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Optimal Control Strategy Research on Aluminum Electrolysis Fault Diagnosis System

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Abstract: Aluminum electrolysis system is a complex industrial process with nonlinear, multivariable, time-varying and large time delay .The mathematical model of it is very difficult to determine, as well as it has a large coupling between the control variable which with high energy consumption. Therefore, research on save power, improve the current efficiency and increase the output and quality of the aluminum electrolysis control system have been become the focus of public concern to be solved. In this paper, by adjusting the controller = s control strategy at real-time, controlling the feeding time and feeding rate of alumina, as well as effectively making the alumina concentration is controlled in the range of ideal value, they can make the electrolytic cell at the best working condition. Experimental results showed that this method was effective, increased the current efficiency, improved the control performance, and it had a great significance to raise the output and quality of aluminum.

Key words: Alumina concentration, aluminum electrolysis, control strategy, neural network

INTRODUCTION

In the process of aluminum electrolysis, aluminum feeding device is the core equipment. It has a significant effect on the indicators of aluminum electrolytic production, the output and quality of aluminum. If the alumina concentration is too high, it will cause the precipitation accumulate at the bottom of the aluminum electrolysis cell, increase its resistance and reduce the current efficiency. On the contrary, the alumina concentration is too low, it will cause the anode effect, destruct the energy balance of electrolysis cell and loss a large amount of energy. Consequently, the alumina concentration control has a vital role, which of great significance to save power. Generally, adopted the method of point feeding control in aluminum electrolytic process, but it has a disadvantage that adopted the unified control mode without according to the working state of each electrolytic cell. This mode of control caused the alumina concentration control of electrolytic cell is not targeted, could not made the electrolytic cell under different working conditions to achieve the best working state, as well as wasted a lot of electricity. Consequently, this paper put forward a optimal control strategy on aluminum electrolysis fault diagnosis system that is adopt different control strategy according to the normal state and the fault state of electrolytic cell, adjusting the feeding time and feeding rate of alumina, made the alumina concentration control in the ideal range, and then enable the electrolytic cell to achieve the best working conditions. Accordingly, to improve the current efficiency, reduce the production costs and energy consumption purposes (Feng, 2006).

CONTROL OF ALUMINA CONCENTRATION

Due to the aluminum electrolytic is a very complicated electrochemical change process, which alumina concentration can = t be measured directly online. However, only the date of cell voltage and series current can be measured online, and the cell resistance can be obtain through the cell voltage and cell current ratio, the formula as follows:

$$R = \frac{V - E}{I}$$

E-the counter electromotive force of electrolytic cell.

Consequently, the first step is measure the voltage and current series, the second step is through these measurements to calculate the cell resistance, the final step is indirectly calculate the alumina concentration through the relation between alumina concentration and cell resistance.

CONTROLLER DESIGN OF NORMAL STATE

Controller structure design: The aluminum electrolytic working feature of normal state is as following: The alumina concentration gradually decreases with the

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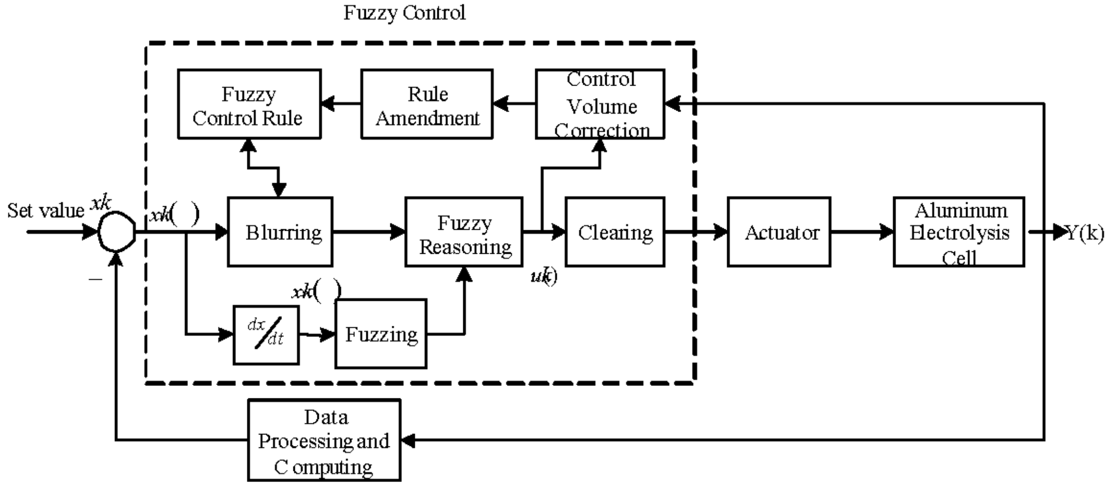

