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Intelligent Multivariable Modeling of Blast Furnace Molten Iron Quality Based on Dynamic AGA-ANN and PCA

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Abstract: Blast furnace (BF) ironmaking process has complex and nonlinear dynamic characteristics. The molten iron temperature (MIT) as well as Si, P and S contents of molten iron is difficult to be directly measured online, and large-time delay exists in offline analysis through laboratory sampling. A nonlinear multivariate intelligent modeling method was proposed for molten iron quality (MIQ) based on principal component analysis (PCA) and dynamic genetic neural network. The modeling method used the practical data processed by PCA dimension reduction as inputs of the dynamic artificial neural network (ANN). A dynamic feedback link was introduced to produce a dynamic neural network on the basis of traditional back propagation ANN. The proposed model improved the dynamic adaptability of networks and solved the strong fluctuation and resistance problem in a nonlinear dynamic system. Moreover, a new hybrid training method was presented where adaptive genetic algorithms (AGA) and ANN were integrated, which could improve network convergence speed and avoid network into local minima. The proposed method made it easier for operators to understand the inside status of blast furnace and offered real-time and reliable feedback information for realizing close-loop control for MIQ. Industrial experiments were made through the proposed model based on data collected from a practical steel company. The accuracy could meet the requirements of actual operation.

Key words: molten iron quality; blast furnace; nonlinear multivariate modeling; dynamic neural network; principal component analysis; adaptive genetic algorithm

Steel is one of the most important industrial raw materials in social development, and blast furnace (BF) ironmaking is the primary unit of the whole steel manufacture process. At present, the molten iron quality (MIQ) determines the level of the products and also reflects the energy consumption state of the blast furnace to some extent[1-4]. Thus, it is essential to accurately learn the parameters of hot metal quality so as to realize optimal control and energy saving of blast furnace. However, the technological parameters that can reflect the MIQ such as temperature of hot metal, contents of Si, P and S, etc. are difficult to be directly detected online using conventional instruments, and the offline analysis process seriously lags behind, which greatly influence and limit the needs of real-time and optimal control in ironmaking process.

Recently, many predictive models for MIQ have been developed to optimize the BF operation and control, including mathematical models for silicon content prediction based on theoretical analysis of BF thermal condition, like Wu[5] and EC[6] structure designed in France and Benelux respectively. Moreover, numerous artificial intelligence models based on expert-like learning method have also been proposed[7-9]. However, these MIQ predictive models are only some idealized descriptions for only one parameter fluctuation among many change factors,

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such as the molten iron temperature (MIT), or Si content prediction[10-12]. BF ironmaking process is a complicated dynamic system with many influential factors, so the target prediction of one component is far from enough in practice.

In artificial intelligence field, artificial neural network (ANN) as an emerging discipline developed in 1980s is an intelligent tool, which simulates the human nervous system to do perception, analysis and problem solving. Currently, there are a lot of research reports on MIQ prediction or estimation models with ANN technique, such as Refs. [13-17]. However, these existing MIQ neural network predictive models are just some static models, and can only predict for one particular parameter[15,18].

Focusing on this practical challenge, a data-driven nonlinear multivariate modeling method was proposed for MIQ in blast furnace smelting process based on dynamic genetic neural network and principal component analysis (PCA) in this study. Firstly, by analyzing the practical process mechanism and installed instrument status, several key process variables or state variables that are directly related to the MIQ (namely MIT, Si content, P content and S content) were determined. Then, the most important variables from state variables were determined as the secondary variables (inputs) for multivariate prediction modeling using the PCA. After that, based on the actual industrial data, a data-based nonlinear multivariate dynamic intelligent model was established for MIT prediction by combining adaptive genetic algorithm (AGA) with ANN. Finally, industrial experiments were made with the proposed predictive model. The results demonstrate that the proposed multivariate AGA-ANN dynamic model for MIQ in BF smelting process can simultaneously make a better prediction for MIT, Si content, P content and S content, according to the change of process parameters.

1 Process Description

The BF ironmaking is a complex nonlinear dynamic process, and the BF body is the most complicated metallurgical reaction vessel with the largest volume and highest energy consumption. The whole BF smelting process is conducted in a closed vertical furnace. Many physical and chemical reactions between furnace charges and gas are intertwined and mixed in the countercurrent movement of the smelting process. Because the closed nature of BF and reaction status cannot be observed by operators directly, strict environments for direct measurement make the operation of ironmaking still depend on indirect measurement by virtue of instruments. Hence, molten iron quality indices are required to indirectly reflect the inside situation of furnace and ensure safe operation of the BF. Being able to make accurate estimation of MIQ makes it easier for operators to discover problems and adjusts operation magnitude earlier so as to reduce pollutant emissions and achieve the optimal control to improve the operational performance of this complex process.

