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FUZZY ADAPTIVE CONTROL MODEL FOR PROCESS IN NICKEL MATTE SMELTING FURNACE[①]

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ABSTRACT

An identification method of fuzzy adaptive control model for the process in nickel matte smelting furnace is developed. This method is mainly based on the data accumulated in operation process. An intelligent decision support system(IDSS) on the process of nickel matte smelter has been designed with this method and put into operation. The electric energy consumption for smelting has been reduced and the coefficient of recovery of nickel has been increased.
Key words: nickel matte smelting furnace fuzzy control

1 INTRODUCTION

There are three 16 500 kVA nickel matte electric smelting furnace in a smeltery. If the slow-varying factors in smelting process are neglected, the smelter can be considered as a multi-input and multi-output(MIMO) system as shown in Fig. 1. where k is the time inputting and outputting

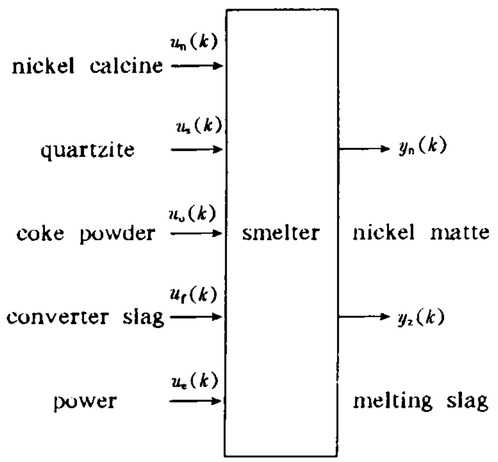

Fig. 1 Nickel matte smelter

matterials.

Calcine is the main charge in electric furnace, its composition is Ni, Cu, Fe, SiO_2, Co, MgO, CaO, etc. and the quantites of calcine composition change sometimes. Quartzite is slag- making flux and its main composition is SiO_2. Coke powder as a reducer has main composition C. The composition of quartzite and coke powder is generally steady. In order to increase the yield of nickel and cobalt, liquidus hot converter slag is partially inputted to the electric furnace.

The objective of process control is to reduce the electric energy consumption per tonne of calcine and nickel loss in slag to be minima, which leads to reduce the energy wastage and increase the smelting yield. The means of achieving the targets is optimizing the input of quartzite flux and coke powder according to calcine weight and composition, then optimizing the power supply and output of nickel matte and melting slag according to smelting charge and state of the furnace.

Because the composition of smelting charge is unsteady, measuring devices are unperfect, the error and delay of measurement are striking, and it is difficult to obtain the accurate mathematical model

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on the process of nickel matte smelter, a fuzzy adaptive control model is developed in this paper and has been used in the IDSS on the process of nickel matte electric furnace.

2 IDENTIFICATION METHOD OF FUZZY CONTROL MODEL

Every group of practical production data is defined as a "sample". A large number of samples accumulated in the smelting process fully reflect the policies of managers and operators at various situations. The policy obtaining optimal performance indexes is defined as "optimal policy", and the corresponding sample is defined as "optimal sample". A fuzzy control rule can be acquired from an optimal sample. When enough optimal samples are acquired, effective fuzzy control model can be established. Optimal control can be made by the fuzzy control rules based on optimal samples.

For example, the result of relative analysis for the input of calcine is shown as follows:

$$u_n(k) = F[u_n(k-1),\ u_n(k-2),\ u_s(k-1),\ u_s(k-2),\ u_e(k-1),\ u_e(k-2),\ u_f(k-1),\ u_f(k-2),\ y_n(k-1),\ y_n(k-2),\ y_z(k-1),\ y_z(k-2)]$$

It can be seen that the input of calcine $u_n(k)$ is independent of coke powder.

If a series of fuzzy subsets are properly defined in the promissive space of variables, then a fuzzy control rule R^i based on an optimal sample can be acquired as follows[1]:

if $u_n(k-1)$ is A_n^{i1}, $u_n(k-2)$ is A_n^{i2}, $u_s(k-1)$ is A_s^{i1}, $u_s(k-2)$ is A_s^{i2}, $u_e(k-1)$ is A_e^{i1}, $u_e(k-2)$ is A_e^{i2}, $u_f(k-1)$ is A_f^{i1}, $u_f(k-2)$ is A_f^{i2}, $y_n(k-1)$ is B_n^{i1}, $y_n(k-2)$ is B_n^{i2}, $y_z(k-1)$ is B_z^{i1}, $y_z(k-2)$ is B_z^{i2},