Fig. 1: Composition principle diagram of adaptive fuzzy control

proceeding of aluminum electrolysis, it needs to add the alumina into the electrolytic cell, and control the feeding time and feeding rate. According to the characteristics of aluminum electrolysis process, in order to ensure keep high performance in it and achieve the goal of energy saving, this paper adopted adaptive fuzzy control technology and made the aluminum electrolysis system was running in the best working state. This method effectively overcomes the low aluminum's rate of PID control and drawback of current reduced efficiency. The composition principle diagram is shown in Fig. 1 (Xu *et al*., 2013).

The adaptive fuzzy control system adopt computer technology and fuzzy control technology, setting the controller's input value as the resistance x (k), setting the fuzzy controller's input value as the cell resistance deviation value x_1 (k) and the cell resistance deviation change rate x_2 (k), u (k) serve as the output of the fuzzy neural network controller, y (k) serve as the actual output value of the cell resistance. Through the adaptive fuzzy optimization control of the cell resistance realize the overall optimization of the aluminum electrolytic system performance. The fuzzy controller is the core equipment, which mainly operate some important process such as blurring the input value, computing the fuzzy relation, fuzzy decision, anti-blurring the decision outcome, and so on.

Fuzzy algorithm of adaptive fuzzy controller: According to the characteristics of aluminum electrolysis process adopt the fuzzy RBF neural network control method, which has two input value respectively are cell resistance x_1 and cell resistance variation x_2.Setting the language value of the fuzzy control as following:

Table 1: The fuzzy control rule

x2 µ xl	NB	NM	NS	ZE	PS	PM	PB
NB	NB	NB	NM	NM	NS	NS	ZE
NM	NB	NM	NM	NS	NS	ZE	PS
NS	NB	NM	NM	NS	NS	ZE	PS
ZE	NM	NS	NS	ZE	PS	PS	PM
PS	NS	NS	ZE	PS	PS	PM	PM
PM	NS	ZE	PS	PS	PM	PM	PB
PB	ZE	PS	PS	PM	PM	PB	PB

- NB (Negative maximum value), NM (Negative middle value)
- NS (Negative minimum value), ZE (Zero)
- PS (Positive minimum value), PM (Positive middle value)
- PB (Negative maximum value)

The fuzzy control rule was shown in Table 1.

The first layer of the fuzzy RBF neural network is the input layer, each node of the input layer connects each component of the input directly, and then transmit the input to the next layer, namely: x_1, x_2 (Xu and Mao, 2013):

$$O_1(i) = X = [x_1, x_2] \tag{1}$$

The second layer is the fuzzy layer, this layer used gaussian function as the membership function of the fuzzy control (Huang *et al*., 2013):

$$O_2(i, j) = \exp[-\frac{(O_1(i) - c_{ij})^2}{b_{ij}^2}] \tag{2}$$

The third layer is the fuzzy rule layer, this layer achieves the matching of fuzzy rules, the output of node j defined as follows:

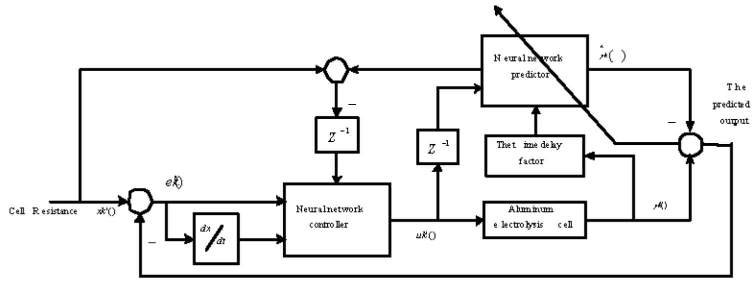

Fig. 2: Principle diagram of the predictive control system

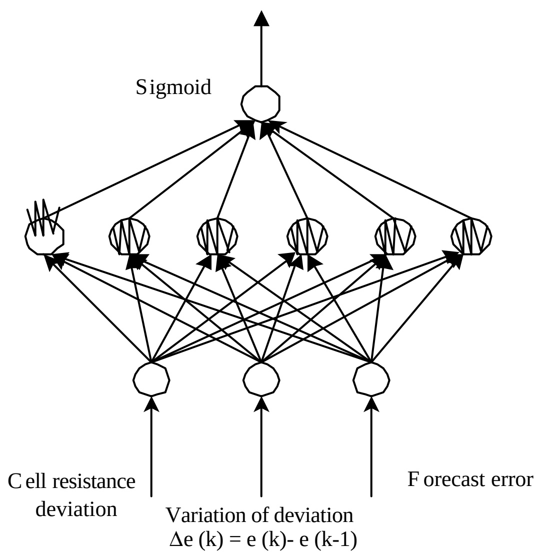

Fig. 3: Structure of wavelet neural network

$$O_3(j) = \prod_{j=1}^{N} O_2(i, j) \tag{3}$$

The forth layer is the output layer, the output of each node in this layer is the weighted sums of the input signal, namely:

$$O_4(l) = W \cdot O_3 = \sum_{j=1}^{N} W(l, j) \cdot O_3(j) \tag{4}$$

In this study, it adopted the approximation algorithm based on fuzzy neural network, the inputs were cell resistance x_1 and the cell resistance variation x_2, the output was controlled quantity y, so y (k) = O_4.

The performance index defined as follows:

$$J = \frac{1}{2}[r(k+1) - y(k+1)]^2 \tag{5}$$

CONTROLLER CONTROLLER DESIGN OF FAULT STATE

In the process of aluminum electrolytic fault occurs frequently, these failures can change the cell temperature, which leads to cell resistance increased, dynamic law is different from normal, liquid aluminum fluctuate wildly, the process parameters change obviously and nonlinear performance is more remarkable.And because of the existence of large time-delay system, adopt the conventional control system may give rise to the response speed is slow, control accuracy is not high and waste much of electricity. Consequently, in this paper adopt predictive control system which can imitate the human's thinking way to control the aluminum electrolysis system. And reasonably combine the predictor and the controller together to realize the optimization control on aluminum electrolysis process, its principle diagram of the system as shown in Fig. 2. The cell resistance and the rate of cell resistance's change serve as the input value, the controller's input set as the cell resistance x′ (k),the output y′ (k) is the actual output value of the cell resistance, the output u′ (k) of neural network controller serve as the input of recursive wavelet neural network prediction structure, the output ŷ (k) of predictor serve as the parameter feedback to the controller in order to improve the system's control accuracy (Xu, 2009).

Controller design based on wavelet neural network: The controller adopt wavelet neural network, its structure diagram as shown in Fig. 3. The inputs of controller are the cell resistance deviation value e (k), the variance of deviation value Δe (k) = e (k)-e (k)-e (k-1) and the forecast error ŷ (k) -x′ (k), respectively. The output of controller is the controlled quantity u′.