MIQ is one of the most important production indexes in the BF ironmaking process. It determines the subsequent steel products quality and energy consumption of the whole melting process. In practical production situation, molten iron temperature (physical heat), silicon mass fraction in molten iron ($w_{[Si]}$, chemical heat), sulfur mass fraction ($w_{[S]}$) and phosphorus mass fraction ($w_{[P]}$) have been chosen to measure the quality of molten iron comprehensively. Many factors affect the MIQ in the whole BF melting process, including not only intrinsic properties of both iron ore and fuel, but also the process operating parameters. And the operating parameters can also be divided into two parts: the operating parameters in loading and charging part, and the parameters in bosh and hearth position. Due to the existing long lag time (always 5—6 h) from the fresh ore into the loading and charging part to the hearth of the BF, the operation parameters in loading and charging part can be ignored in the procedure of modeling and control for MIQ, and just acted as adjustable boundary conditions. Therefore, the secondary variables for MIQ predictive modeling must be appropriately selected from these variables, and the dominant variables of the model are the quality parameters needed to be online estimated such as the molten iron temperature, Si content, P content and S content.

2 Data-driven Nonlinear Multivariate Dynamic Modeling for MIQ in BF

Considering the nonlinear dynamic characteristics like the large time delay, time-varying, and multi-phase and multi-field coupling in complex BF ironmaking process, a multivariate nonlinear modeling method is proposed based on PCA and dynamic AGA-ANN method, as shown in Fig. 1. Firstly, a dynamic feedback link is introduced on the basis of traditional neural network, which stores the previous

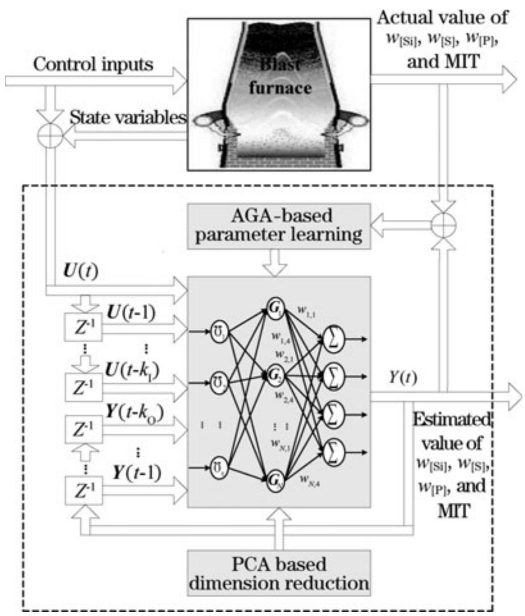

Fig. 1 Structure of hybrid intelligent dynamic modeling

input variables and output variables data with the current input variables together as the current inputs of dynamic neural network, enabling the network to have historical data storage and processing capabilities and improving the adaptability of dynamic BF system. In addition, AGA and ANN are combined for neural network training, which can improve network convergence speed and avoid network into local minima. Too high dimension of input variables may increase computational complexity of predictive model and further affect the prediction efficiency and accuracy; therefore, the data-driven PCA has been used for dimension reduction of the model input variables in offline mode. This factor analysis based dimension reduction method does not require any transcendental knowledge, and has low computation complexity.

Since the previous models are some idealized descriptions for the fluctuation of only one parameter, the target prediction of one component cannot give a comprehensive reflection of blast furnace and offer sufficient guidance for operators. Under this circumstance, a multivariate parameters model is established, which can not only offer more comprehensive information for operators but also enhance the prediction accuracy of the model with the help of introduced feedback structure. The inside correlation of model is enhanced and corresponding accuracy is improved when more variables are led as the inputs of the new model when the model is expanded for multivariate prediction.

2.1 PCA-based dimension reduction and secondary variable selection

PCA is one of the widely used multivariate statistical techniques which consider all the noisy and highly correlated measurements in a process, but project the information down to low dimensional subspaces where all the relevant information about the process are concerned[19,20]. As for principle component,

$$\boldsymbol{u}_i=\boldsymbol{X}\boldsymbol{v}_i \tag{1}$$

where, $\boldsymbol{u}_i$ is the ith score vector; $\boldsymbol{X}_{n\times m}=[x_1, x_2, \cdots, x_m]$ is the n samples' measured data array on m variables; and $\boldsymbol{v}_i$ is the characteristic unit vector of covariance matrix $\boldsymbol{X}^{\mathrm{T}}\boldsymbol{X}$. The variance of $\boldsymbol{X}^{\mathrm{T}}\boldsymbol{X}$ is eigenvalue λ_i, and satisfies $\mathrm{Var}(t_i)=\lambda_i$, $\lambda_1\geqslant\cdots\geqslant\lambda_m\geqslant0$.

