15th Triennial World Congress, Barcelona, Spain

INTELLIGENT CONTROL METHOD and APPLICATION for BOF STEELMAKING PROCESS[1]

Tao Jun Wang Xin Chai Tianyou Xie Shuming

Research Center of Automation, Northeastern University, P.R China, 110006

ABSTRACT: This paper introduces a new intelligent control method for Basic Oxygen Furnace (BOF) steelmaking dynamic process, by combining Neural Network, Fuzzy Inference, Expert System with dynamic process control method of BOF steelmaking. The control system is composed of the preset model of the dynamic requirement for oxygen blowing and coolant adding, bath [C] and temperature prediction model, and judgment Expert System for blowing-stop. The control method of BOF steelmaking process has been successfully applied in some steelmaking plants and improves the bath Hit Ratio (HR) significantly. It shows that the method is effective. *Copyright © 2002 IFAC*

KEYWORDS: Process models; Process Control; Intelligent Control;

1. INTRODUCTION

Basic Oxygen Furnace (BOF) steelmaking is one of the key processes in the iron & steel industry, and its main object is to provide the steel bath, of which the carbon content [C] and temperature both can hit the tapping aim slot at the blowing end-point. In BOF process, [C] and temperature of steel bath can't be measured continuously and operation conditions vary frequently, which makes it difficult to control the BOF end-point bath precisely. Actually, it often happens that operators have to re-smelt the steel bath due to the low control precision of end-point bath. So improving the control precision of BOF steelmaking end-point is quite important.

In fact there always exist many shortcomings in BOF Dynamic Control Models, such as poor self-adaptation ability, poor Hit Ratio (HR) and so on. In order to make up for all the shortcomings above, intelligent methods, such as Neural Network (NN), Fuzzy Control and Expert System (ES), are introduced in this paper. It proves that the control method is effective.

[1] National "Ninth Five" science & technology key project (No. 97-562-03-02)

2. BOF STEELMAKING PROCESS

BOF steelmaking process is executed to raise the bath temperature and reduce the impurity level by blowing proper volume of oxygen into the steel bath surface and adding appropriate amount of flux and coolant into the bath. The main raw materials of the process include main materials (such as hot metal, scrap, pig iron) and sub-material (oxygen, iron ore, lime, dolomite and etc.), and the product is the steel bath of which the temperature and content are required to hit the tapping aim slot. Fig.1 shows the structure of Basic Oxygen Furnace.

According to the characteristics of BOF steelmaking process, the control method combining the Static Process Control with Dynamic Process Control is popularly used. Static Process Control determines the gross requirement of oxygen and coolant for the each heat based on the initial information, when sublance SL1 measurement is processed successfully in the posterior period, Dynamic Process Control is started to adjust the dynamic requirement of oxygen and coolant based on the measurement result of bath [C] ant bath temperature at the SL1 time and the taping target. Dynamic Process Control is more interesting, for it is relative to the BOF tapping operation directly.

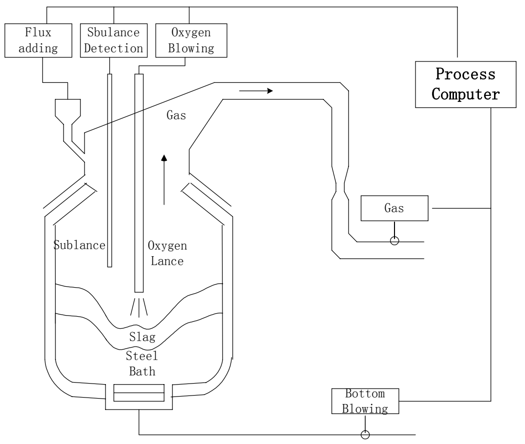

Fig.1 Structure of Basic Oxygen Furnace Steelmaking

With model input $U(t)=[u_1(t),u_2(t)]^{\tau}$ and model output $Y(t)=[y_1(t),y_2(t)]^{\tau}$, the BOF dynamic steelmaking process (during the period of t_0-t) can be expressed with equation (1) and (2)(Yunge et al, 1998; Robertson, et al.,1989; Ramaseder, et al.,1993), where $u_1(t)$ and $u_2(t)$ present the quantity of oxygen blown and dynamic coolant added in BOF dynamic process respectively, $y_1(t)$ and $y_2(t)$ present the bath [C] content and temperature respectively.

