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BOF Intelligent Dynamic Endpoint Control *

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Abstract: Being aimed at BOF (basic oxygen furnace) process which is complicated, has many factors influencing the endpoint, and is difficult to be measured continuously and accurately, the intelligent dynamic endpoint control based on the sublance information is proposed. The BOF endpoint temperature and carbon content are predicted by use of gray model and neural network compensation. On the basis of this, the RBF neural network is regarded as presetting model, and the oxygen and coolant during the reblowing period are adjusted through fuzzy adjustment. A 180t converter is simulated. The results show that the method is effective.

Key words: BOF steelmaking; intelligent control; endpoint control
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转炉炼钢智能动态终点控制

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摘要: 针对转炉炼钢过程复杂,影响终点因素多,而且难以进行连续准确地测量,提出了基于副枪检测信息的智能动态终点控制方法.采用灰色模型并通过神经网络进行补偿对转炉炼钢终点温度和碳含量进行预报,在此基础上,以 RBF 神经网络作为预设定模型,通过模糊调整确定补吹阶段需要的氧气量和加入的冷却剂量,并对一座 180 吨转炉进行仿真计算,结果表明了该方法的有效性.

关键词: 转炉炼钢; 智能控制; 终点控制

1 Introduction

The endpoint control is an important operation in the later period of BOF steelmaking. The so-called BOF endpoint is the moment at which the molten steel temperature and composition reach the desire value. Because of the progress of the BOF steelmaking technology, the endpoint control is mainly to control the endpoint temperature and carbon content. The inaccurate endpoint control will prolong the smelting time, reduce the lining life, increase the metal consume and influence the steel quality. BOF steelmaking is a very complicated, high temperature and many phase physical-chemical process. There are many factors to influence the endpoint, and some factors are difficult to be described quantitatively. Simultaneously, the temperature is very high (more than 1600℃), and the environment is abominable in the smelting process. At present, there are many kinds of continuous measuring method for various kinds of physical quantity, but the most are indirect measurement, and can not achieve higher precision. As a result, it brings enormous difficulty for the BOF endpoint control. At present, more advanced control method is that the static control is combined with the dynamic control based on the sublance measuring information in the world[1-3]. The blown oxygen and the added auxiliary material to be used to make slag are determined only based on raw material condition and smelting target in the static model, and any correction is not made in the middle stage, therefore the endpoint hitting ratio is very low. Frequently, to hit the target needs many reblowings. On the basis of the static control, the dynamic control is to take sublance measurement in the later period and adjust the

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endpoint based on the measured information, therefore the dynamic control is an indispensable link in BOF steelmaking. The accuracy of the dynamic model is directly related to the endpoint hitting ratio.

2 Endpoint control content

BOF steelmaking is an intermittent production process. Fixed interval exists between one heat and another heat. It has great lag property, and is difficult to accurately and timely measure controlled variables. This process has complicated reacting mechanism and constantly changing characteristic with time. Therefore it has time-varying nonlinear characteristic and complicated coupling relationship among the variables. The control for this kind of process is different from general process control. In fact, it is a control problem of "optimization of setting value". The control includes two contents: 1) optimal control of setting value being aimed at technology index. The control model for the BOF process is directly established taking aim at the control for technology index, and the optimal control is realized through continuously correcting and perfecting the model; 2) optimal control of setting value being aimed at economic index. It is a kind of higher level optimal control, that is, on the basis of the former optimal control, the process model is identified using the practical data obtained from the process, then the most optimal solution on the economic index is acquired making use of the most optimal theory. At present, the method of the static control combined with the dynamic control used in the BOF steelmaking is practically the optimal control of setting value to meet the need of the technology index. It can not realize the optimal control of setting value for the economic index.