PCA is a procedure used to explain the variance in a single data matrix $\boldsymbol{X}$. The principal component decomposition of $\boldsymbol{X}$ can be represented as follows:

$$\boldsymbol{X}=\boldsymbol{U}\boldsymbol{V}^{\mathrm{T}}=\sum_{i=1}^{m}\boldsymbol{u}_i\boldsymbol{v}_i^{\mathrm{T}}+\boldsymbol{E} \tag{2}$$

where, $\boldsymbol{U}$ is the score vector; $\boldsymbol{V}$ is the loading vector; $\boldsymbol{u}_i\boldsymbol{v}_i^{\mathrm{T}}$ is the ith principal component; and $\boldsymbol{E}$ is a matrix of residuals.

A rank n matrix $\boldsymbol{X}$ can be decomposed as the sum of one principal component with n rank. However, if correlations and noise exist in the data, then a few principal components are usually sufficient to describe the major variances in the data. The remaining principal components usually describe the variances of noise and by discarding them, noise filtering effects are achieved. The variance contribution and the total variance of principal component can then 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 principal component variance contribution; $C\eta_k$ is the total variance of the first k terms; and k is the number of remaining principal component. And if the noise has been filtered, the measurement data can be mean centered and represented as:

$$\boldsymbol{X}=\boldsymbol{U}_k\boldsymbol{V}_k^{\mathrm{T}}=\sum_{i=1}^{k}\boldsymbol{u}_i\boldsymbol{v}_i^{\mathrm{T}} \tag{5}$$

where, $\boldsymbol{U}_k$ is the score vector of the first k terms; and $\boldsymbol{V}_k$ is the loading vector of the first k terms.

The number of principal component kept is determined by the total variance, which often varies from 85% to 90%. In this way, dimension of the data space could be shrunk without losing any useful message.

2.2 Multivariate prediction modeling for MIQ using dynamic AGA-ANN

2.2.1 *Network structure*

In this study, three-layer dynamic error back propagation neural network architecture is used to achieve the following nonlinear dynamic mapping:

$$\boldsymbol{Y}(t)=\boldsymbol{\psi}_{NN}\{\boldsymbol{U}(t),\cdots,\boldsymbol{U}(t-k_{\mathrm{I}}),\boldsymbol{Y}(t-1),\cdots,\boldsymbol{Y}(t-k_{\mathrm{O}})\} \tag{6}$$

where, $\boldsymbol{x}=\{\boldsymbol{U}(t),\cdots,\boldsymbol{U}(t-k_{\mathrm{I}}),\boldsymbol{Y}(t-1),\cdots,\boldsymbol{Y}(t-k_{\mathrm{O}})\}\in\boldsymbol{R}^d$ is the input vector of dynamic neural network; $\boldsymbol{U}(t)=[\boldsymbol{u}_1(t),\cdots,\boldsymbol{u}_n(t)]$ is the values of secondary variables simplified by PCA at time t; $\boldsymbol{U}(t-k_{\mathrm{I}})=[\boldsymbol{u}_1(t-k_{\mathrm{I}}),\cdots,\boldsymbol{u}_n(t-k_{\mathrm{I}})]$ is the values of secondary variables at previous time $t-k_{\mathrm{I}}$; $\{\boldsymbol{Y}(t)=[y_1(t),\cdots,y_m(t)]$ is the output values of dynamic neural network at time t; $\boldsymbol{Y}(t-k_O)=[y_1(t-k_{\mathrm{O}}),\cdots,y_m(t-k_{\mathrm{O}})]$ is the values of $\boldsymbol{Y}$ at previous time $t-k_{\mathrm{O}}$. Here, $m=4$, and y_1, y_2, y_3, y_4 are the primary variables that need to be predicted and denoted, namely $w_{[\mathrm{Si}]}$, $w_{[\mathrm{P}]}$, $w_{[\mathrm{S}]}$ and MIT, respectively. In addition, the values of k_{I} and $k_{\mathrm{O}}(k_{\mathrm{I}},k_{\mathrm{O}}\in Z^+)$ are selected according to dynamic characteristics of specific process.

The output of jth hidden layer nodes in the proposed dynamic neural network is:

$$z_j=F(\sum_{i=1}^{d}w_{ji}x_i+w_{j0}) \tag{7}$$

where, F is the activation function of hidden layer nodes, which usually uses the popular sigmoid function $F(a)=1/(1+\exp(-a))$, $a\in\boldsymbol{R}$; w_{ji} is the weight connecting the jth hidden node and the ith input nodes; w_{j0} is the bias of the jth hidden node; and d is the number of hidden layer nodes.

The output of network according to x of kth node in output layer is:

$$y_k(x)=\sum_{j=1}^{n}\omega_{kj}z_j+\omega_{k0}=\sum_{j=1}^{n}\omega_{kj}\frac{1}{1+\exp\{-\sum_{i=1}^{d}w_{ji}x_i-w_{j0}\}}+\omega_{k0} \tag{8}$$

where, ω_{kj} is the weight connecting the kth output node and the jth hidden nodes, and ω_{k0} is the bias of the kth output node.