In the controller of wavelet neural network to calculate the hidden nodes, the total input and output of the output nodes respectively, and get the following formulas:

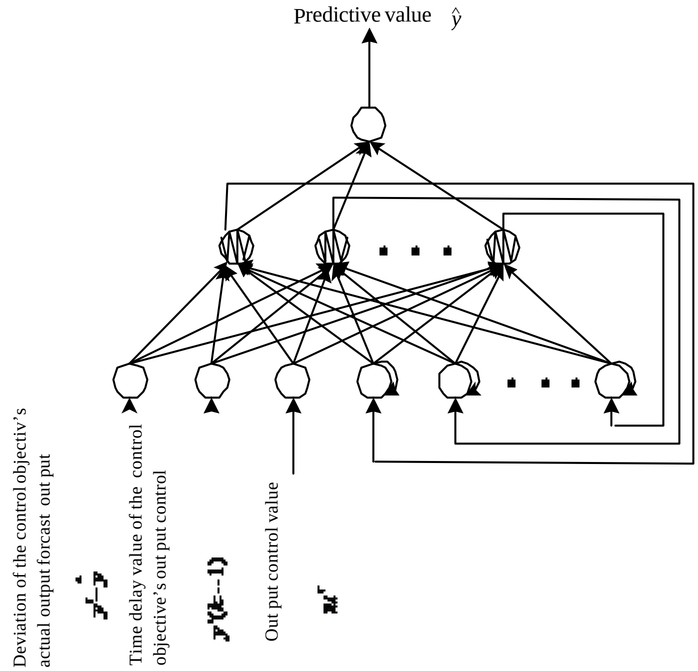

Fig. 4: Structure of the wavelet elman neural network

$$\frac{\partial\psi(X)}{\partial X} = -[X\cos(1.75X) + 1.75\sin(1.75X)]\exp\left|-\frac{X^2}{2}\right| \quad (6)$$

$$X_h^p = i = \sum_{i=1}^{I}(w_{hi} * x_i^p) + \phi_h \quad (7)$$

$$X_o^p = \sum_{k=1}^{H}(w_{oh} * Y_k^p) + \phi_o \quad (8)$$

$$Y_h^p = f_H(X_h^p) = \psi\left(\frac{X_h^p - b_h}{a_h}\right) \quad (9)$$

$$\dot{Y}_h^p = f_H{}'(X_h^p) = \psi'\left(\frac{X_h^p - b_h}{a_h}\right) \quad (10)$$

$$Y_o^p = f_O(X_o^p) = \frac{1}{1 + e^{-X_o^p}} \quad (11)$$

Setting the activation function of the output nodes as the Sigmoid, the output layer has one node that is O = 1 and its energy function of the total error is defined as:

$$E = \frac{1}{2}\sum_{p=1}^{P}\sum_{o=1}^{O}(Y_o^p - \tilde{Y}_o^p)^2 = \frac{1}{2}\sum_{p=1}^{P}(Y_o^p - \tilde{Y}_o^p)^2 = \frac{1}{2}\sum_{p=1}^{P}e^2 \quad (12)$$

Predictor design based on wavelet Elman neural network: The predictor adopts wavelet Elman neural network, the forecast inputs are setting as following: the deviation of the control object's actual output and forecast output y'-$\hat{y}$, the time delay value of the control object's actual output y' (k-1), the output control value of the neural network controller u'. Setting the controller's output value as the predictive value $\hat{y}$. The structure of the wavelet Elman neural network as shown in Fig. 4.

In the controller of wavelet Elman neural network, its mathematical models of the wavelet Elman neural network are shown below: (Kun *et al*., 2003):

$$x_c(k) = \alpha x_c(k-1) + x(k-1) \quad (13)$$

$$x(k) = \psi\left(\frac{h(k-1) - b_i(k)}{a_i(k)}\right) \quad (14)$$

$$y(k) = g(W^3(k)x(k)) \quad (15)$$

$$h(k) = W^1(k)x_c(k) + W^2(k)u(k) \quad (16)$$

Setting the Ψ (•) as the wavelet function, in this paper adopt the Morlet wavelet, a_i serve as the wavelet stretch coefficient, b_i serve as the wavelet translation coefficient.

