Soft sensor system of coke oven flue temperature based on CBR and PCA-RBFNN

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Abstract

The key process indicator – coke oven flue temperature – is difficult to detect online with instruments in the coke oven heating process, thus an intelligent forecasting model is developed which is composed of four parts: the data gathering and handling unit, the optional forecasting unit, the online amendment unit and the effect evaluation unit. The optional intelligent forecasting model and its corresponding algorithm are established for different categories of practice operating conditions. In normal operating condition, the nearest neighbor clustering algorithm based on the principal component analysis and neural network with the radial basis function is selected. In unconventional operating condition, the case-based reasoning technology is selected. The models of different conditions are validated and applied according to the actual data in a steel enterprise coke production, the results show that the established forecasting model can reflect different practice conditions and meet the real-time control requirements.

Keywords: intelligent prediction, neural network, principal component analysis, neighbor clustering algorithm

1 Introduction

In the complex process of industrial production, some of the important variables closely related to the quality of products cannot be measured online directly due to various reasons by measurement instrumentation so that it has become a key factor to restrict the product quality and production efficiency. Coke oven flue temperature is a very important process parameter and refers to the measurement flue temperature average of the whole furnace chamber, which can reflect the whole oven temperature level. At present, the existing flue temperature soft measurement models are mostly linear regression models with the establishment of the regenerator top temperature and the coke oven flue temperature or creating the double parabolic model between them [1]. These models just regard the relationship of the regenerator top temperature and the flue temperature seen as a linear relationship or double parabolic relationship which exists certain limitations and low measurement accuracy. To meet the need of how to achieve the real-time control for coke oven flue temperature has become a constraint key issue.

Soft sensor technique is developed to solve such problems: According to some auxiliary variables being directly measured and the corresponding mathematical model in the process of industrial production to estimate the dominant variables not being measured online [2,3]. At present, soft sensor technique has more and more applications as the effective way to estimate some unpredictable variables in the industrial process. Main research content of soft sensor technology is: Mathematical model is established for a certain process variable. This mathematical model can be called the prediction model based on its characteristic and role modeling. Currently, the neural network soft measurement technology and the case-based reasoning soft measurement technology have been applied more and more widely.

Neural network has some itself characteristics: approximated to any complex nonlinear continuous function, the parallel handling of information and self-learning, adaptive, etc. Among them, the neural network of Radial Basis Function belongs to the local approximation network, and it has some significant features in the approximation capability, the classification ability and the learning speed, etc. [4,5]. Principal Component analysis method is a statistical analysis method to transform multiple related variables into a few independent variables. Soft sensor methods based on PCA and soft RBFNN is able to take advantage of neural network modeling at reduced dimensionality situation [6,7].

Case-Based Reasoning directly uses the past knowledge and experience, the model is easy to implement and maintain, and its training is simple and effective. Case-Based Reasoning adopts incremental learning method and has a strong self-learning ability, being good at using the knowledge and experience to learn [8,9]. The new cases are added increasingly in the learning process to modify the old cases for improving the judge reasoning ability.

The intelligent forecasting model is developed for the problems and needs above which is composed of four

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parts: the data gathering and handling unit, the optional forecasting unit, the online amendment unit and the effect evaluation unit [10,11]. The respective model and the corresponding algorithm are established with neural networks and case-based reasoning combined for different categories of actual operating conditions. In normal operating condition, the nearest neighbor clustering algorithm based on the principal component analysis and neural network with the radial basis function is selected. In unconventional operating condition, the case-based reasoning technology is selected. These two techniques are simultaneously applied to the coke oven flue temperature soft measurement of a coking plant, the practical application results show that the established forecasting model can reflect different actual conditions and meet the real-time control requirements.

2 The entire system of optional intelligent forecasting model

The optional intelligent forecasting model structure which can predict key variables of complex industrial process is displayed in Figure 1. $\hat{X}$ is the output of the optional prediction unit. $\bar{X}$ is the output after amendment; the distributed control system (DCS) generates the process data set Σ. Θ is the manual measurement data set from the online monitoring model. e is the amendment input parameters from the online amendment unit. u is the input of control object; y is the output of control object.