2.2.2 *Hybrid training method for neural networks based on adaptive genetic algorithm*

Traditional BP neural network has the disadvantage of slow convergence speed and will easily get into local dinky value. As known, genetic algorithm (GA) is a global optimization algorithm, and is a good candidate for dealing with the above problem. Therefore, a hybrid algorithm which combines AGA with ANN is used to improve the network convergence speed and avoid network into local minima.

(1) Coding scheme

To ensure the accuracy of network learning and avoid weight step change, real-coded genetic algorithm is adopted here. Sigmoid function is used as a transfer function of hidden layer. In the process of coding, all the weight and bias of neural network are served as gene on chromosome, and every gene constitutes the chromosome vector $\boldsymbol{V}=[v_1, L, v_{\mathrm{L}}]$, where v_i, $i=1,\cdots,L$ is the ith gene.

(2) Fitness function

Following error square measure is used to do the fitness evaluation:

$$\eta=\frac{P}{\sum_{p}\sum_{k}\|\tilde{y}_k-y_k\|^2} \tag{9}$$

where, η is the fitness function; P is the number of training samples; p is the current study sample; $\tilde{y}_k$ is the ideal output of node k; and y_k is the actual output of node k. It is noted that the batch processing method is used to train the sample here.

(3) Crossover operation

Crossover operation is a method used to choose the parent chromosomes engaging in crisscross-inheritance according to a given crossover probability. Here, the following arithmetic crossover algorithm is used to ensure that the resulting offspring lies between the two parent chromosomes:

$$\begin{cases}\hat{\boldsymbol{V}}_1=\alpha\boldsymbol{V}_2+(1-\alpha)\boldsymbol{V}_1\\ \hat{\boldsymbol{V}}_2=\alpha\boldsymbol{V}_1+(1-\alpha)\boldsymbol{V}_2\end{cases} \tag{10}$$

where, $\boldsymbol{V}_1$, $\boldsymbol{V}_2$ are two chromosome vectors; $\hat{\boldsymbol{V}}_1$, $\hat{\boldsymbol{V}}_2$ are the corresponding new chromosome vectors by arithmetic crossover; and α is a random number in [0,1].

(4) Mutation operation

Adaptive mutation operator is developed to adjust the search area adaptively, and this algorithm can obtain better global searching capability and convergence performance:

$$\hat{v}_i=v_i+(\beta_{i,\max}-v_i)\times(1-r^{(1-\frac{\eta}{\eta_{\max}})^\lambda}) \tag{11}$$

or

$$\hat{v}_i=v_i+(\beta_{i,\min}-v_i)\times(1-r^{(1-\frac{\eta}{\eta_{\max}})^\lambda}) \tag{12}$$

where, the range value of the gene in the mutation site v_i is $[\beta_{i,\min},\beta_{i,\max}]$, and $\eta_{\max}$ is the maximum adaptation degree of the problem. It has to be noticed that since $\eta_{\max}$ is always difficult to be determined, the maximum adaptation degree in the present group can be used to substitute $\eta_{\max}$. And r is a random number in (0, 1), $\lambda \in [2, 5]$.

In AGA-ANN hybrid algorithm, the AGA is used to do the global optimal search for the threshold, weight values of BP algorithm and location in a satisfying search space under certain condition in the solution space. Then, the weight value and threshold calculated by the AGA can be used as the corresponding initial weight and bias of BP algorithm. Thus, the global optimal solution converges quickly in the located small space and can be searched easily by the BP algorithm which has excellent local search ability. The specific process is as follows:

Step 1 Determine the parameters of AGA and BP algorithm.

Step 2 Randomly generate n groups of initial weight values and threshold, and use real-coded mechanism to code the weights and bias in order to construct chromosomes one after another.

Step 3 Calculate the error function and determine the fitness function value of each corresponding chromosomes. The greater error is, the smaller fitness value will be.

Step 4 Choose the individual with the biggest fitness function value and inherit its identities to next generation (preservation of optimal individuals).

Step 5 Use genetic operators like crossover and mutation to deal with the current generation of groups and produce the next generation groups.

Step 6 Repeat Step 2 to Step 4 to make the distribution of weight values and bias evolve continuously until the $\eta_{\max}$ is less than the target error.

Step 7 Use the weight values and chromosomes produced by GA algorithm to train the net until reach the target error square. And repeat Step 2 to Step 6, if the error did not meet the target within a prescribed number of training.

3 Acquisition of Basic Database for Model Training and Model Testing

Industrial experiments with the proposed method have been made at BF No. 2 in Liuzhou Iron and Steel Company. This BF went into operation in September, 2012, and its volume is 2 600 m^3. Since the raw material in the ironmaking process is closely related to Si, P and S contents, the relevant parameters are seriously considered in the selection process. Based on the process mechanism and existed instrument status, the process parameters influencing the MIQ are determined including blast temperature, blast pressure, oxygen enrichment percentage, flow rate of oxygen enrichment, gas permeability, gas volume of bosh, bosh gas index, blast kinetic energy, blast humidity, cold air flow, feed blast ratio, resistance coefficient, volume of coal injection, theoretical burning temperature, actual wind speed and furnace top pressure. Fig. 2 shows the schematic diagram of the blast furnace smelting system.