then
$$\begin{aligned} u_n^i(k) = {} & a_0^i + a_{11}^i u_n(k-1) + a_{12}^i u_n(k-2) \\ & + a_{21}^i u_s(k-1) + a_{22}^i u_s(k-2) \\ & + a_{31}^i u_e(k-1) + a_{32}^i u_e(k-2) \\ & + a_{41}^i u_f(k-1) + a_{42}^i u_f(k-2) \\ & + a_{51}^i y_n(k-1) + a_{52}^i y_n(k-2) \\ & + a_{61}^i y_z(k-1) + a_{62}^i y_z(k-2) \\ & + e_n^i(k) \end{aligned} \tag{1}$$

where A_n^{ij}, A_s^{ij}, A_e^{ij}, A_f^{ij}, B_n^{ij}, B_z^{ij} ($j=1, 2$; $i = 1, 2, \cdots\cdots m$. m is the total of optimal samples) denote the fuzzy subsets of the quantity of calcine, quartzite, power supply, converter slag, nickel matte and smelting slag output respectively.

a_0^i, a_{11}^i, a_{12}^i, $\cdots\cdots a_{62}^i$ are consequence parameters. $u_n^i(k)$ is the input of calcine at time k and it is decided by the i-th fuzzy control rule. $e_n^i(k)$ is the error of fuzzy control rule. In the same way, it can be acquired n fuzzy control rules on the input and output of the smelter from n optimal samples.

let
$$\boldsymbol{x} = [u_n(k-1)\ u_n(k-2)\ u_s(k-1)\ u_s(k-2)\ u_e(k-1)\ u_e(k-2)\ u_f(k-1)\ u_f(k-2)\ y_n(k-1)\ y_n(k-2)\ y_z(k-1)\ y_z(k-2)]^T \tag{2}$$

$$\theta_i = [a_0^i\ a_{11}^i\ a_{12}^i\ a_{21}^i\ a_{22}^i\ a_{31}^i\ a_{32}^i\ a_{41}^i\ a_{42}^i\ a_{51}^i\ a_{52}^i\ a_{61}^i\ a_{62}^i]^T \tag{3}$$

Then Eq. (1) may be expressed as

$$u_n^i(k) = \boldsymbol{x}^T \cdot \theta_i + e_n^i(k) \tag{4}$$

The input of calcine at k time is

$$u_n(k) = \sum_{i=1}^{m} \lambda_i \cdot u_n^i(k) / \sum_{i=1}^{m} \lambda_i \tag{5}$$

where m is the total of fuzzy control rules.

$$\begin{aligned} \lambda_i = {} & A_n^{i1}[u_n(k-1)] \wedge A_n^{i2}[u_n(k-2)] \wedge \\ & A_s^{i1}[u_s(k-1)] \wedge A_s^{i2}[u_s(k-2)] \wedge \\ & A_e^{i1}[u_e(k-1)] \wedge A_e^{i2}[u_e(k-2)] \wedge \\ & A_f^{i1}[u_f(k-1)] \wedge A_f^{i2}[u_f(k-2)] \wedge \\ & B_n^{i1}[y_n(k-1)] \wedge B_n^{i2}[y_n(k-2)] \wedge \\ & B_z^{i1}[y_z(k-1)] \wedge B_z^{i2}[y_z(k-2)] \end{aligned} \tag{6}$$

where "$\wedge$" expresses "and" in fuzzy logic.

$A_n^{i1}[u_n(k-1)]$ expresses the membership function value of $u_n(k-1)$ for fuzzy subset A_n^{i1}. The others are similar to $A_n^{i1}[u_n(k-1)]$.

If we insert the Eq. (4) into (5), then

$$u_n(k) = \frac{\lambda_1}{\sum_{i=1}^{m}\lambda_i}\boldsymbol{x}^T \cdot \theta_1 + \frac{\lambda_2}{\sum_{i=1}^{m}\lambda_i}\boldsymbol{x}^T \cdot \theta_2 + \cdots + \frac{\lambda_m}{\sum_{i=1}^{m}\lambda_i}\boldsymbol{x}^T \cdot \theta_m + e_n(k) \tag{7}$$

where $e_n(k)$ is the error of fuzzy control model.