Set as:

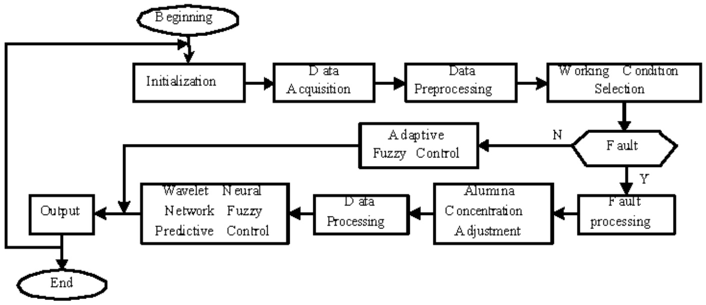

Fig. 5: Flow diagram of control method

$$X = \frac{h(t) - b_i(t)}{a_i(t)} \tag{17}$$

The Morlet wavelet defined as follows:

$$\psi(X) = \cos(1.75X)\, e^{-\frac{X^2}{2}} \tag{18}$$

$$y(k) = g(W^3(k)x(k)) \tag{19}$$

The learning algorithm is as following:
The error function:

$$E(k) = \frac{1}{2}(y_d(k) - y(k))^T (y_d(k) - y(k)) \tag{20}$$

The goal of the learning algorithm is reduce the error function-E (k) gradually through adjust the network weights. Training Elman neural network by adopt the gradient descent algorithm, through the chain rule of a first order partial derivativ , we can conclude that:

$$W^1(k) = W^1_{ij}(k-1) + \Delta W^1_{ij}(k) \tag{21}$$

$$W^2(k) = W^2_{ij}(k-1) + \Delta W^2_{ij}(k) \tag{22}$$

$$W^3(k) = W^3_{ij}(k-1) + \Delta W^3_{ij}(k) \tag{23}$$

$$a_i(k) = a_i(k-1) + \Delta a_i(k) \tag{24}$$

$$b_i(k) = b_i(k-1) + \Delta b_i(k) \tag{25}$$

$$\Delta W^3_{ij}(k) = -\eta \frac{\partial E(k)}{\partial W^3_{ij}(k)} = -\eta[y_{id}(k) - y_i(k)]g_i^{'}(\bullet)x_j(k) \tag{26}$$

$$\Delta W^2_{ij}(k) = -\eta \frac{\partial E(k)}{\partial W^2_{ij}(k)} = -\eta(y_{id}(k) - y_i(k)g_i^{'}(\bullet)W_i^3(k)\psi(\bullet)u_j(k) \tag{27}$$

$$\Delta W^1_{ij}(k) = -\eta \frac{\partial E(k)}{\partial W^1_{ij}(k)} = -\mu(y_{id}(k) - y_i(k))g_i^{'}(\bullet)W_i^3\psi(\bullet)x_{ic}(k) \tag{28}$$

$$\Delta a_i(k) = -\eta \frac{\partial E(k)}{\partial a_i(k)} = -\mu(y_{id}(k) - y_i(k))g_i(\bullet)\psi(X)\frac{\partial X}{\partial a_i(k-1)} \tag{29}$$

$$\Delta b_i(k) = -\eta \frac{\partial E(k)}{\partial b_i(k)} = -\mu(y_{id}(k) - y_i(k))g_i(\bullet)\psi(X)\frac{\partial X}{\partial b_i(k-1)} \tag{30}$$

η-The learning rate of the network

THE REALIZATION OF THE CONTROL METHOD

The aluminum electrolytic energy conservation and optimization system's control program mainly includes initialization module, data acquisition module?data preprocessing module, fault processing module?adaptive fuzzy control module, wavelet neural network predictive control module and so forth. The program flow diagram is shown in Fig. 5 (Zhou *et al.*, 2013).