To realize the optimal control for the BOF steelmaking endpoint, synthetical control strategy must be used so as to realize recursive optimization. It includes two aspects: 1) the control for one heat. On the basis of the static control, the dynamic control is added based on the information measured by sublance to eliminate the problem that the static control model can not accurately determine the control quantity. It is practically open loop control. 2) self-learning control among heats. The BOF steelmaking is a repeating productive process which is very similar among one heat and other heats. Especially the difference between two adjacent heats is less. So the various relevant information obtained after completed the smelting of one heat should be made full use of to modify the parameters in the static control model and the dynamic control model. The next heat is controlled taking advantage of the modified models. It is an adaptive, self-learning process, and embodies the idea of recursive optimization.

Let the objective value of the endpoint temperature and carbon content be T_g and C_g respectively. It is shown as point A in Fig. 1. When BOF steelmaking reaches to the endpoint, if the molten steel temperature and carbon content enter into an area near point A (the shadow area in Fig. 1), the objective is hit. When the main blowing stage ends off, the molten steel temperature T_f and carbon content C_f are measured by sublance. It is shown as point B in Fig. 1. So the dynamic endpoint control of the BOF steelmaking is practically to transfer the molten steel state from point B to point A. In the later period of BOF steelmaking, the molten steel temperature and carbon content are moved according to a definite phase locus. When the molten steel temperature and carbon content measured by sublance are inside two embrace lines, the objective would be hit by blown suitable amount of oxygen. If the molten steel temperature and carbon content measured by sublance are not inside two embrace lines, the objective would not be hit by blown any oxygen. An effective method must be taken to adjust point B into embrace lines. In general, a suitable amount of coolant or carbon powder is added in the molten steel according to specific situation.

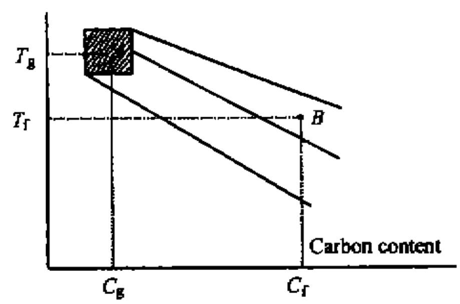

Fig. 1 The changing locus of the molten steel temperature and carbon content

3 Dynamic endpoint control

In the later period, the most part of impurity in the molten steel has removed. The reaction is much steady.

The slag composition, the raising temperature velocity and the reducing carbon velocity of the molten steel appear regular change. So the molten steel carbon content and temperature may be described by the following equations[4]

$$C = C_0 + \beta \ln\{1 + [\exp(\frac{C_f - C_0}{\beta}) - 1]\exp[-\frac{10\alpha}{\beta}(\frac{V_O - V_{Of} + \sum_i b_i W_i}{W_{st}})]\}, \quad (1)$$

$$T = T_f + \gamma \frac{V_O - V_{Of}}{W_{st}} + \delta - \sum_i k_i W_i, \quad (2)$$

where

C, C_f, C_0 - carbon content ($10^{-2}\%$) when blown oxygen is V_O, carbon content ($10^{-2}\%$) when main blowing stage ends off, carbon content ($10^{-2}\%$) at blowing ultimate state;

V_O, V_{Of} - the quantity (Nm^3) of blown oxygen at any time and the end of the smelting;

b_i - taking oxygen coefficient (m^3/t) of ith coolant;

W_i - weight(t) of ith coolant added during the reblowing period;

W_{st} - weight(t) of the molten steel;

α, β - constant;

T, T_f - molten steel temperature (℃) when blown oxygen is V_O and main blowing stage ends off;

γ - raising temperature coefficient (℃/$m^3 \cdot t$);

δ - raising temperature constant (℃);

k_i - cooling coefficient of ith coolant (℃/t).

