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An expert control strategy using neural networks for the electrolytic process in zinc hydrometallurgy

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Abstract: *The final step in zinc hydrometallurgy is the electrolytic process. The most important parameters to control the process are the concentrations of zinc and sulfuric acid in the electrolyte. This paper proposes an expert control strategy for determining and tracking the optimal concentrations, which uses neural networks, rule models and a single-loop control scheme. First, the process is described and the strategy that features an expert controller and three single-loop controllers is explained. Next, neural networks and rule models are constructed based on statistical data and empirical knowledge on the process. Then, the expert controller for determining the optimal concentrations is designed through a combination of the neural networks and rule models. The three single-loop controllers use the PI algorithm to track the optimal concentrations. Finally, the results of actual runs using the strategy are presented. They show that the strategy provides not only high-purity metallic zinc, but also significant economic benefits.*

Key words: *Zinc hydrometallurgy; electrolytic process; process control; expert systems; neural networks; rule models; single-loop control.*

1. Introduction

The three basic steps in zinc hydrometallurgy are leaching, purification and electrolysis. The electrolytic process involves passing an electrical current through insoluble electrodes to cause the decomposition of an aqueous zinc sulfate electrolyte and the deposition of metallic zinc at the cathode (Zhuzhou Smeltery, 1973). The control objective is to recover as much zinc as possible from the electrolyte as a high-purity product. To achieve this, it is imperative to maintain the optimal electrolysis conditions and reduce the electrical power consumed.

The electrolytic conditions are affected by many factors, such as the concentrations of zinc, sulfuric acid and impurities in the electrolyte; the current density at the cathode; and the temperature of the electrolyte. For general operation, the most important factors are the concentrations of zinc and sulfuric acid, so they must be closely controlled. On the other hand, a key factor influencing the power consumption is the current efficiency. Less power is consumed as the current efficiency increases. Optimizing and tracking the concentrations of zinc and sulfuric acid, and improving the current efficiency are primary tasks in the control. Because of the complexity of the relationships among the factors, this process is usually controlled manually. Recently, computer monitoring and control have been developed to do this job; but they do not often provide the desired performance because they are based solely on mathematical models, which do not describe the exact relationships among the key factors (Gui and Wu, 1995; Tang et al., 1996).

Artificial intelligence techniques are steadily advancing and now constitute a powerful method of controlling complex processes; and their extensive applications to engineering problems has proven their effectiveness. Expert systems and neural networks are two rapidly growing areas. Expert systems have been widely studied and used for process control (Efstathiou, 1989; Ishizuka and Kobayashi, 1991; The Society of Chemical Engineers, 1993; Wu, et al., 1996). Such systems use the empirical knowledge of human experts in a specific domain to solve a problem. Neural networks are powerful tools for the modeling, identification and control (Rumelhart, et al., 1986; Narendra and Parthasarathy, 1990; Hagan, et al., 1996). Among them, the backpropagation network has been used the most in process control applications (McAvoy, 1997). The electrolysis is a complex chemical process, and the operating parameters generally have a very narrow range. The relationships among the factors can be expressed through a combination of neural networks and rule models based on statistical data and empirical knowledge on the process. This means that expert systems and neural networks should be able to provide good control of the electrolytic process.

This paper concerns an expert control strategy using neural networks for the electrolytic process. The strategy employs four backpropagation networks and a number of rule models, which express the relationships among main factors, to determine the optimal concentrations of zinc and sulfuric acid in the electrolyte. In addition, it uses a single-loop control scheme to track the optimal concentrations, so as to obtain high-purity metallic zinc and improve the current efficiency as much as possible. This paper first describes the process and the strategy. Secondly, backpropagation networks and rule models are constructed based on statistical data and empirical knowledge. Third, an expert controller for determining the optimal concentrations is designed through a combination of the backpropagation networks and rule models. Three single-loop controllers using the PI algorithm are employed to track the optimal concentrations. Fourth, the results of actual runs are presented. Finally, some conclusions are given.

2. Process description and control strategy

The electrolytic process that was the subjective of this study uses low-zinc, low-acid electrolysis technology. The expert control strategy is proposed for this process.