SIMULATION

In order to verify the rationality of the control scheme and the superiority of the control model, making the simulation experiment which selects the cell resistance deviation and the deviation change rate as input neurons. In this paper adopt the second order model, its transfer function is as follows:

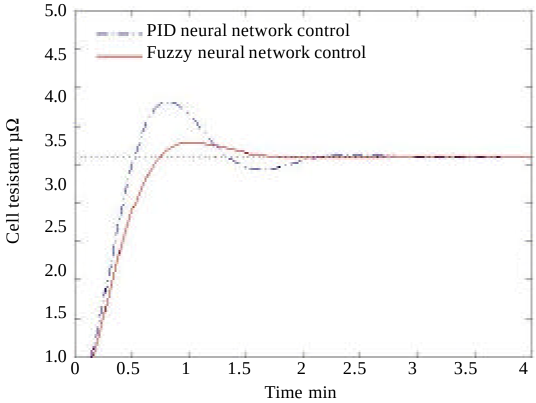

Fig. 6: Control system simulation diagram based on normal state

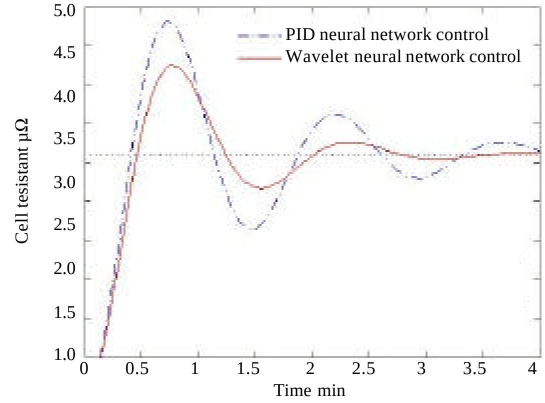

Fig. 7: Control system simulation diagram based on faulted state

$$G(s) = \frac{e^{-\tau}}{(T_1 s + 1)(T_2 s + 1)} \tag{31}$$

$$T_1 = 10, T_2 = 20, \tau = 0.06$$

Cell resistance R, the calculation formula which according to the cell voltage of Cell resistance R, the calculation formula which according to the cell voltage of online synchronous acquisition V_{iE} and series current I_C was shown as following:

$$R = \frac{V_{iE} - E}{I_c} \tag{32}$$

E-the set value of counter electromotive force . In this study, $V_{iE} = 4.2$ V, E = 2.2 V, $I_C = 652$ kA

From the analysis of part 1 of this study, the alumina concentration can indirectly calculated by the cell resistance. And a lot of practical data indicate that in the process of aluminum electrolytic the alumina concentration is usually in a sensitive area, the change is not significant of the cell resistance R which can regard as a constant value. Consequently, select cell resistance as the simulation object to verify the feasibility of the control method.

The control system simulation diagram based on normal state is shown in Fig. 6, the dotted line is the simulation curve of PID neural network control, the solid line is the simulation curve of the fuzzy neural network control. Through the comparison of them, both methods can make the alumina concentration to achieve an ideal scope. But the fuzzy neural network control method has a smaller overshoot amount, it reach the stable state cost about 1.5 minutes earlier than PID control method, with a shorter regulating time and rise time, as well as ensure the control accuracy.

The control system simulation diagram based on faulted state is shown in Fig. 7, the dotted line is the simulation curve of PID neural network control, the solid line is the network control. Through the comparison of them, in the fault state,the oscillation number will increase significantly of the PID control, the wavelet neural network reach the stable state cost about 2 minutes earlier than PID control method, which has a smaller overshoot amount, a shorter regulating time and rise time.

Simulation curve of the wavelet neural Consequently, through the above analysis, put the electrolytic cell alumina content divided into different working condition to control applied in the aluminum electrolysis system, which can greatly optimize the control precision, save the energy consumption and satisfy people's needs.

CONCLUSION

In this study, through the simulation research and the realization of control method, we can draw a conclusion: The optimal control strategy in this paper, compared with other control methods, had a stronger adaptive ability and a better control effect. It is applied to aluminum electrolysis fault diagnosis system which can greatly improve the overshoot?regulating time and rise time, as well as greatly increased the accuracy and the stability of control system. Consequently, the optimal control strategy research on aluminum electrolysis fault diagnosis system has played a vital role to aluminum electrolytic efficiency and stable production.

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