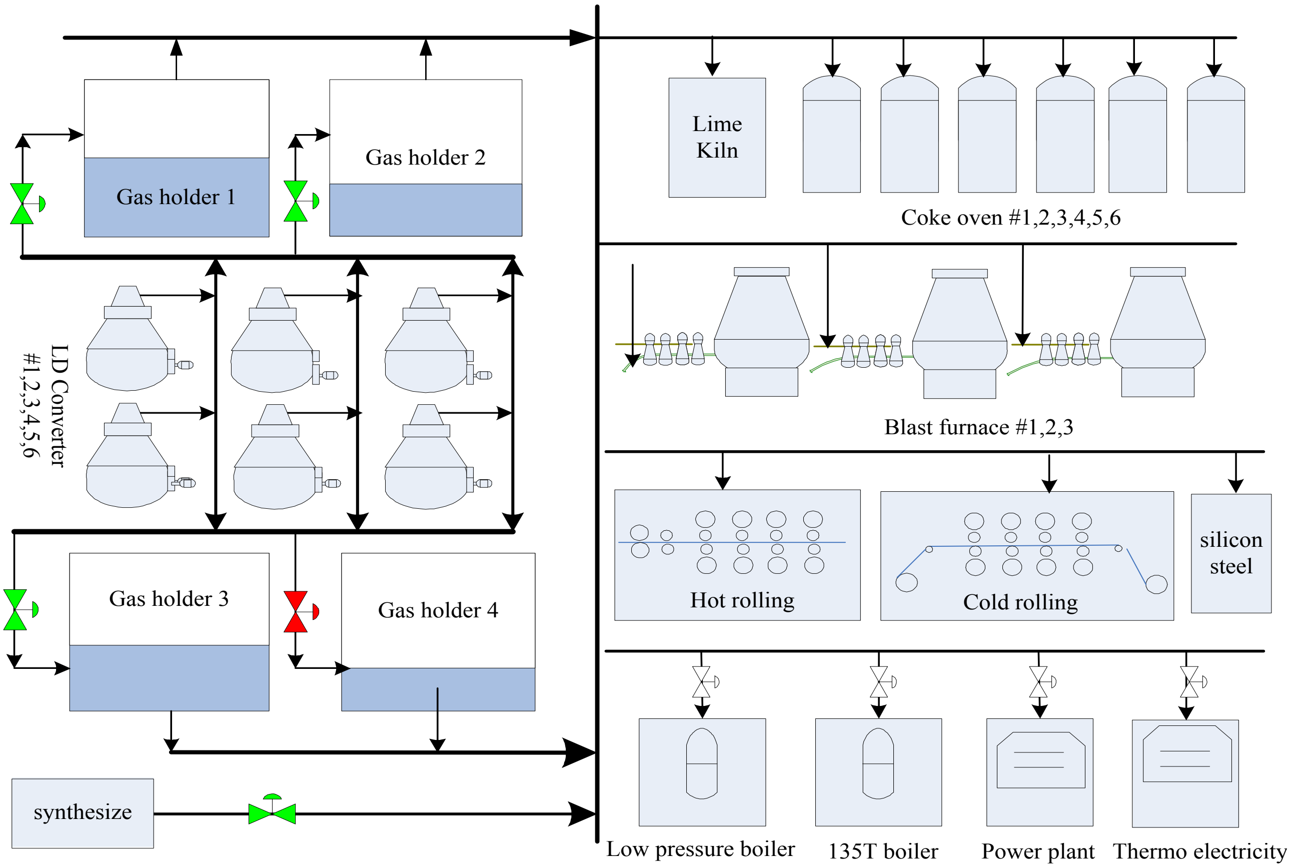

Fig. 1. Structural chart of Converter gas system used in steelmaking plant.

Generation amount of Converter gas has a close relationship with the steelmaking production status. Since the steelmaking production is an intermittent process, so the generation amount of Converter gas occurs intermittently as shown in Fig. 2. In order to ensure the quality of the product, the conditions of different production cycles keep basically consistent. Thus, the Converter gas generation amount of a heat of steel occurs substantially the same. After a heat of steel, there will be a production gap. The occurrence time of the steelmaking and the length of the duration of the production gap are used to describe the production status. Thus, recognition of the laws of the steelmaking production plays an important role in predicting the generation amount of Converter gas in a long time period.

