A FUZZY NEURAL NETWORK DECISION MODEL ON THE OPERATION PROCESS OF ELECTRIC FURNACE FOR CLEANING SLAG AND ITS APPLICATION①

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ABSTRACT A fuzzy neural network decision model(FNNDM) on the operation process of electric furnace for cleaning slag was developed. An intelligent decision support system (IDSS) based on the model has been designed and put into operation since June 1992; the electric energy consumption for smelting has been reduced remarkably, and the coefficient of recovery of cobalt and nickel has been increased.

Key words fuzzy neural network electric furnace for cleaning slag IDSS

1 INTRODUCTION

There are two 5 000 kVA electric furnaces for cleaning slag in a smeltery. If the slow-varying factors in smelting process are neglected, the smelter can be considered as a multivariable system shown in Fig. 1.

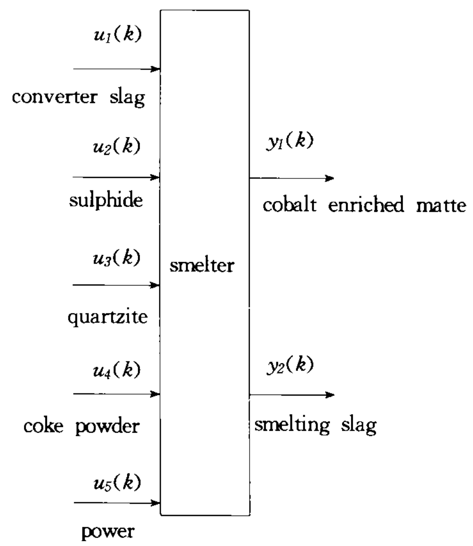

Fig. 1 Electric furnace for cleaning slag

In order to recover cobalt and nickel from converter slag, liquidus converter slag is smelted in the smelter. Sulphide is applied for resolving magnetite in converter slag and producing cobalt enriched matte. Coke powder is reducer. Quartzite is slag-making flux . When electric energy is inputted, charge is smelted and cobalt enriched matte and smelting slag are outflowed.

The operation process is divided into melting stage and cleaning stage. In order to melt charge quickly, prolong the cleaning stage and decrease the cobalt and nickel in smelting slag, it is necessary to intensify the current through the electrodes of smelter during melting stage. For decreasing the electric energy consumption, the current through the electrodes should be reduced during cleaning stage.

The targets of operation process decision are to reduce the electric energy consumption per tonne of converter slag and the loss of cobalt and nickel in smelting slag to the minima. The means of achieving the targets is to optimize the input of sulphide, quartzite and coke powder according to the weight and com-

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position of converter slag, then optimize the power supply and the sustained time in melting stage and cleaning stage as well as the output of cobalt enriched matte and smelting slag according to smelting charge and state of smelter.

Because the composition of smelting charge is unsteady, measuring devices are unperfect, the error and delay of measurement are striking, it is difficult to make optimal decision according to the calculation of substantial and thermal balance. A fuzzy neural network decision model on the operation process of electric furnace for cleaning slag was developed in this paper and has been used in the IDSS of the smelter.

2 THE FUZZY NEURAL NETWORK DECISION MODEL

Let $u_1(k)$ be the input of converter slag at k time, $u_2(k)$ the input of sulphide at k time, $u_3(k)$ the input of quartzite at k time, $u_4(k)$ the input of coke powder at k time, $u_5(k)$ the power supply at k time, $y_1(k)$ the output of cobalt enriched matte at k time, $y_2(k)$ the output of smelting slag at k time.

$A_j^i (j = 1, 2, \cdots, 5)$, B_1^i and B_2^i denote separately a series of fuzzy subsets defined in the universe of discourse of u_j, y_1 and y_2.

$A_j^i[u_j(k)]$, $B_1^i[y_1(k)]$ and $B_2^i[y_2(k)]$ denote separately the membership function value of $u_j(k)$ for A_j^i, $y_1(k)$ for B_1^i and $y_2(k)$ for B_2^i.