2.1. Process description

In the process, the electrolyzing cells are arranged in four cascade series, and 240 electrolyzing cells are serially connected in each series. The electrolyte is added to the cells, and is a mixture of new electrolyte obtained through the purification and spent electrolyte returned from the process. The flow rate of new electrolyte is controlled by regulating the speeds of three pumps, while that of the spent electrolyte is largely fixed. Passing an electrical current through the cathodes and anodes of the cells causes the chemical reaction

$$2ZnSO_4 + 2H_2O = 2Zn + 2H_2SO_4 + O_2 \uparrow . \qquad (1)$$

This result in the deposition of metallic zinc at the cathode, and the formation of sulfuric acid. Part of the spent electrolyte is cooled and cycled back into the process, and part is returned to the leaching (Zhuzhou Smeltery, 1973).

To achieve the control objectives, the factors influencing the electrolysis conditions must be kept within given ranges. The following constraints must be satisfied.

(i) The concentrations of zinc and sulfuric acid are within the ranges 45 - 60 g/l and 150 - 200 g/l, respectively, and the ratio of the hydrogen ion concentration to the zinc ion concentration must be 3.0 - 3.8.

(ii) The temperature of the electrolyte is 30 - 38 ℃.

(iii) The current density is 450 - 600 A/m^2.

(iv) The components (Zn, Cu, Cd and Co, etc.) of the new electrolyte are within the standard allowable ranges.

Constraint (ii) is satisfied by cooling the spent electrolyte to be added, and constraints (iii) and (iv) are met by two designed systems (Wu, et al., 1993 and 1996).

Statistical data and empirical knowledge show that the current efficiency is mainly affected by the concentrations of zinc and sulfuric acid, the temperature and the current density. Therefore, the key points are to determine the optimal concentrations of zinc and sulfuric acid for the given temperature and current density, and to track the optimal concentrations, so as to satisfy constraint (i) and improve the current efficiency as much as possible.

2.2. Control strategy

An expert control strategy is proposed to achieve the control objectives. It uses an expert controller and three 761 series single-loop controllers.

The concentrations of zinc and sulfuric acid are set by adjusting the flow rate of the new electrolyte mixed with the spent electrolyte. The expert controller uses a forward chaining strategy based on a combination of backpropagation networks and rule models to determine the optimal concentrations of zinc and sulfuric acid, and to compute the target flow rate of new electrolyte, so as to yield high-purity metallic zinc and the maximum current efficiency.

Three 761 controllers use the PI control algorithm to track the target flow rate, so as to ensure that the actual concentrations of zinc and sulfuric acid match the optimal values. More specifically, the three control loops are constructed based on the 761 controllers, inverters, pumps and flow meters. The 761 controllers regulate the speeds of three pumps by means of inverters.

3. Neural networks and rule models

The relationships among the current efficiency, the concentrations of zinc and sulfuric acid, the current density and the temperature have very strong nonlinearity, which make them difficult to express using mathematical models alone. However, they can be described by a combination of backpropagation networks and rule models based on statistical data and empirical knowledge, where the rule models are production rules of the If-Then form.

3.1. Neural networks and training

The temperature of the electrolyte, x_T, is divided into six levels: $x_T < 30$, $30 \le x_T < 32$, ..., $36 \le x_T < 38$ and $x_T < 38$. Four backpropagation networks, each with three layers, BP3L1, BP3L2, BP3L3 and BP3L4, are constructed for the middle four levels, $30 \le x_T < 32$, $32 \le x_T < 34$, $34 \le x_T < 36$ and $36 \le x_T < 38$, respectively. The input layer, hidden layer and output layer have three neurons, nine neurons and one neuron, respectively.

In the input layer, the inputs of the three neurons are the current density and the concentrations of zinc and sulfuric acid, which are denoted by x_I, x_Z and x_S, respectively, and their outputs are the same as the inputs. In the hidden layer, the input and output of the *i*-th neuron are defined to be

$$x_i = w_{i,I} x_I + w_{i,Z} x_Z + w_{i,S} x_S + b_i , \qquad (2a)$$

and

$$y_i = \text{tansig}(x_i) \ , \tag{2b}$$

where $w_{i,I}$, $w_{i,Z}$ and $w_{i,S}$ are the weights of the signals from the three neurons of the input layer to the i-th neuron of the hidden layer, respectively, b_i is the bias of the i-th neuron of the hidden layer, and $\text{tansig}(\cdot)$ denotes the tan-sigmoid transfer function, which has the form

$$\text{tansig}(x) = \frac{2}{1+e^{-2x}} - 1 \, , \tag{3}$$

and maps the input to the interval (-1, 1) (Hagan, et al., 1996). In the output layer, the input and output of the neuron are defined to be

$$x_O = \sum_{i=1}^{9} w_{i,O} y_i + b_O \ , \tag{4a}$$

and

$$\eta_I = x_O \, , \tag{4b}$$

where $w_{i,O}$ is the weight of the signal from the i-th neuron of the hidden layer to the neuron of the output layer, b_O is the bias of the neuron of the output layer, η_I and is the current efficiency.