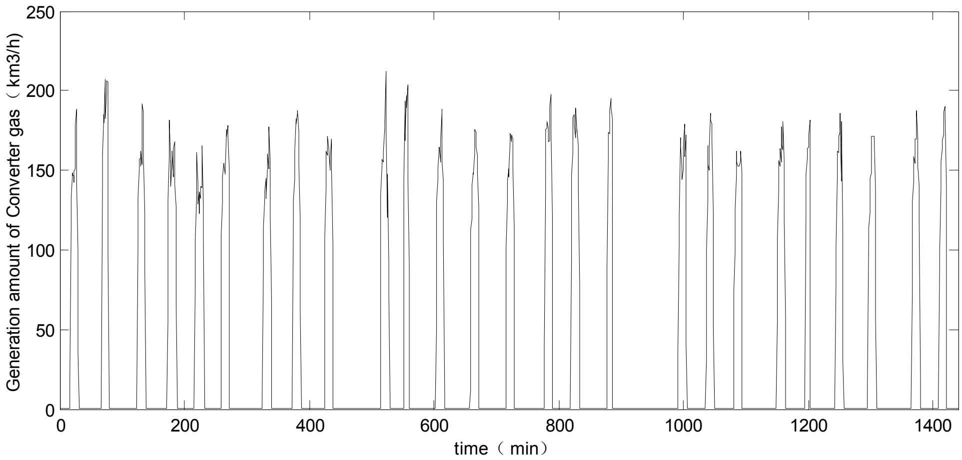

Fig. 2 Chart of generation amount of Converter gas.

III. STEELMAKING PRODUCTION STATUS ESTIMATION

Steelmaking production status is represented by the production gap between two heats of steel. The occurrence time of the steelmaking and the length of the duration of the production gap are different due to the variance of the production conditions. Thus, production gap is described by two features. One is the time domain feature represented by the occurrence time of the steelmaking, and the other is the frequency domain feature represented by the duration of the production gap. Steelmaking production status estimation has two main parts, namely feature extraction and feature fusion, as shown in Fig. 3.