$$\frac{[y_1(t)-y_1(t_0)]+h_0\cdot[u_2(t)-u_2(t_0)]}{W_{ST}}=\frac{\beta}{\alpha}\cdot\ln\left\{\frac{\exp\left[\dfrac{y_1(t_0)-C_0}{\beta}\right]-1}{\exp\left[\dfrac{y_1(t)-C_0}{\beta}\right]-1}\right\} \qquad (1)$$

$$y_2(t)=y_2(t_0)+\gamma\cdot\frac{u_1(t)-u_1(t_0)}{W_{ST}}+f(t_0)\cdot\delta -\varepsilon\cdot[y_1(t)-y_1(t_0)]-k_0\cdot[u_2(t)-u_2(t_0)]-\sum_i k_i\cdot[r_i(t)-r_i(t_0)] \qquad (2)$$

where: C_0 is the constant (the critical of bath [C] content); h_i is the content of oxygen in the sub-material i (Nm^3/Ton); k_i is the cooling coefficient of the sub-material i (℃/Ton); W_{ST} is the aim quantity of the bath steel at tapping time (Ton); α、β is the coefficient of the decarbonization model; γ、δ、ε is the coefficient of the temperature-rise model; if $t_0=0$, $f(t_0)=1$, or $f(t_0)=0$.

Because the bath temperature cannot be measured continuously and the process is a strong nonlinear procedure, the BOF steelmaking end-point control is always operated with the aids of operator experiences or with control model, which often results in the relative poor Hit Ratio of the bath end-point control.

3. INTELLIGENT CONTROL METHOD

In BOF steelmaking dynamic process, the controlled variables are carbon content and temperature of bath steel, and the controlling variables are the amount of oxygen blown-in and that of coolant added in the process. In this intelligent control method, one DCS is used in the controlling of oxygen blowing and coolant adding, and a set of method is applied to determine the set values of dynamic oxygen and coolant, and finally return the set values to the dynamic control system.

The control processes are mainly as follows: On the base of sub-lance measurement result and the tapping target, the initial set value of dynamic oxygen is determined firstly under the condition of no coolant added. And secondly, the calculated quantity of dynamic oxygen and dynamic coolant (initially zero) and other relative information are all transmitted to the forecast model, which precalculates the bath end-point [C] and temperature under the condition of the current calculated quantities of oxygen and coolant. Thirdly adjusting model will modify the quantities of oxygen and coolant with the difference between the forecasting result of bath [C], temperature and their tapping targets. Then the adjusted value is transmitted to the forecast model to predict the bath [C] and temperature under the new operation condition. The process above is recycled until the judgment model for BOF blowing-stop demonstrates that the bath [C] and temperature have hit the tapping targets, then the amount of oxygen and that of coolant obtained are just the final set values and will be sent to the corresponding DCS.

The system structure of the intelligent control method is given in Fig.2, which includes: presetting model, forecasting model, judgement system for BOF Blowing-Stop and the homologous affiliation to each section. The function and the method of each model will be described in detail below.

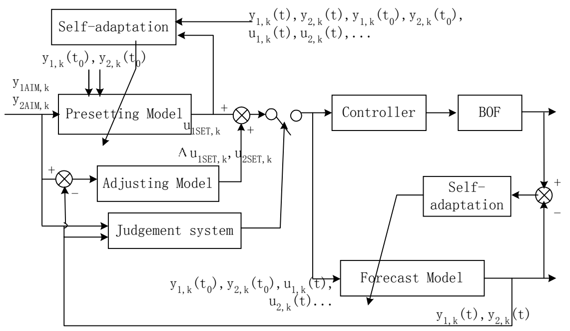

Fig.2 Control Structure of the Intelligent Control Method

3.1 Forecasting model

During the procedure of BOF steelmaking, forecasting model , based on SL1 sublance measurement results $(y_{1,k}(t_0), y_{2,k}(t_0))$ (here k presents the kth heat) and the amount of dynamic controlling variables $(u_{1,k}(t), u_{2,k}(t))$, predict the bath [C] and temperature real-timely, and finally realize the soft-measurement of the BOF bath.

