ELM Based Dynamic Modeling for Online Prediction of Molten Iron Silicon Content in Blast Furnace

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Abstract. Silicon content ([Si]) of the molten metal is an important index reflecting the product quality and thermal status of the whole blast furnace (BF) ironmaking process. Since the direct online measure on this index is difficult and larger time lag exists in the offline assay procedure, quality modeling is required to achieve online estimation of [Si], which is an open problem for realizing BF automation. Focusing on this practical problem, this paper proposes a data-driven dynamic modeling method for [Si] prediction using extreme learning machine (ELM) with the help of principle component analysis (PCA). First, data-driven PCA is introduced to pick out the most pivotal variables from multitudinous factors that influence [Si] to serve as the secondary variables of modeling. Second, since this BF metallurgical process is nonlinearity dynamic system with severe time-varying characteristic, dynamic ELM modeling technology with good generalization performance and strong nonlinear mapping capability is proposed by applying the self-feedback structure on traditional ELM. The self-feedback connection enables ELM to overcome the static mapping limitation of its feedforward network structure so as can cope with dynamic time-series prediction problems very well. At last, industrial experiments and compared studies demonstrate that the constructed model has a better modeling and estimating accuracy as well as a faster learning speed when compared with different modeling method and different model structure.

Keywords: extreme learning machine (ELM), silicon content, dynamic modeling, principle component analysis (PCA), blast furnace.

1 Introduction

Blast furnace (BF) is a giant countercurrent reactor and heat exchanger in metallurgical industry, and is the first step towards the production of steel [1~3]. As one of the most complex industrial reactors, the BF has received broad interests both theoretically and experimentally due to its complexity and the key role of iron and steel industry on the national economy. However, it is true that the operation and control of an industrial BF is a serious problem, and still relies on the manual operation of foremen

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experientially [1, 2]. So far, there remains some open problems both in metallurgical fields and engineering control fields, such as the closed-loop control or operational optimization for the whole BF ironmaking process [4~6].

Undoubtedly, the most crucial obstacle for closed-loop control of BF is that the current regular instruments do not have the ability to feed the need of online measure for molten iron quality, such as the silicon content ([Si]) in the final hot metal. In the past decades, through continuous efforts and attempts, a great deal of models and algorithms have been developed trying to tackle the modeling problem for [Si] prediction. These existing methods including linear model based methods like ARX and ARMAX models [6~8], partial least squares based methods [9], and nonlinear intelligent based methods like artificial neural network (ANN) model [10~12], and support vector machine (SVM) model [1, 2, 13, 14]. Though these existing methods have made some achievements in practical application, most of these studies are only focused on the static modeling for [Si] prediction while little attention has been paid to dynamical modeling of this quality parameter.

The BF ironmaking process is a complicated dynamic system with many influential factors and large time-lag. To capture the system dynamics, the time series and time delays of the relevant input and output variables should be took into account during the process modeling. This also means that the existing static prediction models cannot capture the process nonlinear dynamics very well, thus do not provide much accuracy estimation. Therefore, the self-feedback structure which can construct a dynamic system may appear more important for the BF system with serious nonlinear dynamics and large time lag. Moreover, most of the existing prediction models are trained by gradient-based algorithms such as back propagation (BP) algorithm and its variants. It is clear that the learning speed of such intelligent models is insufficiently fast as larger number of training data may be required. Moreover, the BP-like algorithm usually suffers from high computational burden, poor generalization ability, and local optima and overweighting problems [15].

On the other hand, a new machine learning approach that is termed as the extreme learning machine (ELM) has been recently proposed by Huang et al. in [15~18], and verified on a number of benchmark and real-world problems including pattern classification and prediction modeling [16~25]. The ELM and its variants have been considered as a promising learning algorithm in contrast with other algorithms such as BP NN and SVM. This is because ELM has the following advantages: 1) much faster learning speed; 2) higher generalization performance in comparison with BP NN and SVM; and 3) no extra parameters need to be tuned except the predefined network architecture [15~18, 22~25]. In this paper, a data-driven dynamic modeling method to predict molten iron silicon content using ELM with the help of principle component analysis (PCA) [26,27] is proposed. In the design of this predictive model, data-driven PCA for reducing the input variables space of ELM has been constructed. Moreover, output self-feedback architecture has been introduced to establish a dynamic ELM model for practical BF dynamic system. This self-feedback structure enable ELM to overcome the static mapping limitation of its feedforward network structure so as can cope with dynamic time-series prediction problems very well. Lastly, performance of the proposed dynamic ELM based prediction model is compared with other well-known modeling algorithms by industrial experiments on $2^{\#}$ BF in Liuzhou Iron & Steel Group Co. of China.