Expressions (2) and (4) can be combined in expression

$$\eta_I = \sum_{i=1}^{9} w_{i,O} \text{tansig}(w_{i,I} x_I + w_{i,Z} x_Z + w_{i,S} x_S + b_i) + b_O \ . \tag{5}$$

It express the relationship among η_I, x_I, x_Z and x_S for a given range of temperatures. The weights $w_{i,I}$, $w_{i,Z}$, $w_{i,S}$ and $w_{i,O}$, and the biases b_i and b_O are determined by training the backpropagation network.

To determine these weights and biases, a number of statistical data are acquired from the process. These data are classified into four sets for BP3L1, BP3L2, BP3L3 and BP3L4 according to the temperature of the electrolyte, and are used to train the four backpropagation networks. In the training, the network inputs are x_I, x_Z and x_S; the network output is η_I; and the target output is the actual value of the current efficiency, which is denoted by η_A. The network performance function, J, is the average of the squared errors between the network outputs and the target outputs, i.e.,

$$J = \frac{1}{N} \sum_{j=1}^{N} [\eta_I(j) - \eta_A(j)]^2 \, , \tag{6}$$

where $\eta_I(j)$ and $\eta_A(j)$ are the j-th network outputs and the j-th target outputs, and N is the total number of the target outputs used in training.

The weights and biases of the networks are iteratively adjusted to minimize J during training. A basic backpropagation training algorithm (Rumelhart, et al., 1986; Hagan, et al., 1996) is used to determine the weights and biases. It employs the gradient of J to adjust the weights and biases and minimize that function. The weights and biases are moved in the direction of the negative gradient. Let $x_{wb}(k)$ be the vector of current weights and biases, $g_{wb}(k)$ be the current gradient, and $\gamma_{wb}(k)$ be the current learning rate. Then the training algorithm can be written as

$$x_{wb}(k+1) = x_{wb}(k) - \gamma_{wb}(k) g_{wb}(k) \, , \tag{7a}$$

$$g_{wb}(k) = \frac{\partial J}{\partial x_{wb}}(k) \, , \tag{7b}$$

where k is the number of iterations.

The weights and biases of the four backpropagation networks are determined by off-line training. When the environment and operating conditions of the electrolytic process are changed, it is necessary to determine the weights and biases afresh.

3.2. Rule Models

In the electrolytic process, there is an interaction between the concentrations of zinc and sulfuric acid in the electrolyte because these concentrations are determined in part by the flow rate of new electrolyte mixed with the spent electrolyte. This interaction makes it is difficult to determine the optimal concentrations by using BP3L1, BP3L2, BP3L3 or BP3L4 alone. To determine the best concentrations of zinc and sulfuric acid that can be achieved by adjusting the flow rate of the new electrolyte and that will yield high-purity metallic zinc and the highest possible current efficiency, we need to construct rule models based on the empirical knowledge and data.

All rule models use the If-Then form (Efstathiou, 1989) and are numbered by $R^{\#}$.

In constructing rule models, empirical knowledge is acquired mainly from interviews with experienced engineers and operators working on the process. For instance, an efficient empirical method of determining the optimal concentrations of zinc and sulfuric acid in the electrolyte is used. More specifically, the optimal ranges are first determined from the temperature of the electrolyte and the current density. Next, an initial concentration of zinc is selected from the optimal range, and the appropriate target flow rate is computed for the new electrolyte mixed with the spent electrolyte. Then, the concentration of sulfuric acid is estimated under the assumption that new electrolyte is supplied at the computed target flow rate. If the estimate is in the optimal range, the selected concentration of zinc and the estimated concentration of sulfuric acid are used as optimal values. If this is not the case, the selection, computation and estimation procedures are repeated until optimal concentrations are finally obtained.