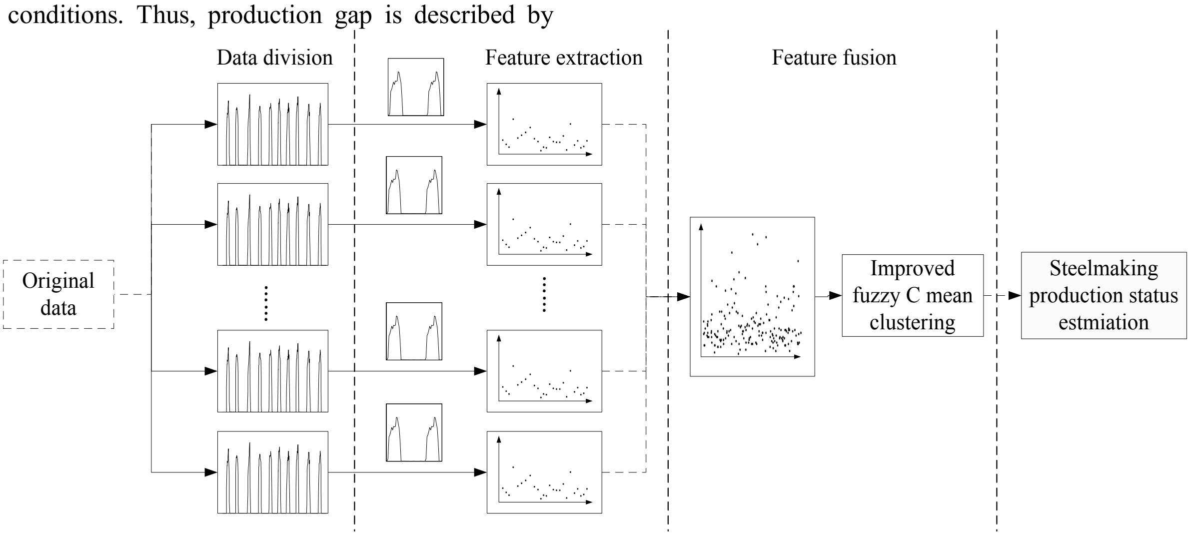

Fig. 3. Flow chart of steelmaking production status estimation

A. Feature Extraction

The generation time series of Converter gas is divided into some data segments with the same length n, each of which can be expressed as $\mathbf{x}(n)$. To extract the feature of the data segments, template matching based method is proposed here. First, the concave template is constructed based on the historical data, as shown in Fig. 4. The choice of the template depends on the features that need to be extracted from the data segments. So the template here is learned from the Converter gas generation amount time series of different production cycles. The data in two dashed boxes of Fig. 4 is the same, which represent the feature of Converter gas generation amount of a heat of steel. The transition time between two heats of steel is the production gap.

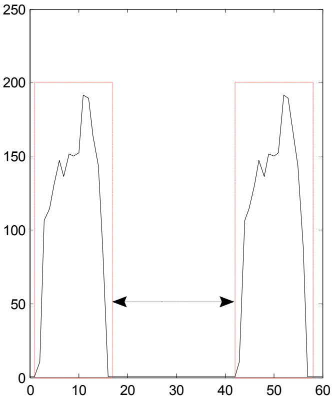

Fig. 4 The chart of the concave template

The template has the time shifted ability and extensibility. The template can be shifted forward or backward along the timeline when the objective signal is matched. Let $\mathbf{x}(n)$ be the objective signal, then the set of the valid time shift characteristics can be described as

$$\mathbf{B} = \{b_1, b_2, \cdots, b_j, \cdots, b_N\}$$

were b_N is the biggest time shift. The extensibility measures the duration of the production gap that depends on the real production conditions. Considering the upper and lower limits of the duration, the set of the extensible characteristics can be described as

$$\mathbf{A} = \{a_1, a_2, \cdots, a_i, \cdots, a_l\}$$

where a_1 and a_l are the upper and lower bounds of the duration of the production gap respectively.

After effectively extended, a set of the templates can be obtained as $\{\mathbf{t}_1, \mathbf{t}_2, \cdots, \mathbf{t}_l\}$. A computation of the cross covariance between the objective signal $\mathbf{x}(n)$ and the ith template $\mathbf{t}_i(m)$ is used to measure the matching degree.

$$\mathbf{y}(j) = \sum_{k=1}^{m_i} \mathbf{t}_i(k)\mathbf{x}(j-k) \tag{1}$$

where m_i is the length of the ith template, $j = n + m_i - 1$. The correlation matrix $\mathbf{Y}$ an be obtained through performing the same computation of each template in the set. $\mathbf{Y}(i, j)$ reflects the similarity between the objective signal $\mathbf{x}(n)$ and the template $\mathbf{t}_i(m)$ with time shift b_j.

The local extrema of $\mathbf{Y}(i, j)$ is the points of best match between the objective signal and the template in the time-frequency domain. The extrema can be found as a new collection, denoted as $\mathbf{Y}^* = \{Y(a_i, b_j)\}$, where $Y(a_i, b_j)$ needs to satisfy the following formula

$$\begin{aligned} & Y(a_i, b_j) > Y(a_x, b_y), \quad 1 < i < l \ \ and \ \ 1 < j < N. \\ & (a_x, b_y) \in \{(a_{i-1}, b_{j-1}), (a_{i-1}, b_j), (a_{i-1}, b_{j+1}) \\ & \qquad , (a_i, b_{j-1}), (a_i, b_{j+1}), (a_{i+1}, b_{j-1}) \\ & \qquad , (a_{i+1}, b_j), (a_{i+1}, b_{j+1})\} \end{aligned} \tag{2}$$

The index values are collected as the feature vector, denoted as $\chi = \{(a_i, b_j)\}$, each of which represents a best match between the objective signal and the template that is well localized in the time domain b_j and in the frequency domain a_i.

B. Feature Fusion

If the number of the data segments equals to N, a feature vector collection $\mathbf{X}$ with N individuals $\boldsymbol{\chi}$ can be obtained. An improved version of fuzzy C-mean clustering method is developed in this study for feature fusion, which integrates the characteristics from different data segments to represent a universal feature of steelmaking production status.