Two Radial Basis Function Neural Networks (RBF NN) are applied to predict [C] and temperature of the steel bath in the BOF dynamic process. The input nodes of the NN calculating bath [C] are bath carbon of sublance SL1 measurement, the amount of dynamic oxygen and that of dynamic coolant, while the input nodes of NN calculating bath temperature are bath temperature of sublance SL1 measurement, the amount of dynamic oxygen and that of coolant.

There are two stages in the training of RBF NNs, one is the learning of the Radial Basis Functions centers, and the other is the training of the connection weight of the output layer (Yongyi and Jian, 1998; Elanayar et al., 1994; Fengbao et al.,2001). In the learning of the Radial Basis Functions centers, Fuzzy C-means method is adopted (Guirong, et al.,1993; Pedrycz, 1998), and the classification object function is to minimize the sum of the square of the distances between the samples and cluster centers. The approximation function of RBF NN is $F(x) = \sum_{i=1}^{c} w_i G(\|x - v_i\|)$, where: $G(x)$ is Gaussian Function.

Self-adaptation module of forecasting model is executed to implement on-line learning function (adjusting the hidden centers and the connection weight) of RBF NN by feedback learning of the network error, which is the difference between the RBF NN output and the actual measurement results of the bath end-point [C] and temperature.

3.2 Presetting Model

The task of presetting model is to determine the dynamic supplementary oxygen requirement with no coolant added, to warrant bath [C] level decreasing from BOF dynamic process start point $(y_1^k(t_0), y_2^k(t_0))$ and hitting the tapping aim (y_{1AIM}^k, y_{2AIM}^k). RBF NN is adopted here.

The oxygen requirement for BOF dynamic steelmaking process is relative to bath [C] level of sublance blowing-in measurement, the [C] tapping target $y_{1AIM}^k(t_{end})$ and the quantity of the coolant added during the BOF steelmaking dynamic procedure. As a result, the input node number of the presetting NN is 3 and the node number of hidden layer is determined in training and the output node number is 1, which is corresponding to the oxygen requirement $\Delta u_{1SET,1}^k$ for BOF dynamic steelmaking process.

After the sample learning and training, the presetting RBF NN can implement the function of presetting the BOF dynamic oxygen requirement. The coolant amount is zero when determining the amount of the supplementary oxygen.

In the process of presetting calculation, the quantity of the added dynamic coolant is set with zero and the amount of the supplementary oxygen obtained from the NN is only an initial value. Based on the initial value of dynamic oxygen requirement, adjusting model will regulate the final quantity of oxygen and coolant for BOF dynamic process.

3.3 Adjusting Model

Presetting model only takes bath [C] content as the controlled variable, and determines the dynamic oxygen requirement under the condition of no coolant added. The bath temperature is controlled with adding coolant, but there exists solid oxygen in the coolant so it is necessary to modulate the dynamic oxygen volume to balance the influence of the coolant on the bath [C] content during the controlling of the bath temperature by adding coolant. Therefore adjusting model includes two sections: the adjusting model of determining the coolant requirement and that of modifying dynamic oxygen volume.