From equation (1), the needful oxygen from taking the first sublance measurement to the endpoint may be easily found

$$\Delta V_O = \frac{\beta W_{st}}{10\alpha}\ln\{[\exp(\frac{C_f - C_0}{\beta}) - 1]/[\exp(\frac{C_e - C_0}{\beta}) - 1]\} - \sum_i b_i W_i, \quad (3)$$

where ΔV_O -blown oxygen (Nm^3); C_e —the molten steel carbon content ($10^{-2}\%$) at the endpoint.

The BOF dynamic endpoint control is made through reblowing oxygen and adding coolant by use of the information measured by sublance. According to the smelting condition, sometime a small amount of auxiliary material is added. It has little influence on the endpoint. Therefore the BOF dynamic endpoint control is a two-input process, in which the inputs are quantity of the reblown oxygen and weight of the added coolant, and the outputs are molten steel temperature and carbon content.

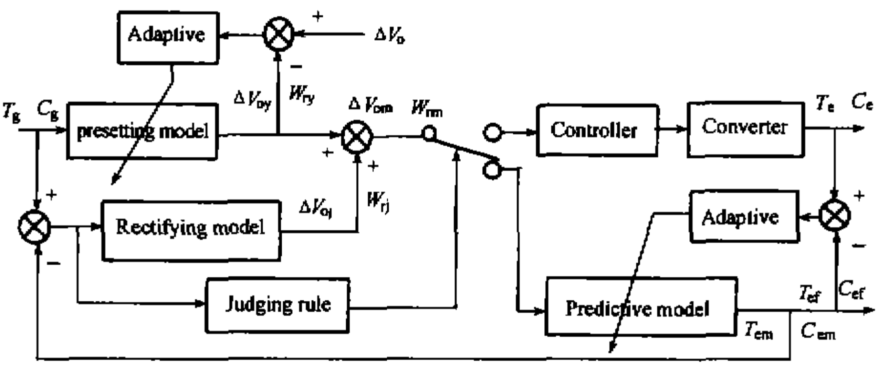

Fig. 2 BOF dynamic endpoint control system based on intelligent control

3.1 Predictive model

The endpoint predictive model for the BOF steelmaking is established by use of gray model and neural network compensation. The predictive model includes two, i.e. the predictive models of the endpoint temperature and carbon content.

Let the practical endpoint temperature or carbon content be $x^{(0)}(i)(i = 1,2,\cdots,n)$. The GM(1,1) model of the endpoint temperature and carbon content may be established according to the method to model gray system[5]. The endpoint temperature and carbon content may be calculated by use of this model. In a sense, the GM(1,1) model reflects an influence trend of the non-quantitative factors on the endpoint, but doesn't completely reflect particular influencing effect on every input. The extent which every input influence on the temperature and the carbon content is different, and the influencing rule is also different. On the other hand, any kind of modeling method based on statistical analysis is not capable of perfectly corresponding with the practical value. The gray model is also without exception. It must exist a certain amount of error. As a result, the prediction by use of this model exists error. To raise the predictive precision, the model must perfectly correspond with the practical value to the utmost. This may be solved through modifying or compensating. In this paper, the error produced by the GM(1, 1) model is compensated based on the information measured by sublance during the steelmaking period by use of RBF neural network so as to raise the model precision.

According to gray modeling method[5], the GM(1,1) model of the endpoint temperature and carbon content is obtained as follows:

$$\hat{x}^{(1)}(k+1) = \left(x^{(0)}(1) - \frac{u}{a}\right)e^{-ak} + \frac{u}{a}. \quad (4)$$

The solution found according to the above equation is not actual output value but progressive value (corresponding to the data calculated by use of accumulated generating operation). To obtain the actual value, these data are restored. That is, inverse accumulated generating operation is made. The inverse accumulated generating operation is

$$\begin{cases} \hat{x}^{(0)}(1) = \hat{x}^{(1)}(1), \\ \hat{x}^{(0)}(k) = \hat{x}^{(1)}(k) - \hat{x}^{(1)}(k-1), \end{cases} \quad (5)$$
$$(k = 2, 3, \cdots, n, n+1, \cdots).$$