Here, the minimum variance criterion is used as the objective function of clustering. Having N_c patterns, and assuming that c clusters are required, we compute a sum of dispersions between the patterns and a set of clustering centers $\{\mathbf{v}_1, \mathbf{v}_2, \cdots, \mathbf{v}_c\}$

$$\begin{aligned} \min \ J(\mathbf{U}, \mathbf{V}) = & \sum_{k=1}^{\mathcal{N}_c} \sum_{i=1}^{c} (u_{ik})^m d^2(\mathbf{X}_k, \mathbf{v}_i) \\ & + \eta \sum_{i=1}^{c-1} \left(\mathbf{v}_{a,i+1} - \mathbf{v}_{a,i} - (\mathbf{v}_{b,i+1} + \mathbf{v}_{b,i}) / 2 - \mathcal{L} \right) \end{aligned} \tag{3}$$

where $d^2(\mathbf{X}_k - \mathbf{v}_i) = \|\mathbf{X}_k - \mathbf{v}_i\|^2 = (\mathbf{X}_k - \mathbf{v}_i)^T(\mathbf{X}_k - \mathbf{v}_i)$ is a certain distance between $\mathbf{X}_k$ and $\mathbf{v}_i$ that are points in two-dimension space. $\mathbf{v}_{a,i}$ denotes the horizontal coordinate of ith clustering center, and $\mathbf{v}_{b,i}$ denotes the vertical coordinate of ith clustering center. $m \in [1, \infty]$ is the weighted index. $\mathcal{L}$ is the duration time of a heat of steel. The second term in the above objective function is based on the prior knowledge of production, e.g. the difference between the occurrence times of two adjacent production gaps equals to the sum of half of those duration time and the duration time of a heat of steel. The important component of (3) is a partition matrix $\mathbf{U} = \{u_{ik}\}$, $i = 1, 2, \cdots, c$, $k = 1, 2, \cdots, \mathcal{N}_c$. The partition matrices satisfy the following conditions:

$$\sum_{i=1}^{c} u_{ik} = 1, \quad 1 \le k \le \mathcal{N}_c \ \ u_{ik} \in [0,1], \ 1 \le k \le \mathcal{N}_c, 1 \le i \le c$$

To solve the above constraint optimization problems, the constraints are incorporated with the aid of Lagrange multipliers. For each pattern $k = 1,2,\cdots,\mathrm{N}_c$, the augmented function is formulated as

$$Q = \sum_{i=1}^{c} (u_{ik})^m d_{ik}^2 - \lambda\left(\sum_{i=1}^{c} u_{ik} - 1\right) + \eta \sum_{i=1}^{c}\left(\mathbf{v}_{a,i+1} - \mathbf{v}_{a,i} - (\mathbf{v}_{b,i+1} + \mathbf{v}_{b,i})/2 - \mathcal{L}\right) \tag{4}$$

where λ denotes a Lagrange multiplier. Compute the derivative of Q with respect to u_{sk} and make it equal to 0,

$$\frac{\partial Q}{\partial u_{sk}} = m u_{sk}^{m-1} d_{sk}^2 - \lambda = 0 \tag{5}$$

Then take into account the identity constraint $\sum_{i=1}^{c} u_{ik} = 1$, we have

$$\left(\frac{\lambda}{m}\right)^{\frac{1}{m-1}} \cdot \sum_{i=1}^{c} \frac{1}{\left(d_{ik}\right)^{2/(m-1)}} = 1 \tag{6}$$

The degree of membership u_{sk} can be expressed as

$$u_{sk} = \frac{1}{\sum_{i=1}^{c} (d_{sk} / d_{ik})^{2/(m-1)}} \tag{7}$$

The computations of the clustering centers are straightforward, as no constraints are imposed on them. The minimum of Q computed with respect to $\mathbf{v}_{a,i}$ and $\mathbf{v}_{b,i}$ yields

$$\frac{\partial Q}{\partial \mathbf{v}_{a,s}} = 2\sum_{k=1}^{\mathcal{N}_c} u_{sk}^m (\mathbf{X}_{a,k} - \mathbf{v}_{a,s}) - \eta = 0 \tag{8}$$

$$\frac{\partial Q}{\partial \mathbf{v}_{a,s}} = 2\sum_{k=1}^{\mathcal{N}_c} u_{sk}^m (\mathbf{X}_{a,k} - \mathbf{v}_{a,s}) - \eta = 0 \tag{9}$$