Assume that x_{ZS} is the selected concentration of zinc, x_{NZ} and x_{OZ} are the concentrations of zinc in the new electrolyte and spent electrolyte to be mixed, respectively, and Q_O is the flow rate of the spent electrolyte to be mixed. Then the target flow rate of the new electrolyte is computed by using the following empirical expression:

$$Q_N = \frac{k_Z x_{ZS} - x_{OZ}}{x_{NZ} - k_Z x_{ZS}} Q_O , \quad (8)$$

where k_Z is an empirically determined coefficient. Under the assumption that new electrolyte is supplied at the computed target flow rate Q_N, the concentration of sulfuric acid in the electrolyte is estimated by using the following empirical expression:

$$x_{SS} = \frac{Q_N x_{NS} + Q_O x_{OS}}{k_S (Q_N + Q_O)} , \quad (9)$$

where x_{SS} is the estimated concentration of sulfuric acid, x_{NS} and x_{OS} are the concentrations of sulfuric acid in the new electrolyte and spent electrolyte to be mixed, and k_S is an empirically determined coefficient.

Rule models are used to select the backpropagation network, determine the optimal ranges of the concentrations, select the initial concentration of zinc from the optimal range, and adjust the concentration of zinc in the optimal range. Table 1 shows some typical rule models used to determine the optimal concentrations of zinc and sulfuric acid, where U_Z and U_S are the optimal ranges of the concentrations of zinc and sulfuric acid, respectively; x_{Zopt} and x_{Sopt} are the optimal concentrations of zinc and sulfuric acid, respectively; Q_{Nopt} is the target flow rate of new electrolyte; and Δx is an empirically determined value.

4. Design of the expert controller

An expert controller was designed to determine the optimal concentrations of zinc and sulfuric acid in the electrolyte, and the corresponding target flow rate of new electrolyte. It uses a reasoning strategy based on forward chaining and a combination of the constructed backpropagation networks and rule models.

4.1. Structure of the expert controller

The expert controller consists of a characteristics-capturing mechanism, a knowledge base, a database, an inference engine, and a man-machine interface.

The characteristics-capturing mechanism handles process data to obtain data on characteristics. These data are used by the database, knowledge base and inference engine.

The knowledge base stores the backpropagation algorithms, rule models, empirical data and operating laws for the process; calculation laws; etc. The database stores the quality requirements, measured data and statistical data on the process; reasoning results from the inference engine; etc.

The inference engine gets the empirical knowledge and data from the knowledge base and database, and uses a reasoning strategy based on forward chaining (Efstathiou, 1989) and a combination of the backpropagation networks and rule models to determine the optimal concentrations of zinc and sulfuric acid, and the corresponding target flow rate of new electrolyte, so as to yield high-purity zinc and the maximum current efficiency.

The man-machine interface is used to edit and modify the knowledge base, and to display and print the results, etc.

4.2. Algorithm for determining optimal concentrations

A flow chart of the reasoning strategy used in the expert controller is shown in Fig. 1. The reasoning strategy is implemented in an algorithm. The algorithm is used to determine the optimal concentrations and compute the target flow rate is as follows:

Step 1: Collect the temperature x_T, the current density x_I, the concentrations x_{NZ}, x_{OZ}, x_{NS} and x_{OS}, and the flow rate Q_O.

Step 2: Obtain data on the characteristics of the temperature x_T by characteristics-capturing, and fire a rule model such as R^{EC1} to select the corresponding backpropagation network.

Step 3: Determine the optimal ranges U_Z and U_S of the concentrations of zinc and sulfuric acid by computing the current efficiency based on the selected network, as so to yield the maximum current efficiency.

Step 4: Set the concentration of zinc to

$$x_{ZS} = \frac{\max(\widetilde{U}_Z) + \min(\widetilde{U}_Z)}{2} . \quad (10)$$

Step 5: Compute the target flow rate Q_N of new electrolyte from expression (8), and estimate the concentration x_{SS} of sulfuric acid from expression (9).

Step 6: Check if $x_{SS} \in U_S$. If so, execute rule model R^{EC6} to obtain the optimal concentrations of zinc and sulfuric acid and the target flow rate of new electrolyte, and stop this algorithm. If not, go to the next step.

Step 7: Check if $x_{ZS} = \max(U_Z)$ or $x_{ZS} = \min(U_Z)$. If so, fire rule models such as R^{EC4} and R^{EC5} and go to the next step. If not, adjust x_{ZS} so that it is in U_Z by rule models such as R^{EC2} and R^{EC3}, and return to Step 5.

Step 8: Determine the optimal ranges U_Z and U_S of the concentrations of zinc and sulfuric acid by computing the current efficiency based on the selected network, so as to yield the highest current efficiency, and return to Step 4.

The optimal concentrations determined in the above algorithm are achieved by tracking the corresponding target flow rate of new electrolyte.

5. Some results of actual runs

The proposed expert control strategy is using in a nonferrous metals smeltery. It not only provides high-purity metallic zinc, but also yields significant economic benefits.