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 decision rule can be acquired from an optimal sample. If enough optimal samples are acquired, then effective fuzzy decision model can be established and optimal decision can be made[1], or else a fuzzy neural network decision model should be established.

In order to decrease the complicated degree and accelerate the learning speed of fuzzy neural network, the structure of decision model should be found with the methods of structure identification and relative analysis[2]. For example, the analysis result for the power supply is shown as follows:

$$u_5(k) = F[u_1(k), u_1(k-1), u_2(k), u_2(k-1), u_3(k), u_3(k-1) \\ u_4(k), u_5(k-1), y_1(k-1), y_2(k-1)] \tag{1}$$

A fuzzy decision rule R^l based on an optimal sample can be acquired as follows[3]:

if $u_1(k)$ is A_1^{l0}, $u_1(k-1)$ is A_1^{l1},
$u_2(k)$ is A_2^{l0}, $u_2(k-1)$ is A_2^{l1},
$u_3(k)$ is A_3^{l0}, $u_3(k-1)$ is A_3^{l1},
$u_4(k)$ is A_4^{l0}, $u_5(k-1)$ is A_5^{l1},
$y_1(k-1)$ is B_1^{l1}, $y_2(k-1)$ is B_2^{l1}
then

$$\begin{aligned} u_5^l(k) = a_0^l &+ a_{10}^l u_1(k) + a_{11}^l u_1(k-1) \\ &+ a_{20}^l u_2(k) + a_{21}^l u_2(k-1) \\ &+ a_{30}^l u_3(k) + a_{31}^l u_3(k-1) \\ &+ a_{40}^l u_4(k) + a_{51}^l u_5(k-1) \\ &+ b_{11}^l y_1(k-1) + b_{21}^l y_2(k-1) \end{aligned} \tag{2}$$

where a_0^l, a_{ij}^l, $b_{i'j}^l (i = 1, 2, \cdots, 5; i' = 1, 2; j = 0, 1)$ are consequence parameters; $u_5^l(k)$ is the power supply decided by the l-th fuzzy decision rule.

Let

$$\begin{aligned} \theta_l = [&a_0^l \quad a_{10}^l \quad a_{11}^l \quad a_{20}^l \quad a_{21}^l \quad a_{30}^l \\ &a_{31}^l \quad a_{40}^l \quad a_{51}^l \quad b_{11}^l \quad b_{21}^l]^{\mathrm{T}} \end{aligned} \tag{3}$$

$$\begin{aligned} \varphi = [&1 \quad u_1(k) \quad u_1(k-1) \quad u_2(k) \\ &u_2(k-1) \quad u_3(k) \quad u_3(k-1) \\ &u_4(k) \quad u_5(k-1) \quad y_1(k-1) \\ &y_2(k-1)]^{\mathrm{T}} \end{aligned} \tag{4}$$

then the equation(2) may be expressed as:

$$u_5^l(k) = \theta_l^{\mathrm{T}} \cdot \varphi \tag{5}$$

The power supply $u_5(k)$ is:

$$u_5(k) = \sum_{l=1}^{L} \lambda_l \cdot u_5^l(k) / \sum_{l=1}^{L} \lambda_l \tag{6}$$

$$\begin{aligned} \lambda_l = A_1^{l0}[u_1(k)] &\wedge A_1^{l1}[u_1(k-1)] \\ \wedge A_2^{l0}[u_2(k)] &\wedge A_2^{l1}[u_2(k-1)] \\ \wedge A_3^{l0}[u_3(k)] &\wedge A_3^{l1}[u_3(k-1)] \\ \wedge A_4^{l0}[u_4(k)] &\wedge A_5^{l1}[u_5(k-1)] \\ \wedge B_1^{l1}[y_1(k-1)] &\wedge B_2^{l1}[y_2(k-1)] \end{aligned} \tag{7}$$

where L is the total of fuzzy decision rules;

" ∧ " expresses the calculation of obtaining minimum. The fuzzy neural network based on equation (6) is shown in Fig. 2.
Where Σ, $\times$, $\div$, $\wedge$, A_j^l and $B_{j'}^l$ denote separately neuron executing addition, multiplication, division, the calculation of obtaining minimum and membership function value.