Finally, the expressions of the clustering centers $\mathbf{v}_{a,i}$ and $\mathbf{v}_{b,i}$ is obtained.

$$\mathbf{v}_{a,s} = \left(2\sum_{k=1}^{\mathcal{N}_c} u_{sk}^m \mathbf{X}_{a,k} + \eta\right) \Big/ 2\sum_{k=1}^{\mathcal{N}_c} u_{sk}^m \tag{10}$$

$$\mathbf{v}_{b,s} = \left(2\sum_{k=1}^{\mathcal{N}_c} u_{sk}^m \mathbf{X}_{b,k} + \eta\right) \Big/ 2\sum_{k=1}^{\mathcal{N}_c} u_{sk}^m \tag{11}$$

Based on the above derivation process, an iterative optimization method is used to obtain the clustering centers. After fusing the features, the universal feature of the steelmaking production status described by the clustering centers $\mathbf{v} = \{\mathbf{v}_1, \mathbf{v}_2, \cdots, \mathbf{v}_c\}$ is estimated.

C. Long Term Prediction of Generation Amount

To obtain the long term prediction of generation amount of Converter gas, the data will be reconstructed from the feature vector of the steelmaking production status to time series by the following equations. Here, the long term prediction is described by a set of piecewise continuous functions.

If $x_1 - \mathcal{L} > 0$ and $x_3 + \mathcal{L} < n$, then

$$\begin{cases} \mathbf{y}(x) = 0 & ,0 \le x \le x_1 - \mathcal{L} \\ \mathbf{y}(x) = \mathbf{t}(x - x_1 + \mathcal{L}) & ,x_1 - \mathcal{L} \le x \le x_1 \\ \mathbf{y}(x) = \mathbf{t}\left(x - x_2\right) & ,x_2 \le x \le x_2 + \mathcal{L} \\ \mathbf{y}(x) = \mathbf{t}\left(x - x_3\right) & ,x_3 \le x \le x_3 + \mathcal{L} \\ \mathbf{y}(x) = 0 & ,else\ \ x \end{cases} \tag{12}$$

If $x_1 - \mathcal{L} < 0$ and $x_3 + \mathcal{L} < n$, then

$$\begin{cases} \mathbf{y}(x) = \mathbf{t}(x - x_1 + \mathcal{L}) & ,0 \le x \le x_1 \\ \mathbf{y}(x) = \mathbf{t}\left(x - x_2\right) & ,x_2 \le x \le x_2 + \mathcal{L} \\ \mathbf{y}(x) = \mathbf{t}\left(x - x_3\right) & ,x_3 \le x \le x_3 + \mathcal{L} \\ \mathbf{y}(x) = 0 & ,else\ \ x \end{cases} \tag{13}$$

If $x_1 - \mathcal{L} > 0$ and $x_3 + \mathcal{L} > n$, then

$$\begin{cases} \mathbf{y}(x) = 0 & ,0 \le x \le x_1 - \mathcal{L} \\ \mathbf{y}(x) = \mathbf{t}(x - x_1 + \mathcal{L}) & ,x_1 - \mathcal{L} \le x \le x_1 \\ \mathbf{y}(x) = \mathbf{t}\left(x - x_2\right) & ,x_2 \le x \le x_2 + \mathcal{L} \\ \mathbf{y}(x) = \mathbf{t}\left(x - x_3\right) & ,x_3 \le x \le n \\ \mathbf{y}(x) = 0 & ,else\ \ x \end{cases} \tag{14}$$

If $x_1 - \mathcal{L} < 0$ and $x_3 + \mathcal{L} > n$, then

$$\begin{cases} \mathbf{y}(x) = \mathbf{t}(x - x_1 + \mathcal{L}) & ,0 \le x \le x_1 \\ \mathbf{y}(x) = \mathbf{t}\left(x - x_2\right) & ,x_2 \le x \le x_2 + \mathcal{L} \\ \mathbf{y}(x) = \mathbf{t}\left(x - x_3\right) & ,x_3 \le x \le n \\ \mathbf{y}(x) = 0 & ,else\ \ x \end{cases} \tag{15}$$

where $x_1 = \mathbf{v}_{a,1} - \mathbf{v}_{b,1}/2$, $x_2 = \mathbf{v}_{a,i} + \left(\mathbf{v}_{a,i+1} - \mathbf{v}_{a,i} - \mathcal{L}\right)\left(\mathbf{v}_{b,i}/\left(\mathbf{v}_{b,i} + \mathbf{v}_{b,i+1}\right)\right)$,