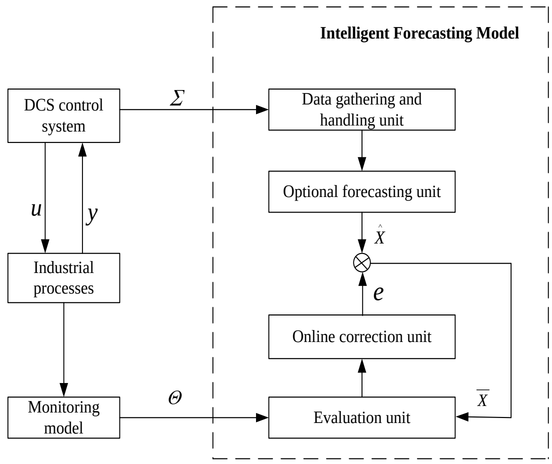

FIGURE 1 The entire system of optional intelligent forecasting model

a) Data gathering and handling unit: Data collected from the scene usually contains various interfering noise, such as the zero drift for the instrument, etc. In order to minimize these noise interference when modeling, these input data must be converted and difference handling, namely data pre-handling. Under certain circumstances, the output of prediction model should be appropriately processed, the reason is that the model is obtained in the context of a series of assumptions, it is impossible fully consistent with the practice situation and there is a model discrepancy.

b) Optional forecasting unit provides different categories forecasting model, depending on the actual condition, a prediction model and algorithm is selected. In normal condition, the neural network forecasting model is selected. Through learning and training, the neural network can obtain the knowledge of the key variables for the forecasting. In unconventional conditions, the case-based reasoning model is selected, the similar cases in the case base are retrieved according to the characteristics working conditions and the retrieved cases are matched and reused based on resemblance threshold to obtain the case solution of current condition which is the soft measurements of estimated dominant variable to predict.

c) Online amendment unit: the output of prediction model will drift with the passage of time after the forecasting model being put into use, therefore, some appropriate corrective measures must be taken to increase the accuracy of forecast values. Yet general, the online amended parameters is taken:

$$e = \frac{1}{n}\sum_{i=1}^{n}\left(X_i^* - \hat{X}_i\right), \tag{1}$$

$\hat{X}_i$ is the output of prediction model, X_i^* is the practical measured value.

The amended output is:

$$\bar{X} = \hat{X} + e\,. \tag{2}$$

This amendment pattern is easy to implement, the output of neural network prediction model should be calibrated to compensate for drift according to Equations (1) and (2) to increase the accuracy of forecast.

d) Evaluation unit will make corresponding evaluation results for forecasting the results of different categories, the output for neural network prediction model is compared with the manual measurement data obtained with the monitoring model, if the difference exceeds the set of upper and lower limit, the training and learning of neural network is conducted. The output of forecasting model for case-based reasoning is compared with manual measurement data obtained with monitoring model to evaluate the prediction accuracy.

3 Two different categories of the model structure in the optional prediction unit

3.1 THE FORECAST MODEL STRUCTURE FOR NORMAL OPERATING CONDITIONS

When the prediction model of flue temperature established, after considering the actual values of these factors: the statistics of regular testing T^*. The load pressure of furnace n, the flow of heating gas u, the pressure of heating gas p, the energy value of heating gas h, the flow of heating air v, the flue temperature of combustor is analyzed by principal component analysis and neural network technology in order to achieve the intelligent prediction of flue temperature. The structural principle is displayed in Figure 2.