The learning algorithm of fuzzy neural network is inferred as follows:
Let

$$\Theta = [\theta_1^{\mathrm{T}}\ \theta_2^{\mathrm{T}} \cdots \theta_L^{\mathrm{T}}]^{\mathrm{T}} \tag{8}$$

Then equation (6) may be expressed as:

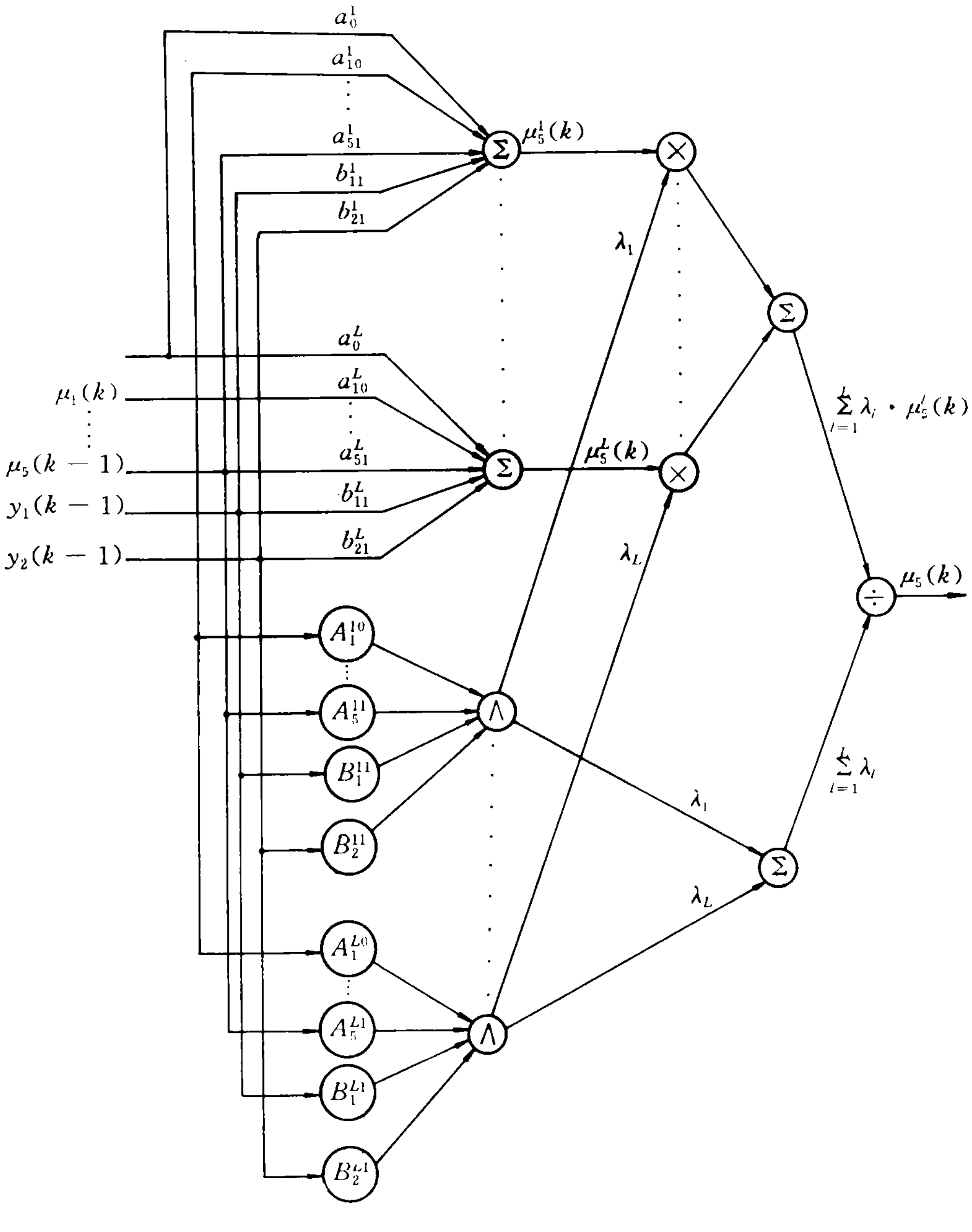

Fig. 2 Fuzzy neural network decision model of $u_5(k)$

$$u_5(k) = \frac{1}{\sum_{l=1}^{L} \lambda_l}[\lambda_1\ \lambda_2 \cdots \lambda_L] \cdot \Theta \cdot \varphi \tag{9}$$

Let error function J be:

$$J = 1/2[u_5^*(k) - u_5(k)]^2 \tag{10}$$

where $u_5^*(k)$ is practical input in optimal sample and $u_5(k)$ is the output calculated by fuzzy neural network. The study target of fuzzy neural network is to reduce J to minimum.

Because

$$\frac{\partial J}{\partial a_0^l} = \frac{\partial J}{\partial u_5(k)} \cdot \frac{\partial u_5(k)}{\partial a_0^l} = -[u_5^*(k) - u_5(k)] \cdot \frac{\lambda_l}{\sum_{l=1}^{L} \lambda_l} \tag{11}$$

$$\frac{\partial J}{\partial a_{l,j}} = \frac{\partial J}{\partial u_5(k)} \cdot \frac{\partial u_5(k)}{\partial a_{ij}^l} = -[u_5^*(k) - u_5(k)] \cdot \frac{\lambda_l}{\sum_{l=1}^{L} \lambda_l} \cdot u_i(k-j) \tag{12}$$

$$\frac{\partial J}{\partial b_{i'j}^l} = \frac{\partial J}{\partial u_5(k)} \cdot \frac{\partial u_5(k)}{\partial b_{i'j}^l} = -[u_5^*(k) - u_5(k)] \cdot \frac{\lambda_l}{\sum_{l=1}^{L} \lambda_l} \cdot y_{i'}(k-j) \tag{13}$$

Let $\Delta u_5(k) = u_5^*(k) - u_5(k)$ (14)

$$\lambda = [\lambda_1\ \lambda_2 \cdots \lambda_L]^{\mathrm{T}} \tag{15}$$

then

$$\Theta = \Theta_0 + \Delta\Theta = \Theta_0 + \frac{\eta \cdot \Delta u_5(k)}{\sum_{l=1}^{L} \lambda_l} \cdot \lambda \cdot \varphi^{\mathrm{T}} \tag{16}$$

where η is the learning speed of neural network; Θ_0 is the original value of Θ.

The equation (16) is the learning algorithm of neural network. The neural network can be trained with optimal samples. When the study process of neural network is completed, Θ may be determined. Because the study samples of neural network are optimal ones, the decision model obtained is optimal model and the optimal operation decision can be decided by the fuzzy neural network.

If the fuzzy neural network is trained with new optimal samples acquired in the smelting process, the fuzzy neural network decision model can be modified automatically and possesses self-learning and self-adaptive properties.

In the same way, other decision models can be acquired.

3 APPLICATION

The fuzzy neural network decision model on the operation process of electric furnace for cleaning slag has been established with the method in this paper. An intelligent decision support system (IDSS) based on the model has been designed and put into operation since June 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 electric energy consumption per tonne of converter slag is reduced by 39.6%.

(2) The cobalt in smelting slag is reduced by 23.7%.

(3) The nickel in smelting slag is reduced by 61.4%.

4 CONCLUSIONS

(1) A new fuzzy neural network decision model for making decision of industrial process is developed.

(2) The IDSS on the operation process of electric furnace for cleaning slag based on the model can make optimal operation decision, operating state of the smelter can be improved gradually, and electric energy consumption and the loss of cobalt and nickel in smelting slag can be reduced.

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