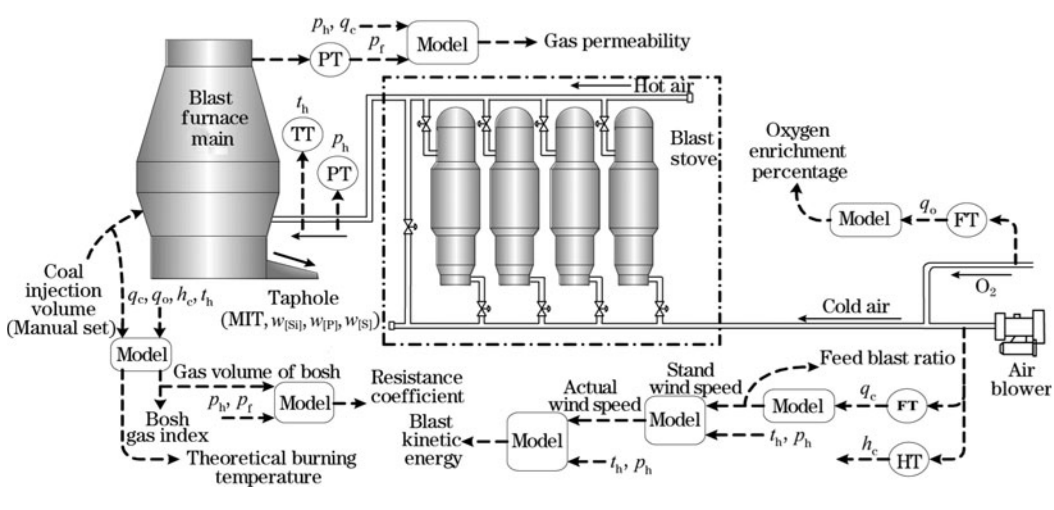

Fig. 2 Schematic diagram of blast furnace ironmaking system

Direct detecting variables in Fig. 2 are explained as follows.

(1) Two flowmeter FTs are located on the pipeline of cold air and oxygen to measure the flow of cold air q_c and flow of oxygen enrichment q_o online.

(2) Two DPharp EJA pressure transmitter PTs are mounted on the inlet air pipe of hot air and the top of blast furnace separately to measure the hot air pressure p_h and the pressure of the top blast furnace p_f, respectively.

(3) A temperature transmitter TT is mounted on the pipeline of hot air to detect the temperature of hot air t_h.

(4) An air humidity sensor HT is located on the entrance of blower to regulate the humidity of blowing air h_c.

The rest of used preliminary input variables in Fig. 2 are given in Table 1. All of them are calculated by the above directly detected variables, and their relationships can also be seen clearly from Fig. 2. The name of these indirect variables and their calculation formulas are demonstrated in Table 1.

Table 1 A list of preliminary input variables

Variable name	Unit	Calculation formula
Oxygen enrichment percentage	mass%	$\left\{\left(0.0163q_o+\left[\left(0.21+\frac{0.29h_c}{800}\right)\times\frac{q_c}{60}\right]\right]/\left(\frac{q_c}{60}+\frac{q_o}{60}\right)-\left(0.21+\frac{0.29h_c}{800}\right)\right\}\times100$
Gas permeability	$m^3\cdot min^{-1}\cdot kPa^{-1}$	$100q_c/(p_h-p_f)$
Gas volume of bosh (A_g)	$m^3\cdot min^{-1}$	$\frac{1.21q_c}{60}+\frac{q_o}{30}+\frac{44.8h_cq_c}{6000}+\frac{44.8h_cq_o}{6000}+\frac{22.4A_v\times A_h}{12}$
Bosh gas index	$m^3\cdot min^{-1}\cdot m^{-2}$	$A_g/78.5398125$
Blast kinetic energy	$kJ\cdot s^{-1}$	$\left\{0.021q_c+\left(\frac{q_ch_c}{60000}+\frac{q_oh_c}{60000}/\left(1-\frac{h_c}{803.6}\right)\right\}/0.2A_a^2/50$
Feed blast ratio	mass%	$q_c/2000$
Resistance coefficient		$[(10000p_h)^2-100p_h^2]/A_g^{1.7}$
Volume of coal injection (A_v)	$kg\cdot t^{-1}$	Manual set
Theoretical burning temperature	℃	$1559+(0.839t_h)+(4972q_o/q_c)-(6.033h_c)-(3.15A_v\times1000000/q_c)$
Actual wind speed (A_a)	$m\cdot s^{-1}$	$0.101325(273+t_h)/[273(0.101325+p_h)]\times(q_c/3600\times4/3.14/30)$

Note: A_h—Hydrogen content in coal.