2 Description of BF Ironmaking System and Its Quality Index

The BF ironmaking is a continuous production process conducted in a closed vertical furnace where materials reduction from iron ore to molten iron takes place every time using carbon coke and gas in high temperature and high pressure environment. When a BF ironmaking system runs, the solid raw materials consisting of coke and fresh ore are charged layer by layer with definite quantities from the top, while the preheated compressed air, together with pulverized coal, is introduced at the bottom through tuyeres, entering just above the hearth, which is a crucial region of BF where the final molten metal product gathers. The hot air at approximately 1200℃ passes upward through the charge and reacts with the descending coke and the supplementary injected oil to generate carbon dioxide, which then changes to CO and H_2 at high temperature. A lot of heat energy is released during this period that can heat up the hearth as high as 2000℃. The generated CO and H_2 further reduces the descending iron ore to form hot metal accumulating in the hearth, and some unreduced impurities (mainly SiO_2) form the slag (mainly $CaSiO_3$) floating on the hot metal being lighter. The liquid hot metal and slag are periodically tapped out by opening a clay-lined tapholes for the subsequent processing. Generally, it will take 6~8 hours for each period of BF ironmaking [28].

For a practical BF production process, silicon content ([Si]) is an important index indicating the chemical heat of molten iron. High [Si] means a large quantity of slag, and this would be easier to wipe off the phosphorus and sulphur in the hot metal. However, excessive [Si] will make cast iron become stiff and brittle, even lead lower yield of metal and easier splashing. In addition, high [Si] will result in a corresponding increase of SiO_2 in the slag, thereby influencing slagging speed of calclime, extending converting time and intensifying corrosion to furnace lining. From an energy point of view, it would be desired to operate the BF process at low molten metal silicon content, still avoiding the risk of cooling the hearth which may result in chilled hearth. Generally, the content of silicon should be controlled in 0.5%~0.7%.

Nowadays, it is still an insoluble dilemma to realize the closed-loop control of molten iron quality in ironmaking BF. The main bottleneck is that the directly online-measurement on [Si] parameter is difficult to be realized with the existing conventional measuring means. Moreover, the offline assaying process for this index takes a long lag time, usually more than 1 hour. Therefore, online prediction based [Si] modeling must be established. Effective online prediciton or estimation for [Si] not only can offer useful information for operators to judge the inner smelting state and operational condition, but also plays a key role in realizing closed-loop control and operational optimization as well as energy-saving and cost-reducing.

3 Modeling Strategy

The proposed data-driven modeling strategy for [Si] prediction is shown in Fig.1. First, data-driven PCA technology with a strong ability to handle strong high-dimensional nonlinear correlated data is introduced to pick a few key factors as the input variables of model so as to reduce the dimension and difficulty for prediction modeling. Then, ELM with better nonlinear mapping and fast process capability modeling technology is brought in this paper. In the meantime, output self-feedback structure is put into use on the basis of traditional ELM in this method, and the output variables derived from previous time are feed back to the network input layer. This feedback outputs together with input variables at different time constitutes a dynamic ELM structure which has a storage capacity and has the ability to tackle data in different time, thus overcoming the limitation of static modeling of traditional ELM.