$x_3 = \mathbf{v}_{a,c} + \mathbf{v}_{b,c}/2$, $\mathbf{t}$ is the template signal, n is the prediction length and $\mathbf{y}$ is the prediction output. Finally, $\mathbf{v}_{a,c}$ and $\mathbf{v}_{b,c}$ denote the features in the time and frequency domain of the last heat of steel, respectively.

IV. EXPERIMENTS AND ANALYSIS

In this paper, the prediction with the use of the real-time data is performed. The real-world data covers the generation amount of Converter gas in August 2013, and the sampling interval of the generation amount series is 1 minutes. Based on the historical data, the proposed method is to predict the Converter gas generation amount in the following 1440 minutes.

First, the original generation amount series are divided into 8 data segments with the same length that is equal to 1440 minutes. Template matching based method is used for feature extraction of each of the data segment. Taking one data segment as the matching target, a matching matrix that reflects the similarity between the template and the data segment can be obtained, whose local extrema are the points of best matching. The matching matrix is plotted on the three-dimensional coordinate space as shown in Fig. 5.

The local extrema are picked out to construct a new collection, whose index values can be expressed as the feature vector of steelmaking production status. Sequentially, according to the above operation, the feature vectors that are used to represent the steelmaking production status can be extracted from the other seven data segments. The feature vectors of eight data segments can be plotted on the two-dimensional space, as shown in Fig. 6.