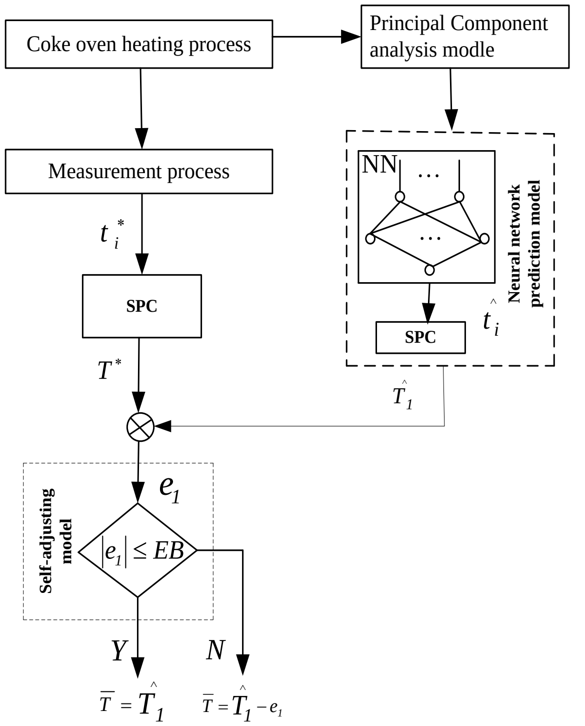

FIGURE 2 Neural network forecasting model of coke oven flue temperature

Intelligent forecasting model for flue temperature is composed of several parts which mainly are the principal component analysis model, neural network prediction model, self- amendment model. $\hat{T}_1$ is the output of neural network prediction model; $\hat{t}_i\left(i=1,2,...,n\right)$ is the output value of neural networks within a certain period of time. $t_i^*\left(i=1,2,...,n\right)$ is the actual measured value of flue temperature within a certain period of time. T^* is the statistics of manual measurement. e_1 is the difference between output value of neural network prediction model and manual measurement result; TB (>0) is the preset difference limit. $\bar{T}$ is the amended output of flue temperature.

The model structure of PCA and RBFNN is displayed in Figure 3. PCA extracts PCA components about some preliminary selection input variables to reduce the number of input variables and simplify RBFNN model under the premise of avoiding the loss of multi-variable information. RBF neural network is composed by three layers, the input layer nodes only pass the input signal to the hidden layer, the hidden layer nodes is composed by the effect function of radial structure like Gaussian functions, and the output layer node is a simple linear function. The basis function of hidden layer nodes will be generated in the local response for the input signal, that is, when the input signal is close to the central range of the base function, the hidden layer node will have a great output.

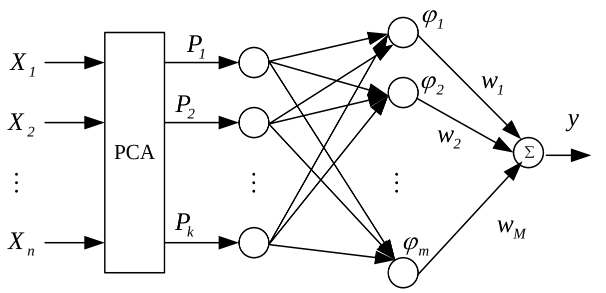

FIGURE 3 The model structure of PCA and RBFNN

The tasks of the hidden layer and output layer are different in the RBF neural Networks, therefore their learning strategies are also different. The hidden layer adopts nonlinear optimization strategy to adjust the mapping function parameters, thus it has the relative slower learning rate. The output layer adopts linear optimization strategies to adjust linear weights, thus the learning rate is faster.

There are many forms of radial basis functions, this paper selects the Gaussian function:

$$\varphi\left(\left\|P-P_i\right\|\right)=\exp\left(-\frac{\left\|P-P_i\right\|^2}{2\delta^2}\right), \tag{3}$$

In the type, $\varphi(\cdot)$ is the radial basis function; $\|\cdot\|$ is the European norm; $P_i \in R^{n_i}$ is the center of RBF; δ is the standard deviation of the neurons P_i determining the shape of the Gaussian function:

$$\delta=\frac{d_m}{\sqrt{2M}}, \tag{4}$$

where d_m is the maximum distance among the selected centers; M is the center number (the number of hidden layer units).