Table 1. Some typical rule models for determining the optimal concentrations.

Number	If	Then
R^{EC1}	$34 \le x_T < 36$	Use BP3L3 to determine $\tilde{U}_Z$ and $\tilde{U}_S$, and select x_{ZS} in $\tilde{U}_Z$
R^{EC2}	$x_{ZS} \in \tilde{U}_Z$, $x_{SS} > \max(\tilde{U}_S)$ and $x_{ZS} \ne \max(\tilde{U}_Z)$	$x_{ZS} = x_{ZS} + \Delta x_Z$
R^{EC3}	$x_{ZS} \in \tilde{U}_Z$, $x_{SS} < \min(\tilde{U}_S)$ and $x_{ZS} \ne \min(\tilde{U}_Z)$	$x_{ZS} = x_{ZS} - \Delta x_Z$
R^{EC4}	$x_{ZS} = \max(\tilde{U}_Z)$ and $x_{SS} > \max(\tilde{U}_S)$	Use the corresponding backpropagation network to determine $\tilde{U}_Z$ and $\tilde{U}_S$, and select x_{ZS} in $\tilde{U}_Z$, again
R^{EC5}	$x_{ZS} = \min(\tilde{U}_Z)$ and $x_{SS} < \min(\tilde{U}_S)$	Use the corresponding backpropagation network to determine $\tilde{U}_Z$ and $\tilde{U}_S$, and select x_{ZS} in $\tilde{U}_Z$, again
R^{EC6}	$x_{ZS} \in \tilde{U}_Z$ and $x_{SS} \in \tilde{U}_S$	$x_{Zopt} = x_{ZS}$, $x_{Sopt} = x_{SS}$ and $Q_{Nopt} = Q_N$

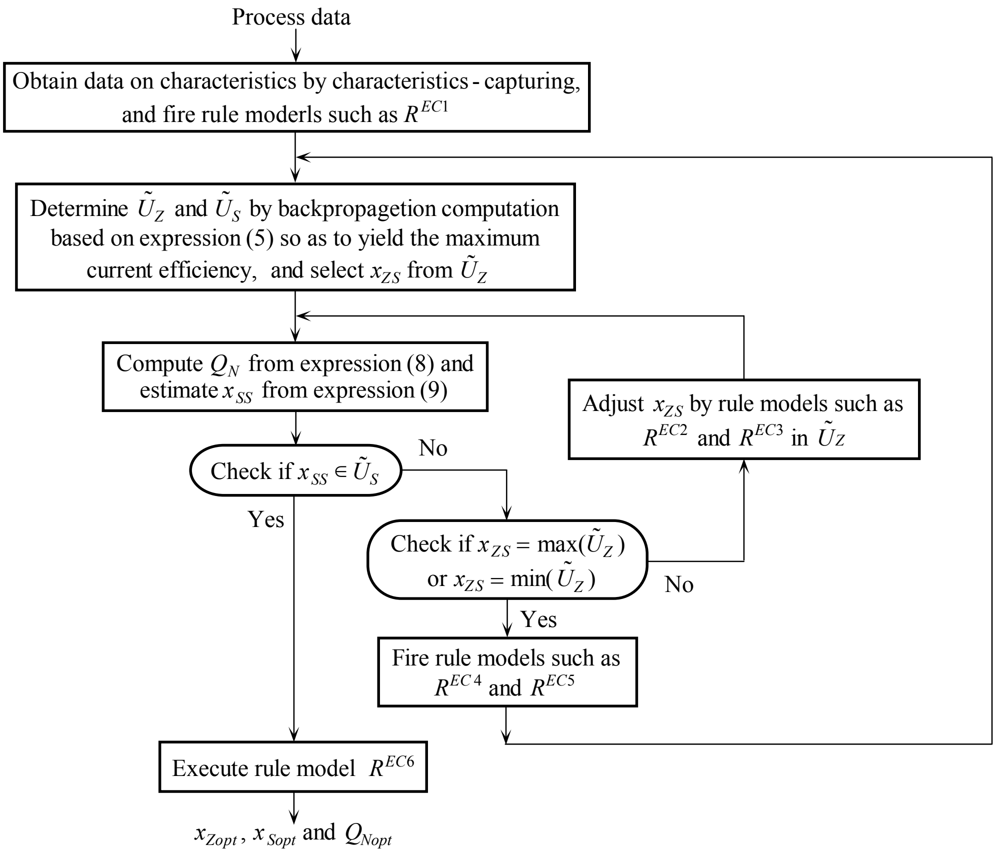

Fig. 1. Flow chart of reasoning using combination of backpropagation networks and rule models.