After calculated the endpoint temperature or carbon content in the light of the above equation, the difference between the calculated value and the practical value may be calculated according to the following equation:

$$\Delta x(i) = x(i) - \hat{x}^{(0)}(i), \ (i = 1, 2, \cdots, n). \quad (6)$$

The RBF neural networks of the endpoint temperature error and the endpoint carbon content error are established based on the information measured by sublance at the end of the main blowing. From equation (1) and (2), it is known that the endpoint temperature is related to the temperature measured by sublance at the end of the main blowing, an amount of the blown oxygen and weight of the added auxiliary material during the reblowing period, while the endpoint carbon content is relevant to the carbon content measured by sublance at the end of the main blowing, an amount of the blown oxygen and weight of the added auxiliary material during the reblowing period. Therefore the network input nodes are 7 corresponding to an amount of the blown oxygen x_1 (Nm³), weight(t) of the added lime x_2, mixed material x_3, iron sheet x_4, ore x_5, dolomite x_6 during the reblowing period and the molten steel temperature x_7 (℃) or carbon content x_7 (10^{-2}%) measured by sublance at the end of the main blowing. The hidden nodes are determined through the training. The output node is 1 corresponding to the temperature error ΔT or the carbon content error ΔC. The network is shown in Fig. 3.

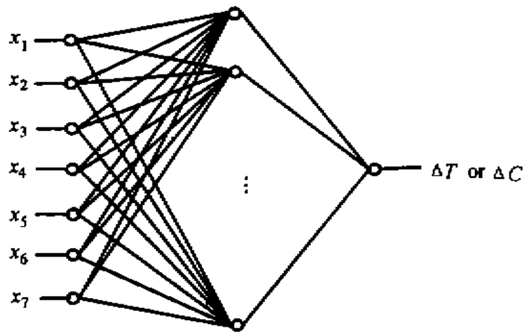

Fig. 3 The neural network of the endpoint temperature and carbon content

RBF neural network is not weights but a radial basis function from the input layer to the hidden layer. Therefore the network centres not only are directly related to the mapping capability of the hidden nodes to the input variables but also play a very important role in the whole network property. The network centres must be rationally determined so as to make the input variables be in an important area. In this paper, the network centres are determined by use of K-mean-accumulation algorithm[6]. After the network centres are determined, the network may be trained. The weights are adjusted by means of recursive least square (RLS) method[7].

From the above GM(1, 1) and RBF neural network models, the future heat prediction for the BOF endpoint temperature and carbon content are obtained.

$$\hat{x}(k) = \hat{x}^{(0)}(k) + \Delta\hat{x}(k), \quad (7)$$

where $\hat{x}(k)$ is the calculated value ($1 \leqslant k \leqslant n$) and the predictive value ($k > n$). $\hat{x}^{(0)}(k)$ is the value calculated from GM(1, 1) model. $\Delta\hat{x}(k)$ is the error obtained from the neural network model.

3.2 Presetting model

The presetting model is used to determine the blown oxgen which makes the endpoint carbon content enter the goal area on condition that no coolant is added. It is a RBF neural network. From equation (3), it is known that an amount of the reblown oxygen is related to the molten steel carbon content at the end of the main blowing, the goal endpoint carbon content, the added coolant during the reblowing period and the other auxiliary material. The auxiliary material is added to make slag. In the later period of the BOF steelmaking, making slag has completed basically and the smelting process is more stable. The less auxiliary material is added in the reblowing stage, the influence of it on the endpoint temperature and carbon content is also less. Moreover this influence has been considered in the predictive model. The variety and the amount of adding auxiliary material are determined according to the slag condition. They are still determined by use of general methods which are widely used at present. As a result, the number of the neural network input nodes are 3 including the molten steel carbon C_f at the end of the main blowing, the goal endpoint carbon content C_g and the coolant W_r added in the reblowing stage. The numbers of the hidden nodes are determined through the training. The output node is 1 corresponding to an amount of the reblown oxygen. The network is shown in Fig. 4. Determining the network centres and training the network are the same as the predictive model.