The output is:

$$F\left(x\right)=\sum_{i=1}^{M} w_i\varphi\left(\left\|P-P_i\right\|\right)+w_0, \tag{5}$$

where w_i is the weight of hidden unit to output unit; w_0 is the bias item.

PCA model needs a data set of the normal working conditions as the modeling data. Suppose the test data vectors matrix process $X \in R^{n\times n}$ is composed by m process variable and n data vector samples. In order to avoid different dimensions impact on the results and ease to handle mathematical, it is necessary to normalize the data. μ is the mean vector of set X, σ is the standard deviation vector, the normalized process variable is:

$$\tilde{x}_{ij}=\frac{\left(x_{ij}-\mu_j\right)}{\sigma_j}, i=1,2,...,n; j=1,2,...,m, \tag{6}$$

$\tilde{X}$ is the normalized vector of process variables, V is the covariance matrix for $\tilde{X}$. Based on principal component analysis for $\tilde{X}$, the process of principal components selected as the input vector of RBF network based on Principal Component Analysis is as the followings.

a) The each eigenvalue λ_j and corresponding unit orthogonal eigenvector P_j are calculated for the covariance matrix;

b) The principal component t_j of the order j is calculated:

$$t_j = \tilde{X}P_j \, , \tag{7}$$

c) The model of principal component is calculated:

$$\hat{X} = t_1P_1^T + t_2P_2^T + ... + t_jP_j^T \, , \tag{8}$$

where $t_j \in R^n$ is called as the score vector; $P_j \in R^m$ is called as the load vector; P_j is the corresponding eigen-vector matched with the order j eigenvalue in descending order for the matrix V, including various interrelated information among the variables. Each pair t_j, P_j is sorted by the descending of the eigenvalue λ_j for the correspon-ding eigenvector P_j. Where in the first pair intercepts the maximum information volume among all decomposition of the load vector and principal component vector. So on, $T = [t_1, t_2, ..., t_m]$ is the score matrix; $P = [P_1, P_2, ..., P_m]$ is the load matrix, the Equation (9) can be written as:

$$\hat{X} = TP^T \, . \tag{9}$$

d) The contribution rate is calculated before the principal component $k(1 \le j \le m)$:

$$\eta_k = \frac{\sum_{i=1}^{k} \lambda_i}{\sum_{i=1}^{m} \lambda_i} \, . \tag{10}$$

Next step, the number of principal component for PCA model should be determined. Since there is high corre-lation between the process variables based on experience, generally, the cumulative contribution rate of all principal components before the principal component k more than 85% is considered to reflect the body information of process variables. The k vectors for the corresponding prin-cipal components are selected main element vectors in the matrix as the input vector of RBF neural network training.

3.2 THE FORECAST MODEL STRUCTURE FOR UNCONVENTIONAL OPERATING CONDITION

The intelligent forecasting model of case-based reasoning is established for flue temperature after considering the actual values of these factors: the statistics of regular testing T^*, the load pressure of furnace n, the flow of heating gas u, the pressure of heating gas p, the energy value of heating gas h, the flow of heating air v. The model structure is displayed in Figure 4. Ξ is the set of measurement data obtained from the coke oven heating process. $\hat{T}_1$ is the output of case-based reasoning prediction model; $t_i^*(i = 1, 2, ..., n)$ is the actual measured value of flue temperature within a certain period of time. T^* is the statistics of manual measurement. e_1 is the difference between output value of case-based reasoning prediction model and manual measurement result. TB (>0) is the preset difference limit. $\bar{T}$ is the amended output of flue temperature. Model selector gets the measurement data from the coke oven heating process, the forecast values are completed by case-based reasoning model, and the self-correction model based on artificial measured temperature statistics to determine how to deal with the results of prediction, the target of forecast is to get at last.