Some results of actual runs are shown in Fig. 2. The dotted lines indicate the constraints on the electrolysis conditions given in Section 2.1.

When the concentrations of the components of the new electrolyte used fall within the standard allowable ranges, and the temperature of the electrolyte and the current density satisfy the constraints given in Section 2.1, the optimal concentrations of zinc and sulfuric acid in the electrolyte are determined by the designed expert controller and tracked by the 761 controllers. In this case, the electrolysis conditions are optimal and the optimal electrolysis conditions are maintained. It is clear that the optimal concentrations of zinc and sulfuric acid and the ratio of the hydrogen ion concentration to the zinc ion concentration satisfy the constraints given in Section 2.1.

Statistical data on the electrolytic process shows not only that high-purity metallic zinc is obtained, but also that the power consumption for electrolysis is considerably reduced. In particular, compared with the results for control based on the conventional method, the purity of metallic zinc is improved from 99.990 - 99.995 % to 99.9999 %, and the current efficiency is about 4.2 % higher, which mean that the power consumption per ton of zinc used for recovery is about 200 - 400 kwh lower.

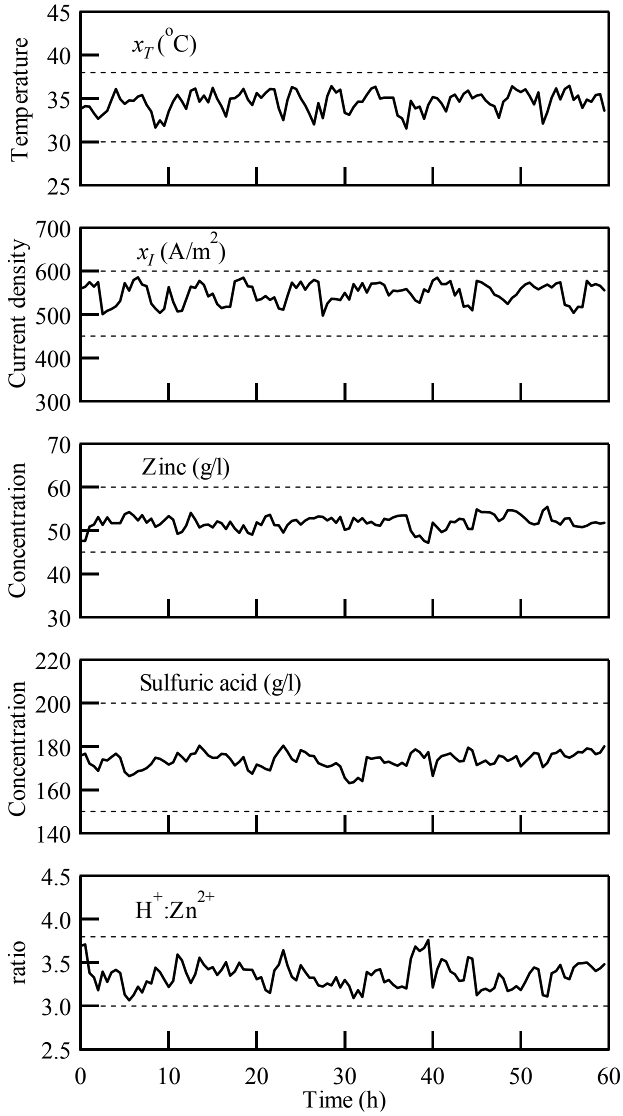

Fig. 2. Some results of actual runs.

6. Conclusions

This paper has describes an expert control strategy using backpropagation networks, which is currently being used for the electrolytic process of a nonferrous metals smeltery. The results of actual runs show that the proposed strategy effectively control the electrolytic process. The main features are as follows:

(1) Backpropagetion networks and rule models that express the complex relationships among the factors influencing the electrolysis conditions and electrical power consumption are constructed based on statistical data and empirical knowledge on the process.

(2) The optimal concentrations of zinc and sulfuric acid and the corresponding target flow rate of new electrolyte are determined by a reasoning strategy that combines backpropagation networks and rule models, and uses forward chaining.

(3) The optimal electrolysis conditions are maintained by tracking the target flow rate of new electrolyte, while the tracking is implemented by conventional single-loop control technique.

(4) The proposed strategy provides not only high-purity metallic zinc, but also significant economic benefits.

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