In adjusting model, the control errors $\Delta y_{1,j}^k, \Delta y_{2,j}^k$ of bath [C] and temperature are both selected as model inputs, and the adjusting results $\Delta u_{1SET,j}^k, \Delta u_{2SET,j}^k$ as model outputs. Here, the two models both adopt Fuzzy Inference technology and Fuzzy Inference Rules are adopted *T-S* rules as follows(Cengke,1997; Jin,1995).

$$\text{If} \quad y \quad \text{is} \quad A_i \quad \text{then} \quad \Delta u \quad \text{is} \quad u_i .$$

The input variable of the adjusting model is $\Delta y_{1,j}^k = y_{1AIM}^k - y_{1,j}^k(t)$ or $\Delta y_{2,j}^k = y_{2AIM}^k - y_{2,j}^k(t)$, the output variable is $\Delta u_{1,SET}$ or $\Delta u_{2,SET}$ and the membership functions of input and output variables are triangular.

$$\begin{aligned}
\Delta Y_1 &= \{NVB, NB, NM, NS, ZE, PS, PM, PB, PVB\} \\
&= \{-4,-3,-2,-1,0,1,2,3,4\} \\
\Delta Y_2 &= \{NB, NM, NS, ZE, PS, PM, PB\} \\
&= \{-15,-10,-5,0,5,10,15\} \\
\Delta U_{1SET} &= \{NVB, NB, NM, NS, ZE, PS, PM, PB, PVB\} \\
&= \{20,10,5,2,0,-2,-5,-10,-20\} \\
\Delta U_{2SET} &= \{NB, NM, NS, ZE, PS, PM, PB\} \\
&= \{0.1,0.05,0.02,0,-0.02,-0.05,-0.1\}
\end{aligned}$$

The relationship between the quantity of dynamic oxygen and bath [C], and that between coolant and bath temperature, is obvious, so the adjusting rules of the quantity of dynamic oxygen and coolant can be easily obtained. The output of the adjusting model is obtained by fuzzy inference (Mamdani method here) and defuzzication operation (Gravity method).

3.4 Judgment Model for BOF Blowing-Stop

Based on the soft-measurement result $\left(y_1^k(t), y_2^k(t)\right)$ of the forecasting model and the taping aim slot $\left(y_{1AIM}^k, y_{2AIM}^k\right)$, judgment model for BOF blowing-stop accomplishes the BOF blowing-stop function by judging whether the bath [C] content and temperature has hit the tapping target with Expert System technology. When the tapping target [C] and temperature are both hit, this model will send the blowing-stop command to DCS of oxygen blowing system if computer control style is selected.

The whole judgment system mainly includes: knowledge bases (composed of rule base and data base) and inferencer (Chunyi, 1996). Rule base is the center of the whole judgment system, which collects the experience and knowledge about the BOF blowing-stop operation. Data base is responsible for saving BOF steelmaking condition, steel grade information, environment condition, expert experience, inference result and so on. Positive inference method is used here.

According to the BOF material condition, the bath taping target and other information, inference system forms the context data base and deduces the output of the blowing-stop identification with knowledge base, then decides whether taping should be proceeded.

Rules connecting directly with BOF blowing-stop operation mainly include:

if $(y_{2AIMMIN}^k < y_2^k(t))$ then Flag1=True

if $(y_{1AIMMAX}^k > y_1^k(t))$ then Flag2=True

if $(y_{2AIMMAX}^k - y_{2AIMMIN}^k) \times (y_1^k(t) - y_{1AIMMIN}^k) \leqslant (y_2^k(t) - y_{2AIMMIN}^k) \times (y_{1AIMMAX}^k - y_{1AIMMIN}^k)$ then Flag3=True；

if Flag1=True and Flag2=True and Flag3=True then Flag_tap=True

where: $y_{1AIMMAX}^k$ 、 $y_{1AIMMIN}^k$ are the upper and lower limit of the bath aim [C] content respectively； $y_{2AIMMAX}^k$ 、 $y_{2AIMMIN}^k$ are the upper and lower limit of the bath aim temperature respectively； $y_1^k(t)$ 、 $y_2^k(t)$ are the forecasting results of the bath [C] content and temperature at the time *t*.

The intelligent control method of BOF steelmaking dynamic process can be concluded as:

- applying one DCS to control the oxygen blowing-in circuit and the coolant adding circuit;
- determining quantity of oxygen to be blown-in and that of coolant to be added with a set of intelligent method;

- sending the determined value to homologous control circuits.

In addition, forecasting model and expert system for blowing-stop are also introduced to supervise and control the BOF steelmaking dynamic process.