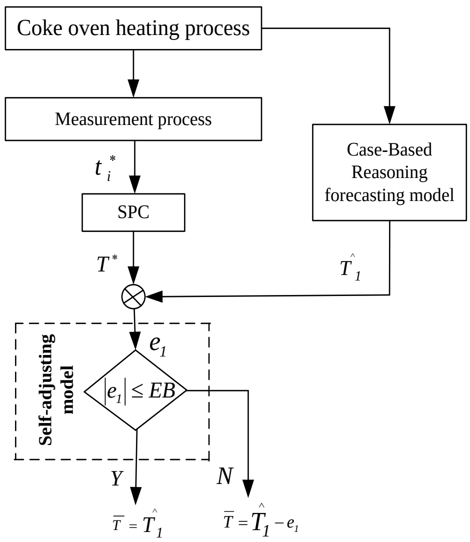

FIGURE 4 Case-based reasoning forecasting model of coke oven flue temperature

4 Model algorithms under different conditions

4.1 THE SELF- CALIBRATION ALGORITHM

The initial forecast results should be amended online to ensure the forecast accuracy, while the self-calibration algorithms for the prediction models of two conditions are the same, the same self-calibration algorithm is available [12,13].

Generally, the flue temperature of combustion is mea-sured through the Infrared Thermometer held by the operator. Setting that the set for the manual measurement data is $\{t_i^*, i = 1, 2, ..., k\}$, statistical process control (SPC) mechanism is used to deal with these data.

$$T^* = \frac{\sum_{i=1}^{k} t_i^*}{k} \, , \tag{11}$$

$\hat{T}_1$ is the original forecast value of flue temperature from the forecasting model, the effect of flue temperature forecast can be assessed by the following equation:

$$e_1 = \hat{T}_1 - T^* \, , \tag{12}$$

where e_1 is the difference between the original forecast value of flue temperature and the manual measurement data. If the absolute value of the difference e_1 is beyond a preset difference limit *TB*, thus $|e_1| > TB$, then the output of prediction model should be amended, the amended parameter is e_1. Otherwise, the output needn't be amended, the value of amended parameter e_1 is 0. The amended output is as follows:

$$\bar{T} = \hat{T}_1 - e_1. \tag{13}$$

4.2 THE NEAREST NEIGHBOR CLUSTERING LEARNING ALGORITHM OF RBF NEURAL NETWORK

K-mean clustering algorithm is a classical clustering algorithm to determine the centric value of RBF network, its main problem is that the number of network hidden layer nodes must match the number of input patterns, or it may seriously affect network performance. The number of centers is fixed in advance and depends on the initial position of the cluster center, there is likely to fall into local extreme point. This paper uses the nearest neighbor clustering algorithm with a variable number of hidden layer center to select the center of the hidden layer, the algorithm is as follows:

Select the appropriate width of the Gaussian function;

Begin from the first learning sample (P^1, Y^1), establishing the first cluster center for P^1, taking $C^1 = P^1$;

Consider a second study sample (P^2, Y^2); calculate the distance $|P^2 - C^1|$ of the cluster centers between P^2 and C^1, if $|P^2 - C^1| < r$, then C^1 is the nearest neighbor clustering for P^2, if $|P^2 - C^1| > r$ then P^2 is as the new neighbor clustering center, taking $C^2 = P^2$; then add a hidden unit in the establishment of the RBF network.

Suppose there are *M* cluster centers before consider the order *k* learning sample (P^k, Y^k). The central points are $C^1, C^2, ..., C^M$. The distance of these points to *M* cluster centers is respectively calculated, $|P^k - C^i|, i = 1, 2, ..., M$. If $|P^k - C^i|$ is the minimum distance among them, then C^i is the nearest neighbor clustering for P^k; if $|P^k - C^i| < r$, then C^i is the nearest neighbor clustering for P^k. If $|P^k - C^i| > r$, then P^k is as the new neighbor clustering, taking $C^{M+1} = P^k$, $N = M + 1$.

For each pair of the input – output data is likely to generate a new clustering, the self-adjust of two processes for parameters and structure is carried out simultaneously; therefore, the value of determines the complexity of the dynamic adaptive RBF network, reflecting one kind of generalization ability of the RBF network.