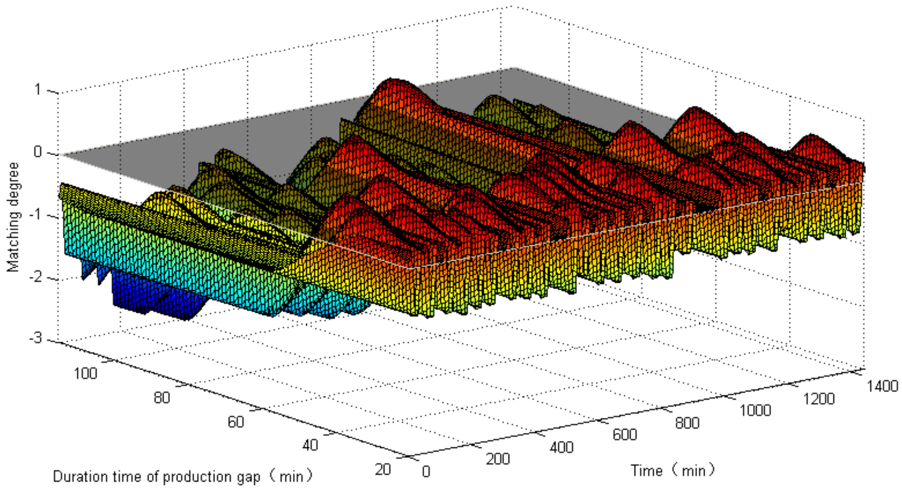

Fig. 5 Chart of the matching matrix

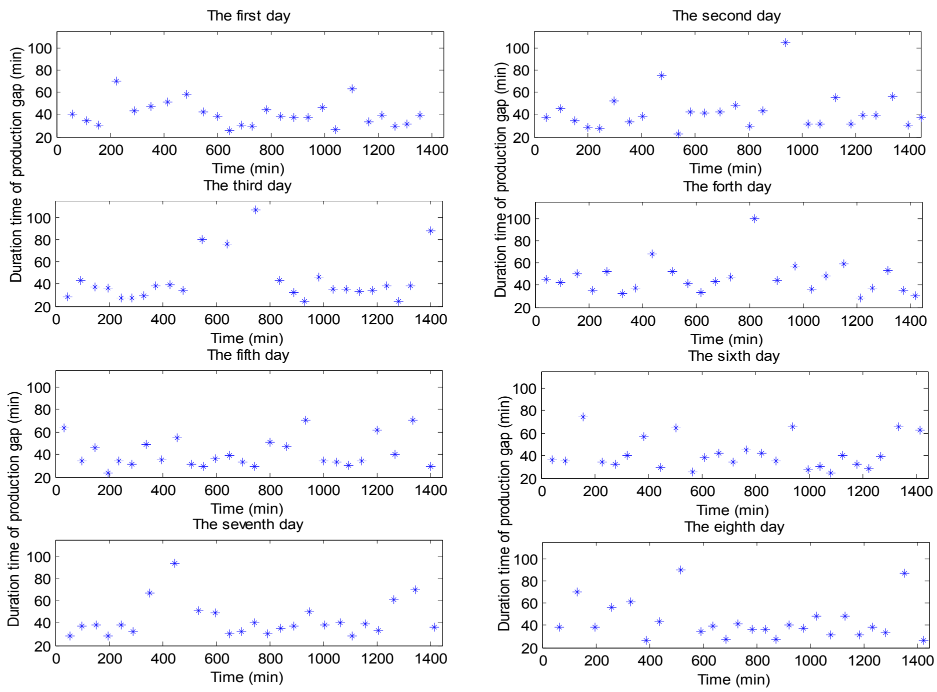

Fig. 6 Chart of the feature vectors of eight data segments

Then, we use the improved fuzzy C-mean clustering method that integrates the feature vectors of eight data segment to obtain a universal feature of the steelmaking production status. Generally, before clustering, some outliers are removed for a better cluster result. Fig. 7 shows the effect of feature fusion based on clustering. In Fig. 7, points marked with an asterisk are all feasible features of eight data segments, and points marked with small red circle represent the clustering center that reflects the universal feature of the steelmaking production status.

According to the feature vector of the steelmaking production status, the long term prediction of generation amount of Converter gas can be completed. Fig. 8 (c) shows the results based on the proposed method, in which the predicted generation amount of Converter gas basically meets the actual production. Fig. 8 (a) and (b) show the results of the ESN and the LSSVM, respectively. From Fig. 8 (a), we can see that the predicted generation amount will be more and more diverged from the real one with the course of time due to the iterative error accumulation. Similarly, the prediction results of LSSVM are also not good as shown in Fig. 8 (b).