4. INDUSTRIAL TEST

The intelligent control method above for BOF steelmaking dynamic process was applied successfully to one control system of 250t BOF, which was established in 1992. The computer network is constructed by Ethernet technology, and the operation system is VMS and the server is Alpha DS20. The original control model was built by mechanism and its hit ratio of bath [C] and temperature was about 83%.

In general, in the industrial test there are two procedures, establishing the control model and validating the control model. In the process of establishing control model, 150 heat records of the BOF steelmaking are collected firstly, which contains bath weight, sublance blowing-in measurment result, bath end-point [C] content and temperature, expenditures of oxygen and coolant in BOF dynamic process and etc.. Secondly, the bath [C] and temperature forecast models (the RBF NNs for forecasting the bath [C] and temperature) are established, then the presetting RBF NN (presetting model) is trained with the collected records.

Table.1 Parameters of Each RBF Neural Network

	λ	Learning Speed η	Nodes of Hide Layer
EP [C]	0.005	0.002	28
EP Temperature	0.005	0.001	28
Dynamic Oxygen	0.01	0.001	20

During the industrial test, the BOF intelligent dynamic control system operates as follows:

A. Data Preparation: Some information of present heat, such as material information, bath aim [C] and temperature, BOF static process information and etc, is collected.

B. Presetting Control : Based on the sublance blowing-in measurement results and the taping target, presetting model determines the quantity of oxygen to be blown-in during BOF dynamic process with no coolant added.

C. Bath Level Forecasting: RBF NNs forecast the bath end-point [C] content and temperature with the information of sublance blowing-in measurement results and the supposed expenditure of dynamic oxygen and dynamic coolant.

D. Judgment of Blowing-Stop : Expert System judges whether the bath [C] and temperature of the forecast model output has hit the tapping target. If the target is hit, the quantity of oxygen and coolant selected at that time are exactly the control quantity for the dynamic process of this heat, then the quantity is transmitted to the relative DCS and then operating goes to step (F).

E. Adjusting Calculation : According to the difference between the bath forecasting results and the tapping target, adjusting model rectifies the quantity of oxygen and coolant with fuzzy inference. Then step (C) is returned to.

F. Process Control: Dynamic oxygen blowing-in and coolant adding are controlled directly by basic control circuit, and when bath [C] and temperature hit the aim range, the judgment system will send blowing-stop command and the oxygen lance will be raised.

G. Self-Learning: If certain conditions are satisfied, each self-adaptation model will update the according forecast RBF NN or the presetting RBF NN with a certain speed, after bath taping operation and information collection.

In the industrial test, experimental records of 116 heats are obtained to validate the BOF intelligent dynamic control system. The results are shown in Fig.4 and Fig.5, where "◇" denotes the bath end-point carbon content or temperature and "*" denotes the bath taping target.

Among those test heats above, when the hit aim slots are selected as ±1.5% for temperature and ±12℃ for [C], there are 109 heats of bath end-point carbon hitting the target [C], and 110 heat of bath end-point temperature hitting the target temperature, and 106 heats of both bath [C] and bath temperature hitting the taping targets. Statistically, the Hit Ratio of bath [C], bath temperature and both of them, are