After determining the network center, the weights of the hidden layer of the network to the output layer can be adjusted, this paper adopts the recursive least squares algorithm with a weighted forgetting factor to adjust the weights of the output layer, the specific algorithm is as followings:

a) The initial values of the weights $w_i\left(i = 1, 2, ..., M\right)$ are given, the initial value *Q*(0) of the inverse correlation matrix is the positive definite diagonal matrix for the matrix *M*×*M* (*M* is the hidden layer nodes).
b) Taking a loop variable *k* = 1.
c) The output hidden layer node output is calculated:

$$\varphi_k = \varphi\left(\left\|P^k - C^i\right\|\right) = \exp\left(-\frac{\left\|P^k - C^i\right\|}{2\delta^2}\right), \tag{14}$$

$$J\left(k\right) = Q\left(k-1\right)\varphi_k\left[\rho + \varphi_k^T Q\left(k-1\right)\varphi_k\right]^{-1}, \tag{15}$$

$$Q\left(k\right) = \frac{1}{\rho}\left[Q\left(k-1\right) - J\left(k\right)\varphi_k^T Q\left(k-1\right)\right], \tag{16}$$

$$\hat{w}\left(k\right) = \hat{w}\left(k-1\right) + J\left(k\right)y_d\left(k\right) - \varphi_k^T \hat{w}\left(k-1\right), \tag{17}$$

where $\rho\left(0 < \rho < 1\right)$ is the weighted forgetting factor; this article takes: $\rho = 0$. $\hat{w}\left(k\right)$ is the amendment result of weight matrix after the sample in the order *k* is input. φ_k is the output vector of hidden node after the sample in the order *k* is input. $y_d\left(k\right)$ is the expected output of the sample in the order *k*.

d) The target cumulative difference is calculated:

$$E\left(k\right) = \rho E\left(k-1\right) + \frac{1}{2}\left[y_d\left(k\right) - \varphi_k^T \hat{w}\left(k-1\right)\right]^2, \tag{18}$$

$E\left(k\right)$ is the cumulative difference between the network output and the actual output after the sample in the order is the input.

$E\left(k\right) < E$ is judged, if it do, then $k < N$ is judged, if this relationship $k < N$ is true, taking $k = k + 1$, going to the step 3, else going to the step 1. *N* is the number of samples, *E* is the preset target difference.

4.3 LEARNING ALGORITHM OF CASE-BASED REASONING

The specific algorithm of case-based reasoning is as the followings:

The case is expressed, the specific method is as the following: The following parameters are selected as the dominant variable for the flue temperature soft measurement model: the flow of heating gas, the suction of flue, the energy value of heating gas, the pressure of heating gas, and the load pressure of furnace. The cases of flue temperature are stored in the computer in the form of database. The case database are composed of several of the case data, they is displayed in Table 1.

TABLE 1 The case for flue temperature of machine side and coke side

	Case for flue temperature of machine side	**Case for flue temperature of coke side**
Condition Expression	Machine-side gas flow	Coke side gas flow
	Machine-side flue suction	Coke side flue suction
	Gas heat value	Gas heat value
	Machine-side gas pressure	Coke-side gas pressure
	Furnace load pressure	Furnace load pressure
Case Solution	Machine side forecast value	Coke side forecast value

The resemblance of case is identified: The cases in the case base are defined as:

$$F_k = \left(f_{1,k}, f_{2,k}, ..., f_{n,k} \right), k = 1, 2, ..., m, \tag{19}$$

m is the number of cases in the case base.

Assuming the current operating condition is C_r. The resemblance function is defined as the following between the current condition C_r and the described case C_k:

$$Sim(C_r, C_k) = \sum_{i=1}^{n} w_i Sim\left(f, f_{i,k} \right), \tag{20}$$

where $Sim\left(f, f_{i,k} \right)$ is the resemblance between the feature $f_i \left(1 \le i \le n \right)$ of operating condition C_r and the described feature $f_{i,k}$ of the case, which is defined in the real interval $\left[0,1 \right]$ and meets the symmetry and reflexivity. w_i is the weight coefficient of case described feature and $\sum_{i=1}^{n} w_i = 1$.