Remark 1: The proposed modeling strategy has two advantages: 1) The dynamic property of time series and time delays is considered by feeding the output and inputs in previous time through a self-feedback structure. This self-feedback connection enables ELM to overcome the static mapping limitation of its feedforward network structure. Thus the improved version of ELM can capture the process nonlinear dynamics very well by remembering prior input and output states and using both the prior and current states to calculate new output value; 2) Different from the BP-like modeling algorithm usually suffering from high computational burden, poor generalization ability, and local optima and overweighting problems, the ELM based modeling profits from much faster learning speed, higher generalization performance, and easy of implantation and use (no extra parameters need to be tuned except the predefined network architecture). □

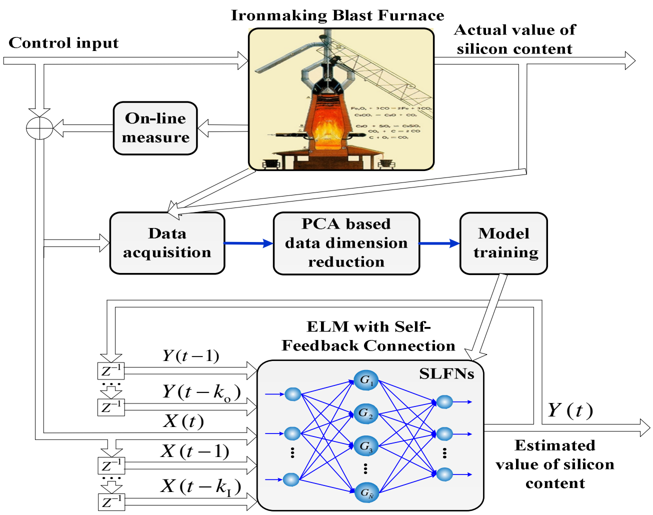

Fig. 1. Strategy diagram of nonlinear intelligent modeling for silicon content prediction

4 Modeling Algorithm

4.1 Selection of Secondary Variables by PCA-Based Dimension Reduction

PCA is a kind of method trying to grasp the main contradiction part in statistical analysis process and analyze the main influencing factors from multiple objects in order to simplify the complex problems. Actually, the principle components conducted by PCA are the combination of column vectors picked by varimax from input matrix. Since correlations and noises are always existed in practical industrial data, principle components with a small variance are usually some noisy information. Abandoning this data will not cause a crucial information loss and can even achieve de-noising in some extent.

Consider the following data set

$$u_i = \mathbf{X} v_i \tag{1}$$

where $\mathbf{X}_{n\times m}$ is the measured n data array on m variables, u_i is the score vector, v_i is the characteristic unit vector of covariance matrix $\mathbf{X}^{\mathrm{T}}\mathbf{X}$, named load vector. The variance of u_i is λ_i which is also the eigenvalue of $\mathbf{X}^{\mathrm{T}}\mathbf{X}$, and satisfies $\mathrm{Var}(t_i) = \lambda_i$, $\lambda_1 \ge \cdots \ge \lambda_m \ge 0$. PCA is also a procedure used to explain the variance in a single data matrix. The principal component decomposition of $\mathbf{X}$ can be represented as follows:

$$\mathbf{X} = \mathbf{U}\mathbf{V}^{\mathrm{T}} = \sum_{i=1}^{m} u_i v_i^{\mathrm{T}} + \mathbf{E} \tag{2}$$

In Eq.(2) $u_i v_i^{\mathrm{T}}$ is the ith principal component, and $\mathbf{E}$ is a matrix of residuals. It is to be noted that the score vectors are orthogonal and so are the loading vectors which are of unit length. Eq.(2) indicates that a rank n matrix $\mathbf{X}$ can be decomposed as the sum of n rank 1 principal components. The number of principle component kept in Eq.(2) is determined by the total variance. The variance contribution and the total variance of principal component can be represented as follows:

$$\eta_k = \lambda_k / (\sum_{j=1}^{m} \lambda_j) \tag{3}$$

$$C\eta_k = \sum_{i=1}^{k} \eta_i = \sum_{i=1}^{k} \lambda_i / \sum_{j=1}^{p} \lambda_j \tag{4}$$

where η_k is the kth principle component variance contribution; $C\eta_k$ is the total variance of the first k terms. Usually, the total variance varies should be larger than 85%. Only in this case, the data dimension can be reduced on the premise of not losing useful information.