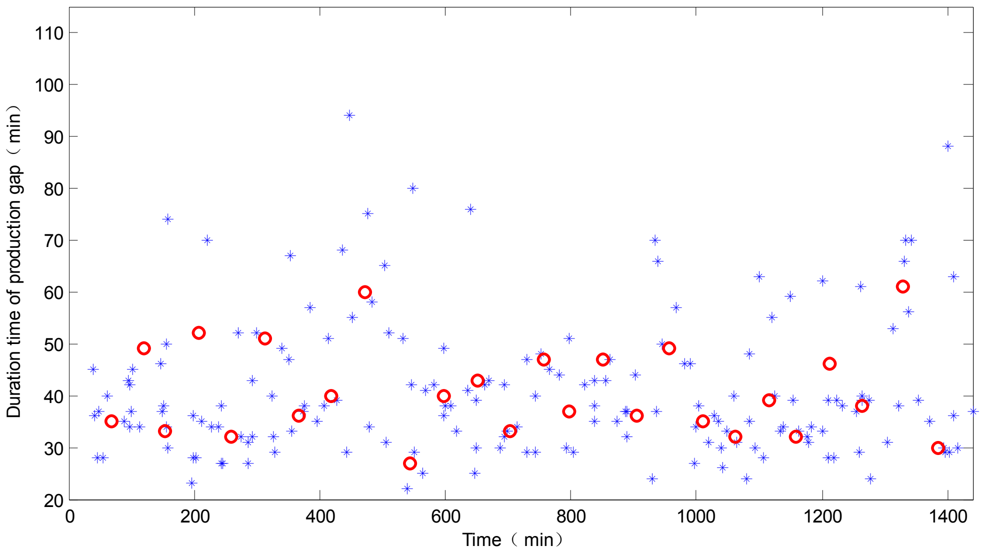

Fig. 7 The results of the improved fuzzy C-mean clustering

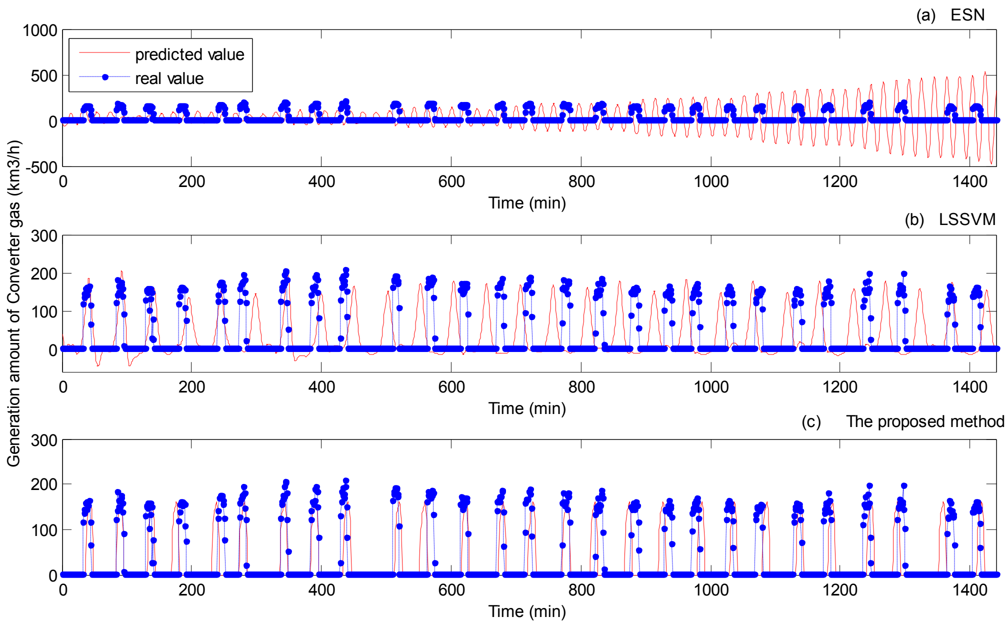

Fig. 8 Long term prediction comparison of Generation amount of Converter gas

To further analyze the performance of the proposed method for the long term generation amount prediction, statistical experiments are conducted, and the results are shown in Table 1, where the root of mean square error (RMSE) and the overlapping area (OA) are listed. RMSE is frequently used to measure the difference between the predicted values and the targets. OA defined here is to measure the matching degrees between the predicted steelmaking production statuses and the actual ones.

$$RMSE = \sqrt{\sum_{i=1}^{n} (y_i - f_i)^2 / n} \quad (16)$$

$$OA = \sum_{i=1}^{l} \min\left(y_i, f_i\right) \times 1, \quad y_i > 1 \ \ and \ \ f_i > 1. \quad (17)$$

Where n is the number of predicted data points, l is the length of the overlapping area, y_i is the observed value and f_i is the predicted value. From Table I, we can see that the proposed method exhibits better performance for long term generation amount prediction of Converter gas than the ESN and LSSVEM methods.

TABLE I

COMPARATIVE PREDICTION RESULTS OF DIFFERENT METHODS

Methods	RMSE (km3/h)	OA (km3)
ESN	171.34	287.2
LSSVM	88.17	166.1
The proposed method	67.69	318.1

V. CONCLUSIONS

Long term prediction of generation amount of Converter gas plays a significant role in scheduling and balancing the byproduct gas system. In this study, steelmaking production status estimation based long term prediction is proposed for generation amount of Converter Gas. Steelmaking production status estimation has two main parts, e.g. feature extraction and feature fusion. Steelmaking production status expressed by a feature vector can be used to reconstruct the long term generation amount of Converter gas. When using the proposed method, accumulation of the prediction error can be avoided because there is no iteration in the process of prediction. Moreover, the data completeness is not required for the proposed method since the step of feature extraction and fusion is built based on discrete data. To verify the effectiveness of the proposed method, a set of experiments is conducted based on the real-world data from an iron and steel enterprise. In addition, experiments based on the ESN and LSSVEM methods are also performed for comparison. The experimental results demonstrate that the proposed method exhibits highest accuracy among the three and can provide an effective guidance for balancing and scheduling the byproduct Converter gas.

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