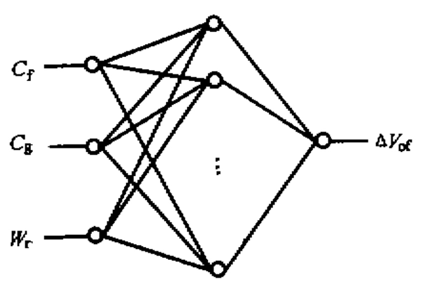

Fig. 4 The reblow oxygen neural network

3.3 Modifying model

The reblown oxygen is determined by use of the presetting model on condition that no coolant is added. Hitting the endpoint carbon content is primarily considered. The endpoint control also includes the control for the endpoint temperature which is realized through adding coolant. The coolant would take some oxygen to the molten steel. Considering the oxygen, the reblown oxygen calculated through the presetting model need to be adjusted. As a result, the modifying model includes two. One is to determine the coolant, and the other one is to adjust the reblown oxygen. Blown oxygen may reduce the molten steel carbon content and raise the molten steel temperature. On the one hand, added coolant would reduce the molten steel temperature. On the other hand, the oxygen taken by the coolant would influence the molten steel temperature and carbon content. Coupling exists between them. Through analyzing, it may be found that the added coolant is less in general, the oxygen taken by it is less compared with the reblown oxygen. The reblown oxygen has influence on the change of the carbon content. Effect of the modifying model is to adjust the reblown oxygen which is not still blown into the converter. As a result, the input of the modifying model to determine the reblown oxygen is 1 corresponding to ΔC. The added coolant and the reblown oxygen have influence on the molten steel temperature. Here, the coolant is adjusted after adjusted the oxygen every time. So the input of the modifying model to determine the added coolant is also 1 corresponding to ΔT. Adjustment is made by use of fuzzy rules in the modifying model of both the reblown oxygen and the added coolant. For the convenience of modifying control variables, the *T-S* rule[8] is used in the fuzzy adjusting rule.

$$\text{IF } e \text{ is } A_i, \text{ THEN } u \text{ is } u_i,$$

where $u_i \in U(i \in I)$ is determinate functions or determinate value but not fuzzy set.

From Fig.2, it is known that the inputs of the fuzzy modifying model for the reblown oxygen and the added coolant are $\Delta C = C_g - C_{em}$ and $\Delta T = T_g - T_{em}$ respectively. In general, the control range for the endpoint carbon content is $\pm 5(\times 10^{-2}\%)$, and the control range for the endpoint temperature is $\pm 15℃$. ΔC and ΔT are divided into fuzzy subset as follows

$$\Delta C = \{NVB,NB,NM,NS,ZE,PS,PM,PB,PVB\} = \{-5,-4,-3,-2,0,2,3,4,5\},$$

$$\Delta T = \{NB,NM,NS,ZE,PS,PM,PB\} = \{-15,-10,-5,0,5,10,15\}.$$

The corresponding membership function is shown in Fig. 5 (a) and (b).

Let ΔT and ΔC membership function be μ_T and μ_C respectively, use product-sum inference method, and use gravity centre method to defuzzy. ΔT and ΔC membership function is triangular as shown in Fig.5. Two rules are activated at each point, and sum of two membership degree is 1, therefore the outputs of the fuzzy modifying model of the reblown oxygen and the added coolant are respectively

$$\begin{cases}\Delta V_O = \sum_i \mu_C(\Delta C_i)\Delta C_i, \\ W_r = \sum_i \mu_T(\Delta T_i)\Delta T_i.\end{cases} \tag{8}$$