Meanwhile, because the excessive computational complexity might be increased, and the efficiency and accuracy of system could also be affected when there is a strong correlation among these 16 input variables; therefore, factor analysis based on PCA algorithm is used to analyze the original samples to ascertain the principal components influencing Si content y_1(%), S content y_2(%), P content y_3(%) and MIT y_4(℃) of molten iron. As a result, 6 principal components, namely gas volume of bosh u_1 (m^3/min), blast temperature u_2(℃), blast pressure u_3 (kPa), oxygen enrichment percentage u_4(%), blast humidity u_5(g/m^3) and volume of coal injection u_6 (kg/t), are chosen to constitute a new sample set as the secondary variables for dynamic neural network modeling.

Considering the dynamic characteristics of ironmaking, the time sequential and lagging correlations between input and output, the data on both input and output layer at previous time were led to the input layer of the model to construct a self-feedback model. And the nonlinear dynamic function and map is given below:

$$(y_1(t),y_2(t),y_3(t),y_4(t))=\psi_{NN}\{u_1(t),u_2(t),u_3(t),u_4(t),u_5(t),u_6(t),u_1(t-1),u_2(t-1),u_3(t-1),u_4(t-1),u_5(t-1),u_6(t-1),y_1(t-1),y_2(t-1),y_3(t-1),y_4(t-1)\} \tag{13}$$

In this study, the secondary variables at current time $u_1(t),\cdots,u_6(t)$, the secondary variables at last time $u_1(t-1),\cdots,u_6(t-1)$, and the estimated MIQ outputs at last time $y_1(t-1),\cdots y_4(t-1)$ are taken as the comprehensive inputs of the dynamic neural network, so the number of neural network input node is 16. In addition, through numerous experiments, when the number of hidden nodes is set as 33, a reasonable result is achieved. Finally, a 16-33-4 three-layer net model is built and a dynamic feedback-introduced neural network structure is achieved.

In order to validate the feasibility and the generalization ability of the developed model, industrial experiment has been made based on the data collected from 7am November 18th, 2013 to 4am November 21st, 2013 at BF No. 2 in Liuzhou Iron and Steel Company with a sampling frequency about 1 h^{-1}. The data selected in this paper has obvious volatility and typicality, which can show the fluctuation condition of working condition under widespread load disturbance. Through repetitive training, an ANN model with less mean square error (MSE=[0.1678, 0.1584, 0.1504, 0.1736]) is obtained. The modeling results and its corresponding probability density function (PDF) as well as the error autocorrelation curve are shown in Figs. 3 and 4, respectively. The modeling