Remark 2: A problem of the PCA-based dimension reduction is that the conducted principle components are comprehensive representation of the original higher-dimension physical variables. However, by computing the *component matrix* which contains the correlations between the principle component and the original physical variable, one can obtained the lower-dimension physical variables which related to the principle components mostly, according to some specific requirements. □

4.2 ELM with Self-feedback Connection

Extreme learning machine (ELM) is an algorithm for single hidden layer feedforward networks (SLFNs) with additive or radial basis function (RBF) hidden nodes whose learning speed can be thousands of times faster than conventional feedforward network learning algorithm like BP algorithm while reaching better approximation performance. The procedure of the ELM algorithm used here can be summarized as follows: For N arbitrary distinct samples $(\mathbf{X}_i, \mathbf{Y}_i)$, where $\mathbf{X}_i = [x_{i1}, x_{i2}, \cdots, x_{in}]^{\mathrm{T}} \in \mathbf{R}^n$ and $\mathbf{Y}_i = [y_{i1}, y_{i2}, \cdots, y_{im}]^{\mathrm{T}} \in \mathbf{R}^m$, the output of a SLFN with $\tilde{N}$ hidden nodes can be represented by

$$f_{\tilde{N}}(\mathbf{X}) = \sum_{i=1}^{\tilde{N}} \beta_i G(\mathbf{a}_i, b_i, \mathbf{X}), \quad \mathbf{X} \in \mathbf{R}^n, \mathbf{a}_i \in \mathbf{R}^n \tag{5}$$

where $\mathbf{a}_i$ and b_i are the learning parameters of hidden nodes, β_i is the output weigh, and $G(\mathbf{a}_i, b_i, \mathbf{X})$ is the output of the ith hidden node with respect to the input data $\mathbf{X}$.

In supervised batch learning, the learning algorithms use a finite number of input-output samples for training. For N arbitrary distinct samples $(\mathbf{X}_i, \mathbf{Y}_i)$, if an SLEN with $\tilde{N}$ additive hidden nodes can approximate these N samples with zero error, it then implies that there exist $\mathbf{a}_i$, b_i and β_i such that

$$f_{\tilde{N}}(\mathbf{X}_j) = \sum_{i=1}^{\tilde{N}} \beta_i G(\mathbf{a}_i, b_i, \mathbf{X}) = \mathbf{Y}_j, \quad J = 1, \cdots, N \tag{6}$$

Eq.(6) can be written compactly as:

$$\mathbf{H}\beta = \mathbf{Y} \tag{7}$$

where

$$\mathbf{H}(\mathbf{a}_1, \cdots, \mathbf{a}_{\tilde{N}}, b_1, \cdots, b_{\tilde{N}}, \mathbf{x}_1, \cdots, \mathbf{x}_N) = \begin{bmatrix} g(\mathbf{a}_1 \odot \mathbf{x}_1 + b_1) & \cdots & g(\mathbf{a}_{\tilde{N}} \odot \mathbf{x}_1 + b_{\tilde{N}}) \\ \vdots & \ddots & \vdots \\ g(\mathbf{a}_1 \odot \mathbf{x}_N + b_1) & \cdots & g(\mathbf{a}_{\tilde{N}} \odot \mathbf{x}_N + b_{\tilde{N}}) \end{bmatrix}_{N \times \tilde{N}} \tag{8}$$

$\beta = \left[\beta_1^{\mathrm{T}} \cdots \beta_{\tilde{N}}^{\mathrm{T}}\right]_{\tilde{N} \times m}^{\mathrm{T}}$, $\mathbf{Y} = \left[y_1^{\mathrm{T}} \cdots y_N^{\mathrm{T}}\right]_{N \times m}^{\mathrm{T}}$, and $\mathbf{a}_i \odot \mathbf{X}$ denotes the inner product o f vector $\mathbf{a}_i$ and $\mathbf{X}$ in $\mathbf{R}^n$.