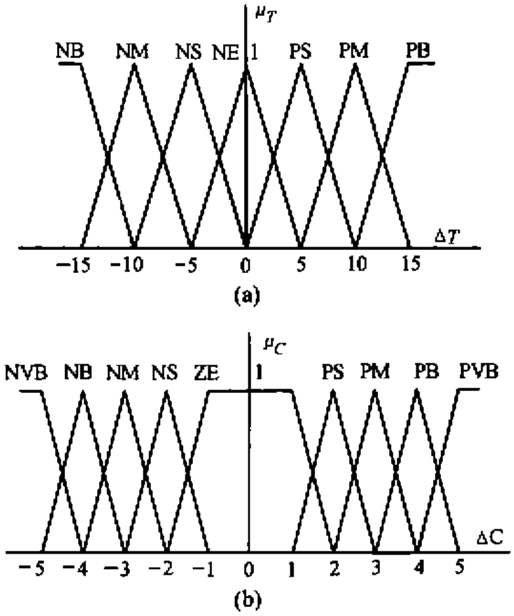

Fig. 5 ΔT and ΔC membership function

An amount of the blown oxygen and the weight of the added coolant have more definite relation with the molten steel temperature and carbon content in BOF steelmaking. The more oxygen is blown, the more the carbon content is reduced. The more coolant is added, the more the temperature is reduced. As a result, the adjusting rule of the blown oxygen and the added coolant may be easily obtained. They are shown in Table 1 and 2 respectively.

Table 1 Fuzzy adjusting rule of the blown oxygen

ΔC	NVB	NB	NM	NS	ZE	PS	PM	PB	PVB
ΔV_O	20	10	5	2	0	−2	−5	−10	−20

Table 2 Fuzzy adjusting rule of the added coolant

ΔT	NB	NM	NS	ZE	PS	PM	PB
W_r	0.1	0.05	0.02	0	0	0	0

In Table 1, ΔV_O unit is normal cube meter (Nm^3). In Table 2, W_r unit is ton(t). They are all adjustment value per heat. To obtain adjustment value per ton, the adjustment value per heat needs to be divided by the molten steel weight. When the temperature calculated by the predictive model is lower than the goal temperature, the coolant should not be added. Moreover the blown oxygen is calculated by use of the presetting model on condition that no coolant is added. So when ΔT is positive, W_r is 0 in table 2.

4 Simulating research

The practical data of 60 heats of a 180t converter in a factory are simulated, in which the data of the former 35 heats are used for establishing the predictive model and the presetting model, the other 25 heats are calculated. The hidden nodes of the neural network to be used for compensation are 12. The hidden nodes of the neural network as the preset model are 7. Both the learning rates are $\lambda = 0.995$. Both the error rules are $\varepsilon = 0.001$. In simulation, firstly the predictive model and presetting model are established taking advantage of the sample data. Secondly the reblown oxygen is calculated by the presetting model making use of the data measured by sublance and the goal data on condition that no coolant is added. Thirdly the endpoint temperature and carbon content are calculated through the predictive model in the case of the above circumstance. They are compared with the goal endpoint temperature and carbon content. The reblown oxygen and the added coolant are adjusted by use of the modifying model. The adjusted value is sent to the predictive model to calculate the endpoint temperature and carbon content until the endpoint temperature and carbon content are in the goal area ($|\Delta C| \leqslant 3$, $0℃ \geqslant \Delta T \geqslant -10℃$). At last, the reblown oxygen (Nm^3)) and the added coolant(t) are determined. The whole simulating process corresponds to the practical steelmaking process. First, the predictive model and the presetting model are established using the data of the former 35 heats. The 36th heat is calculated. Then the sample data of the 36th heat are added to the modeling data, and the data of the first heat are simultaneously removed so as to hold unchangeable the number of data to be used for establishing model. The above process is repeated until all 25 heats are calculated. The reblown oxygen and the added coolant of the other 25 heats are calculated as shown in Fig.6 (a) and (b). The corresponding endpoint temperature (℃) and carbon content (10^{-2}%) are shown in Fig.7 (a) and (b). In the figures, "——" is the actual value "------"is the calculated value based on the model. From the figures, it is known that the reblown oxygen and the added coolant calculated are close to the practical value in most heats. The mean-square error between the calculated value and the actual value of the endpoint carbon content ($\times 10^{-2}\%$) $\sigma_c = 2.4032$, while the mean-square error between the calculated value and the actual value of the endpoint temperaure (℃) $\sigma_T = 7.6226$. It is shown that the precision of this method is higher and it may be completely used for the endpoint dynamic control in practical BOF process.