The resemblance threshold is identified. The threshold value of resemblance is determined before the case is matched, Sim_t is the threshold value of resemblance.

$$Sim_t = \begin{cases} X_t, Sim_{\max} \ge X_t \\ Sim_{\max}, Sim_{\max} < X_t \end{cases}, \tag{21}$$

where the threshold value X_t is decided by specific process or experience according to the situation of object, generally taking $X_t = 0.9$. The $Sim_{\max}$ is marked as $\max\limits_{k=1,2,...,m} \left(Sim\left(C_r, C_k \right) \right)$.

The case is retrieved and matched: $\tilde{C}$ is the case with the greatest resemblance $Sim_{\max}$. $\tilde{J}$ is marked as the solution after the case reused.

$$J_u = \begin{cases} \tilde{J}, \left(Sim_{\max} = 1 \right) \vee \left(Sim_t = Sim_{\max} \right) \\ \sum_{k=1}^{h} Sim_k \times J_k / \sum_{k=1}^{h} Sim_k, others \end{cases}, \tag{22}$$

In the type, $\vee$ is the "OR" operator, expressing the "or" relationship between before and after. The result is output after the case reused, and this time, the description working condition and its solution of solving this case are stored in real-time database.

5 Application example of intelligent forecasting model

The intelligent prediction model of coke oven flue temperature proposed in this paper has been successfully applied to the heating intelligent control system of a steel company's coke oven [14]. The forecast results of the machine side and coke side are shown respectively in Figures 5 and 6; According to the statistics, the model prediction difference of the machine side and coke side which is within ±7°C respectively reaches 92.5% and 90.8%, meeting the requirements of industrial production.

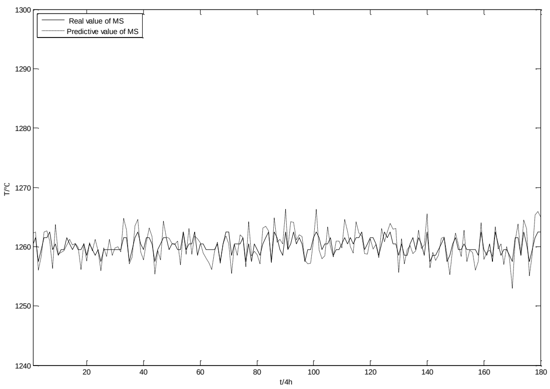

FIGURE 5 The forecast result for the machine side

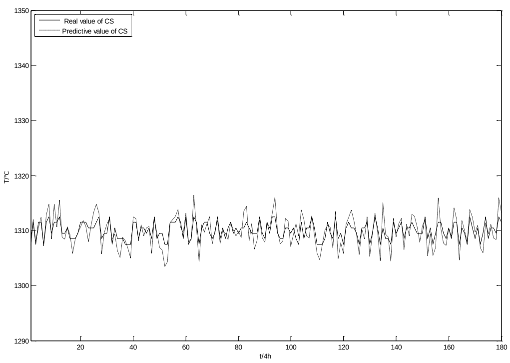

FIGURE 6 The forecast result for the machine side

6 Conclusions

The key process variables are difficult to detect online with instruments for the complex industrial processes, an intelligent forecasting model is developed which is composed of four parts: the data gathering and handling unit, the optional forecasting unit, the online amendment unit and the effect evaluation unit. The optional forecasting model and its corresponding algorithm are established for differrent categories of practice operating conditions. In normal operating condition, the nearest neighbor clustering algorithm based on the principal component analysis and neural network with the radial basis function is selected. In unconventional operating condition, the case-based reasoning technology is selected. The two techniques are simultaneously applied to the intelligent forecast of coke oven flue temperature which can give full play to their strengths in different conditions. The model has a certain self-learning ability with higher intelligence. At the same time, the application results of the prediction model in the optimazation control of coke oven heating process show that the model has high accuracy. This method is effective and can be applied in real-time control of coke oven flue heating process.

Acknowledgments

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