Let
$$\boldsymbol{x}_i = \frac{\lambda_i}{\sum_{j=1}^{m}\lambda_i}\boldsymbol{x}^T \tag{8}$$

$$\boldsymbol{x}^L = [\boldsymbol{x}_1\ \ \boldsymbol{x}_2 \cdots \boldsymbol{x}_m]^T \tag{9}$$

$$\theta = [\theta_1\ \ \theta_2 \cdots \theta_m]^T \tag{10}$$

Then the optimal control model of calcine input $u_n(k)$ is expressed as

$$u_n(k) = (\boldsymbol{x}^L)^T \cdot \theta + e_n(k) \tag{11}$$

where θ is the unknown consequaence parameter vector.

By regarding the electric energy consumption per tonne calcine and nickel loss in slag as targets to be optimized, N optimal samples ($N > 12m$) are selected from a large number of data accumulated in the smelting process. When these samples are substituted into Eq. (9), N vectors $\boldsymbol{x}^1$, $\boldsymbol{x}^2$, $\cdots$, $\boldsymbol{x}^N$ can be obtained. When N optimal samples and $\boldsymbol{x}^1$, $\boldsymbol{x}^2$, $\cdots$, $\boldsymbol{x}^N$ are substituted into Eq. (11), N linear equations can be acquired as follows:

$$\begin{aligned} u_n(k_1) &= (\boldsymbol{x}^1)^T \cdot \theta + e_n(k_1) \\ u_n(k_2) &= (\boldsymbol{x}^2)^T \cdot \theta + e_n(k_2) \\ &\cdots\cdots \\ u_n(k_N) &= (\boldsymbol{x}^N)^T \cdot \theta + e_n(k_N) \end{aligned} \quad (12)$$

let $\boldsymbol{u}_N = [u_n(k_1)\ u_n(k_2) \cdots u_n(k_N)]^T$ (13)

$\Phi = [(\boldsymbol{x}^1)^T (\boldsymbol{x}^2)^T \cdots (\boldsymbol{x}^N)^T]^T$ (14)

$\boldsymbol{e} = [e_n(k_1)\ e_n(k_2) \cdots e_n(k_N)]^T$ (15)

Then $\boldsymbol{u}_N = \varphi \cdot \theta + \boldsymbol{e}$ (16)

Let $J = \boldsymbol{e}^T \boldsymbol{e}$ (17)

In order to obtain the optimal θ, J should reach its minimum.

Let $\dfrac{\partial J}{\partial \theta} = \dfrac{\partial}{\partial \theta}(\boldsymbol{e}^T \boldsymbol{e}) = 0$ (18)

Then $\Phi^T \Phi \cdot \theta - \Phi^T \boldsymbol{u}_n = 0$ (19)

If $\Phi^T \Phi$ is not queer, then:

$\hat{\theta} = [\Phi^T \cdot \Phi]^{-1} \cdot \Phi^T \cdot \boldsymbol{u}_N$ (20)

$\hat{\theta}$ is optimal estimate of θ.

In the same way, fuzzy control models of power supply, output of nickel matte and smelting slag, and input of quartzite, coke powder, and converter slag can be obtained.

3 ADAPTIVE CONTROL MODEL

Every new optimal sample in the smelting process can determine a new fuzzy control rule. If the worst rule is removed from Eq. (14) and the new rule is appended to Eq. (14), then new $\hat{\theta}$ can be obtained by solving Eq. (20). Then, the fuzzy control model can be modified automatically and possesses self-learning and self-adaptive properties.

When we calculate the input of calcine, quartzite, coke powder and converter slag, it is necessary to understand what the types of nickel calcine are. Because the calcine composition is unsteady and the results of measurement are not available during one or two days, the calcine composition forecasting model on time sequence is established by means of model identification and can be modified automatically[2].

4 APPLICATION

The IOSS has been used successfully since May 1992. Comparing the production indexes from July to December 1992 with that of the same period in 1991, the improvement made by the application of this technique is as follows:

(1) The nickel in smelting slag is reduced from 0.247% to 0.233%. In practice one smelter operates 300 days every year and produces 600 tonne slag every day, then the nickel production increassed every year is 75.6 tonne.

(2) The electric energy consumption per tonne of calcine is reduced by 18 kW·h. And one furnace smelts 450 tonne calcine every day, then the electric energy consumption saved every year is 7.29×10^6 kW·h.

5 CONCLUSIONS

(1) A new practical identification method of adaptive fuzzy control model is developed. The method can be applied to computer control of industrial process.

(2) The IDSS on the process of nickel matte smelter based on this method can make optimal control policy, in consequences, the operating state is improved gradually, electric energy consumption and nickel loss in smelting slag are reduced and the coefficient of recovery of resource is increased.

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