The purpose of ELM is training the net to find a least-squares solution $\hat{\beta}$ of the linear system $\mathbf{H}\beta = \mathbf{Y}$

$$\left\|\mathbf{H}(\mathrm{a}_1,\cdots,\mathrm{a}_{\tilde{N}},\mathrm{b}_1,\cdots,\mathrm{b}_{\tilde{N}})\hat{\beta}-\mathbf{Y}\right\| = \min_{\beta}\left\|\mathbf{H}(\mathrm{a}_1,\cdots,\mathrm{a}_{\tilde{N}},\mathrm{b}_1,\cdots,\mathrm{b}_{\tilde{N}})\beta-\mathbf{Y}\right\| \quad (9)$$

And the solution of the above linear system can be solved by the inverse of matrix β by the Moore-Penrose method, which is

$$\hat{\beta} = \mathbf{H}^{\dagger}\mathbf{Y} \quad (10)$$

where $\mathbf{H}^{\dagger}$ is the Moore-Penrose generalized inverse of $\mathbf{H}$ [15~17].

Remark 3: For the simplicity of the paper, the prediction modeling process based on ELM with additive hidden node is summarized as follows: Giving a training set $\mathbf{Z} = \{(\mathbf{X}_i, \mathbf{Y}_i) \mid \mathbf{X}_i \in \mathbf{R}^n, \mathbf{Y}_i \in \mathbf{R}^m, i = 1, \cdots\}$ for prediction modeling, and hidden neuron number $\tilde{N}$, the input weight $\mathbf{a}_i$ and bias b_i can be assigned arbitrarily to calculate the output matrix $\mathbf{H}$ of hidden layer by using Eq.(8). After that, the output weight β can be calculated by Eq.(10), which is essential for estimating output only based on estimating inputs. □

Remark 4: The hidden node number $\tilde{N}$ is the only parameter need to be predefined in the presented modeling method. In order to achieve optimal approximation ability of training and realize fast convergence aiming complex industrial data, a proper (maybe optimal) $\tilde{N}$ can be determined as the one which results in the lowest validation error through several trainings and validations. □

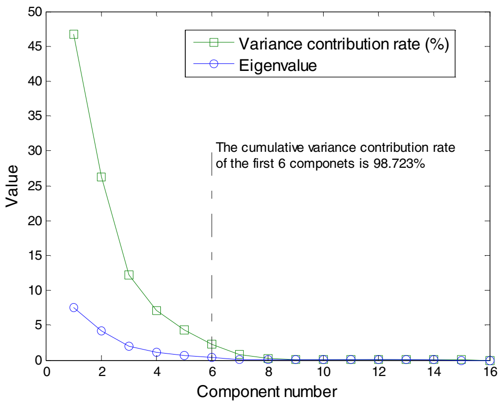

Fig. 2. Eigenvalue and variance contribution rate of each component

5 Industrial Experiments

In this section, a medium-sized blast furnace with the working volume of 2000 m^3 in Liuzhou Iron & Steel Group Co. is chosen to perform the validation of silicon content prediction model. On the foundation of process mechanism and existing monitoring instruments status, 16 measurable parameters influencing [Si] are determined as blast temperature (℃), blast pressure (kPa), blast humidity (g/m^3), and so on. Considering that the impact of strong correlation between the selected 16 input variables, PCA is used to determine the key input variables that influence the molten iron silicon content mostly. According to Eq.(3) and Eq.(4), the eigenvalue and the variance contribution rate of each component can be calculated as shown in Fig.2. It can be summarized that the cumulative variance contribution rate of the first 6 terms is 98.723%>98%. This means these 6 principal components are sufficient to describe the major variances in the data. Then, by computing the component matrix of principle components, 6 process variables can be determined as the secondary input of the [Si] prediction model. These secondary variables include hot blast pressure x_1 (kPa), hot blast temperature (℃), oxygen enrichment percentage (%), volume of coal injection (Kg/t), blast humidity (g/m^3), and gas volume of bosh (m^3/min).

The optimal number of hidden units is selected as the one which results in the lowest validation error. Through experiments analysis, the optimal number of hidden nodes with sigmoidal function is set as $\tilde{N} = 25$. The corresponding modeling result of the developed ELM model with self-feedback structure is shown in Fig.3, where the good modeling accuracy with practical data has been demonstrated.