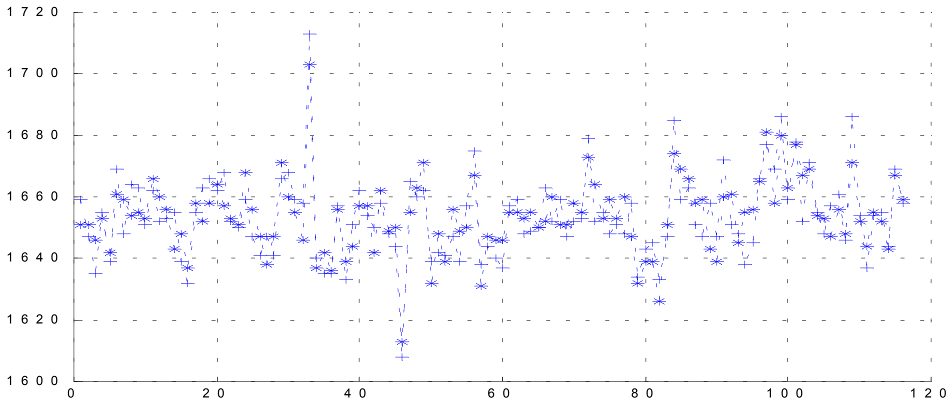

Fig.4 The Bath end-point Temperature and the Tapping Target

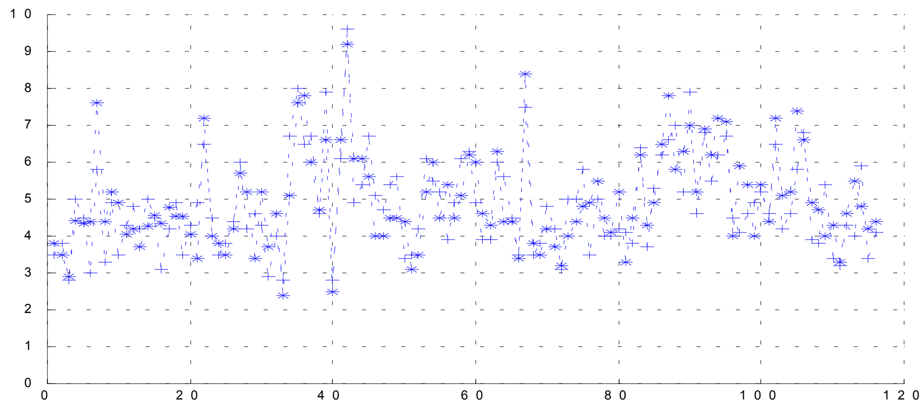

Fig.5 The Bath end-point carbon and the Tapping Target

93.97%, 94.83% and 91.38% respectively. It demonstrates that the new method of BOF intelligent dynamic control introduced in this paper can improve the bath Hit Ratio greatly (about by 7~8%), and also shows wonderful ability of control the end-point bath.

REFERENCE

Chunyi Shi, Changning Huang et al (1996). *Artificial Intelligence Principle*. Tsinghua University Press, Beijing. (in Chinese)

Elanayar Sunil, Yung v.t, Shin C. (1994). radial basis function neural network for approximation and estimation of nonlinear stochastic dynamic systems. *IEEE transactions on neural networks*,**5**,pp.594-603

Fengbao Li, Yuxiang Gao, Tian-xiang Gu (2001). Modeling and Predictive Control of Paper-making process Based on Neural Network. Basic Automation. **8**,pp. 40-45(in Chinese)

Guirong Guo, Weixin Xie, Zhaoweng Zhuang, et al (1993). *Fuzzy Pattern Identification*. National Defence University Press, Changsha. (in Chinese)

Jin Zhu (1995). *The theory and application of Fuzzy Control*. Mechanism Industrial Press, Beijing. (in Chinese)

Pedrycz Witold (1998). Conditional Fuzzy Clustering in the Design of Radial Basis Function Neural Networks. *IEEE Transactions on Neural Networks*,**9**,pp. 601-612

Ramaseder N., Pirklbauer W., Kalisch J. (1993). Slanted. Sublance System for Blowing Process Control. *Metallurgical Plant and Technology*. pp. 42-45

Robertson, K.J., Balajee S.R., Shearer J.M. et al.(1989). The Sublance Dynamic Control Operation and its Effect on the Performance of the Inland Steel Company's No.4 BOF Shop. *Steelmaking Conference Proceedings*. pp.159-166

Yongyi Wang, Jian Tu (1998). *Neural Network Control*. Mechanism Industrial Press, Beijing. (in Chinese)

Yunge Dai, Wenxiu Li, Tengchun Long（1998）. In: *Modern BOF Steelmaking*. Northeastern University Press，Shenyang, (in Chinese)

Zhang Cengke (1997). *The Application of Fuzzy Mathematics in automation technology*. Tsinghua University Press, Beijing .(in Chinese)