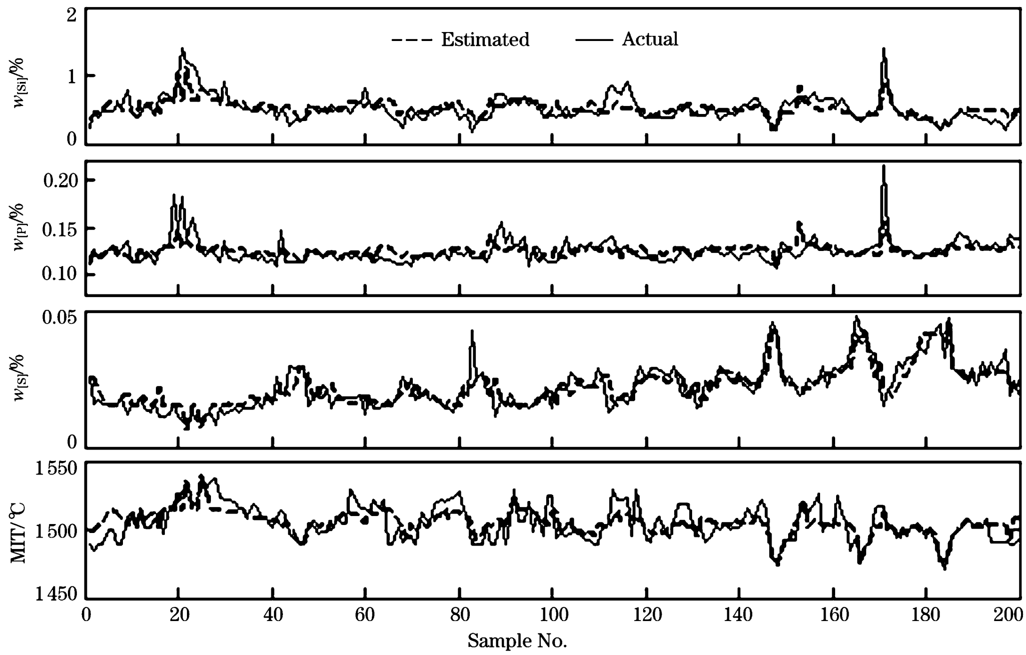

Fig. 3 Modeling results of the developed nonlinear dynamic AGA-ANN model

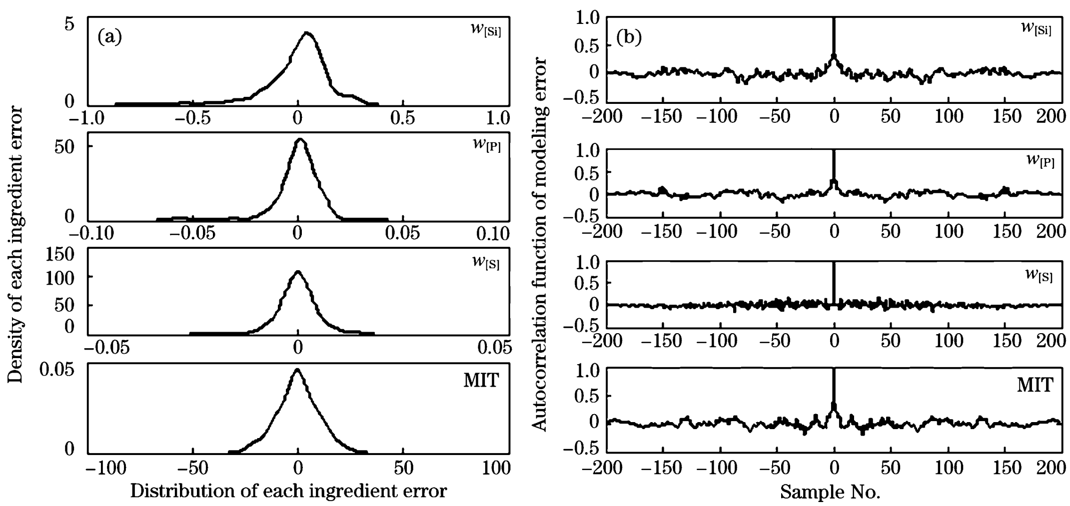

Fig. 4 Probability density function (a) and autocorrelation curve (b) of modeling error with the proposed method

results show that the developed ANN prediction model is excellent and the actual and estimated values agree well with each other.

Fig. 5 illustrates the testing results and the corresponding estimation MSE is [0.1140, 0.1036, 0.1904, 0.2086]. The PDF of estimation error and the error autocorrelation curve using the proposed method are presented in Fig. 6, and the PDF of estimation error and the error autocorrelation curves by the conventional ANN modeling method are shown in Fig. 7. It can be seen that quite good estimation has been obtained when practical industrial data are used for testing, and the model can accurately describe the MIQ index in each ironmaking time, which is much better than that with the conventional ANN modeling. The average estimation accuracy with the proposed method is 87%, when the average relative error by the model is less than 0.05.

It is thus obvious that the proposed model based on PCA and dynamic AGA-ANN has high estimation precision and good generalization capability for multivariate prediction of MIQ. The experiments show that the model can meet the actual production requirements and could be used as a useful guide for operators in practical BF operation process.

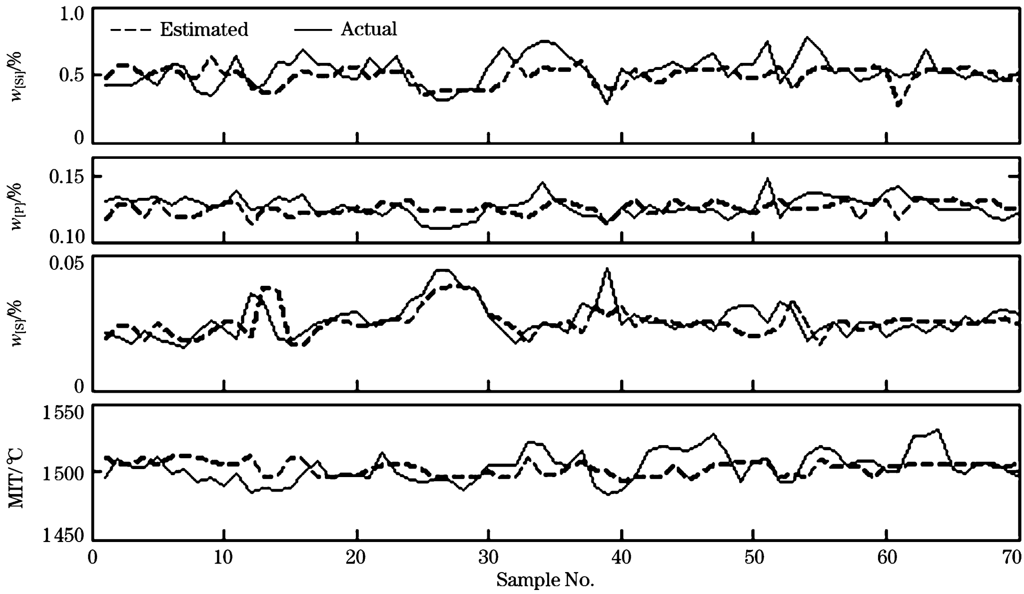

Fig. 5 Actual molten iron quality and its estimation in time series for BF No. 2 at Liuzhou Iron and Steel Company