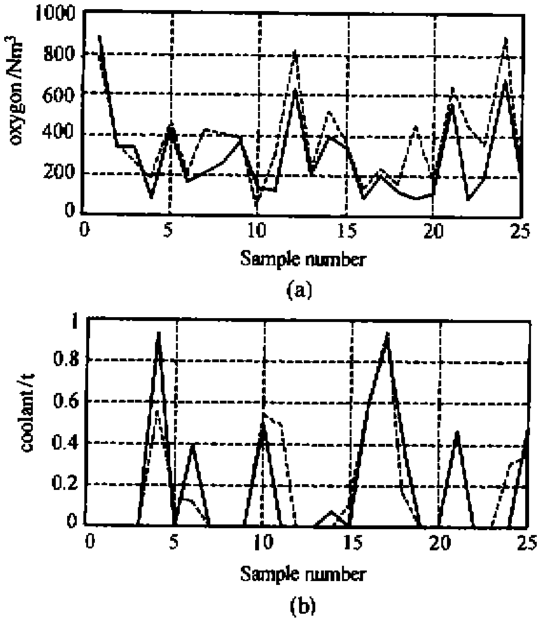

Fig. 6 The blown oxygen and the added coolant

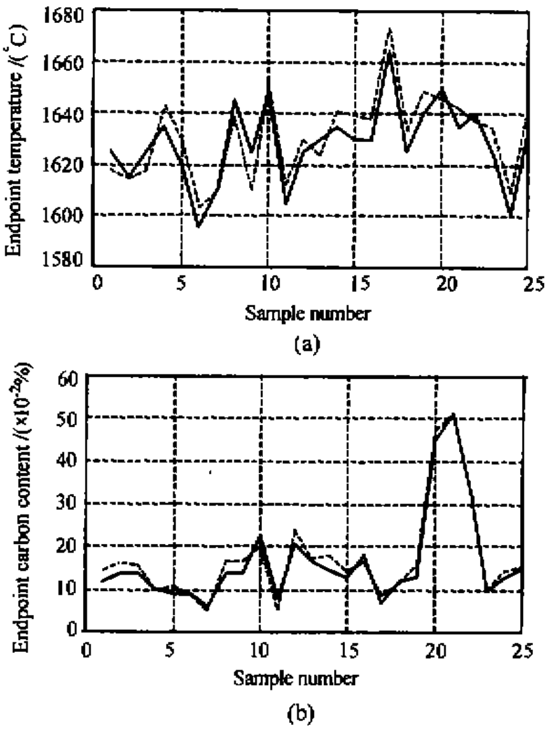

Fig. 7 The endpoint control temperature and carbon content

5 Conclusion

The control for the BOF endpoint is different from general process control. It is practically an optimal setting problem. In the intelligent dynamic endpoint control, the influence of the nonquantitative factors on the endpoint is reflected by the GM(1,1) model, while the influence of the quantitative factors on the endpoint is reflected by the compensation of a neural network. So the model precision is raised. A neural network is regarded as presetting model, and the reblown oxygen and the added coolant are adjusted by use of fuzzy rules. In result, the shortcoming which any adjustment is not made after determined the reblown oxygen and the added coolant in the existing method is overcome. The endpoint hitting ratio is further raised.

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