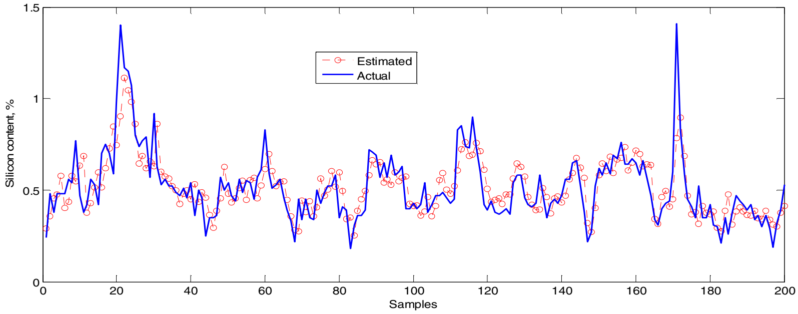

Fig. 3. Modeling results with proposed method

The developed ELM prediction model has been test on 2# blast furnace in Liuzhou Steel of China for quite a long time. Fig.4 shows the estimated results using the proposed modeling method for predicting [Si], where the figure compares the predicted trend with the actual one. Moreover, in order to show the superiority of the proposed method more intuitively, comparisons with various popular prediction models have been made. Here, BP NN without self-feedback (SFB) connection, BP NN with SFB connection, and traditional ELM without SFB connection have been chosen to conduct the prediction comparison on the same observations. From Fig.4, it can be seen that the proposed model has the best estimation performance among all the developed prediction models. For example, it results in the best estimation trend and accuracy, and the shape of the estimated curve values match the measured ones very well and better than that with other three methods.

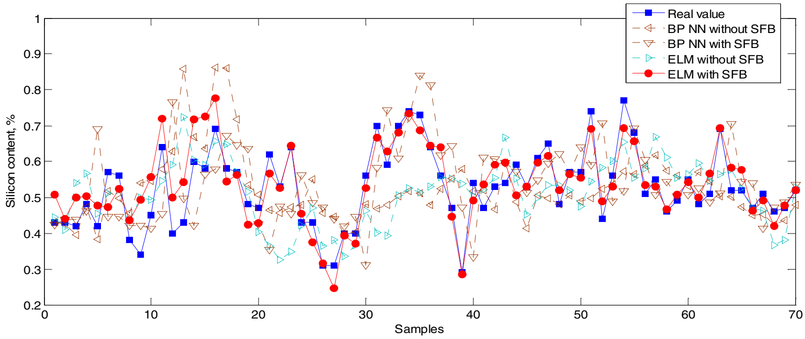

Fig. 4. Estimation results of molten iron silicon content with different models

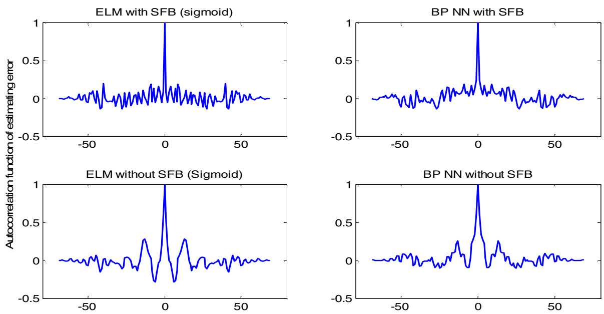

Fig. 5. Autocorrelation function of estimating error of different models

It is well known that a good model should have its estimated error autocorrelation close to a white noise. So in this text, we draw the autocorrelation function of estimating error of different models as shown in Fig.5. It can be seen that the autocorrelation results of algorithm like BP NN without SFB connection, and ELM without SFB connection is much worse than that with a SFB structure, respectively. Although one can obtain that the measuring error autocorrelation of the proposed ELM with SFB connection and BP NN with SFB connection are all satisfactory and close to the shape of the white noise here, the above estimation result confirmed the effectiveness and superiority of the proposed method in predicting accuracy.

6 Conclusions

This paper proposed a data-driven modeling for prediction of molten iron silicon content using PCA and ELM with self-feedback structure. Performance of the proposed ELM based prediction model is compared with BP algorithm and different model structure on practical industrial data from $2^{\#}$ BF in Liuzhou Steel Company of China. The accuracy can basically meet the requirements of actual operation.

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