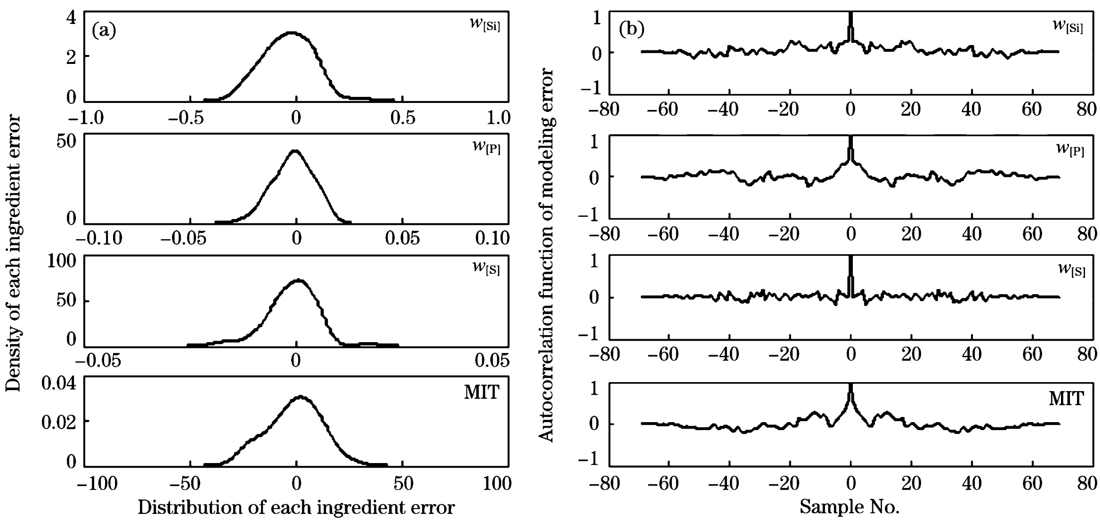

Fig. 6 PDF (a) and autocorrelation curve (b) of estimation error with the proposed method

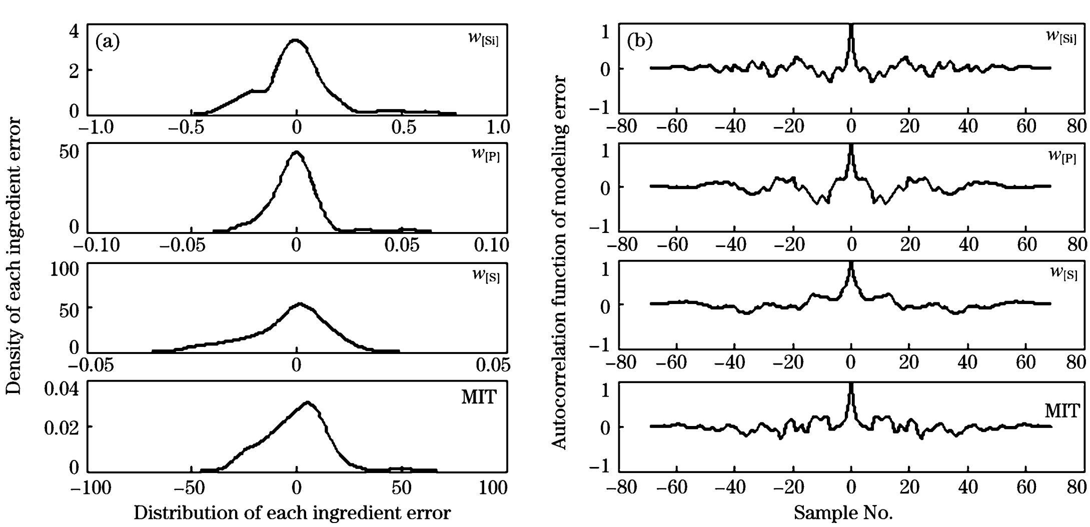

Fig. 7 PDF (a) and autocorrelation curve (b) of estimation error with the conventional ANN modeling

4 Conclusion

A new nonlinear modeling method has been proposed based on PCA and dynamic genetic neural network to make multivariate parameters prediction for Si content, S content, P content and MIT. To establish this model, time hysteresis existing in every process parameters is seriously considered. Input and output data at last time are stored in this model, and the whole network has the capacity of storing and handling data, thus improving the adaptability of this network. At the same time, adaptive genetic algorithm and neural network have been adopted for network training, which improve the network convergence speed and effectively avoid the network into local minima. A compressed variables dimension and more simple and effective model are obtained by pretreating data with principal component analysis on the premise of keeping all the relevant information of original data. And through multivariate nonlinear prediction, more precise accuracy can be obtained to reflect the status inside blast furnace than a single parameter forecasting, which can guide operators to take timely operation and realize optimal control. Industrial experiments for molten iron quality prediction have been made through the proposed model based on the data collected from practical industry field, and a high hit rate of prediction is realized. Therefore, the method and the model proposed are feasible.

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