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An expert control system 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, which 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. For the electrolytic process studied, the most important process parameters for control are the concentrations of zinc and sulfuric acid in the electrolyte. This paper describes an expert control system for determining and tracking the optimal concentrations of zinc and sulfuric acid, which uses neural networks, rule models and a single-loop control scheme. The system is now being used to control the electrolytic process in a hydrometallurgical zinc plant. In this paper, the system architecture, which features an expert controller and three single-loop controllers, is first explained. Next, neural networks and rule models are constructed based on the chemical reactions involved, empirical knowledge and statistical data on the process. Then, the expert controller for determining the optimal concentrations is designed using 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 system are presented. They show that the system 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.

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1. Introduction

The three basic steps in the production of zinc by hydrometallurgy are leaching, purification and electrolysis. The electrolytic process is the final step, and 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 (Mathewson, 1959; Zhuzhou Smeltery, 1973). The control objectives for this process are to recover high-purity metallic zinc from the electrolyte, and to reduce the electrical power consumed during recovery. To achieve these, it is imperative to maintain the optimal electrolysis conditions. This requires effective process control.

The electrolytic conditions are mainly affected by the process parameters, such as the concentrations of zinc and sulfuric acid in the electrolyte, the current density at the cathode, and the temperature of the electrolyte. To obtain high-purity metallic zinc, these parameters must be controlled within specific ranges. On the other hand, the power consumption is mainly reduced by improving the current efficiency, which is defined to be the ratio of the actual amount of zinc obtained to the theoretical value for the same current and time. Empirical knowledge and statistical data on the process show that the current efficiency depends mainly on the process parameters, with the concentrations of zinc and sulfuric acid being the most important ones for standard operation. The key problem in process control is to determine the optimal concentrations of zinc and sulfuric acid, and to track them, so as to obtain high-purity metallic zinc and improve the current efficiency as much as possible.

The conventional method involves classical control techniques. It only tracks fixed concentrations of zinc and sulfuric acid, and makes adjustments by adding new electrolyte to the process. The concentrations are selected in advance from experience. The amount of new electrolyte is computed solely from the mathematical models obtained from the main chemical reaction equation (Gui and Wu, 1995; Tang, *et al.*, 1996). Since fixed concentrations of zinc and sulfuric acid are not usually optimal for the reactions involved, and the mathematical models neither consider variations in the reaction conditions, nor describe complex relationships among the current efficiency and the process parameters, it is difficult to achieve the desired control performance by using this method. To improve the control performance, it is important to utilize empirical knowledge and statistical data on the process.

Artificial intelligence techniques are steadily advancing and now constitute a powerful method of controlling complex processes; and their extensive application to engineering problems has proven their effectiveness. Expert systems and neural networks are two rapidly growing areas. Expert systems have been widely studied (Hayes-Roth, *et al.*, 1983; Åström, *et al.*, 1986; Jackson, 1986; Liebowitz, 1988; Mockler and Dologite, 1992; Passion and Lunardhi, 1996). Such systems use the empirical knowledge of human experts in a specific domain to solve a problem, and have been used for process control (Efstathiou, 1989; Ishizuka and Kobayashi, 1991; The Society of Chemical Engineers, 1993; Wu, *et al.*, 1996). Neural networks are powerful tools for the modeling, identification and control of complex systems (Rumelhart, *et al.*, 1986; Narendra and Parthasarathy, 1990; Piovoso, *et al.*, 1992; Hagan, *et al.*, 1996). Among them, the backpropagation network has been used the most in process control applications; and it is particularly useful in approximating the nonlinear relationships of complex processes (Hornik, *et al.*, 1989; Su and McAvoy, 1997). The electrolytic process involves complex chemical reactions, and the relationships among the process parameters and the current efficiency are nonlinear. But the process generally runs within a specific operating range, and the complex relationships can be described using neural networks and a number of rule models based on the chemical reactions involved, empirical knowledge and statistical data on the process. This means that expert systems and neural networks should provide good control of the electrolytic process.

This paper describes an expert control system using neural networks (ECSNN) to solve the key problem in the control of the electrolytic process. ECSNN is now being used in a hydrometallurgical zinc plant. It employs four backpropagation networks and rule models to determine the optimal concentrations of zinc and sulfuric acid, and uses a single-loop control scheme to track them, so as to obtain high-purity metallic zinc and yield the maximum current efficiency. Both the backpropagation networks and rule models reflect the nonlinear relationships among the current efficiency and the process parameters. They fully considered the chemical nature and complexity of the process.

This paper first describes the electrolytic process and the architecture of ECSNN. Second, 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 system implementation and the results of actual runs are presented. Finally, some conclusions are given at the end.

2. Process description and system architecture

The electrolytic process that was the subject of this study uses low-zinc, low-acid electrolysis technology. ECSNN is designed for this process.

2.1. Process description and control problem

The electrolytic process is shown in Fig. 1 (Zhuzhou Smeltery, 1973). It employs a mixing cell and also a number of electrolyzing cells arranged in four cascade series, with serial connections in each series. The electrolyte is a mixture of new electrolyte and spent electrolyte, and is continuously added to the electrolyzing cells. The flow rate of new electrolyte can be adjusted by regulating the speeds of three pumps, while that of the spent electrolyte is largely fixed. Passing an electric current through the cathodes and anodes of the electrolyzing cells causes chemical reactions to occur. The basic reaction is

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

This results in the deposition of metallic zinc on the cathode, the release of oxygen at the anode, and the formation of sulfuric acid through the combination of hydrogen and sulfate ions. Part of the spent electrolyte containing sulfuric acid is cooled and cycled back into this process, and part is returned to the leaching process.

[Insert Fig. 1 about here]

The input of this process is new electrolyte. The process requires that the constituents of the new electrolyte be kept in the standard allowable ranges shown in Table 1. An expert control system has been developed to meet the requirements regarding those constituents (Wu, *et al.*, 1996).

[Insert Table 1 about here]

The output of this process is zinc, which is also the product of the process. To obtain high-purity metallic zinc, the process parameters influencing the electrolysis conditions, such as the concentrations of zinc and sulfuric acid in the electrolyte, the current density at the cathode, and the temperature of the electrolyte, must be closely controlled. Empirical knowledge and statistical data on the process show that the following constraints must be satisfied to control these parameters.

(1) The concentrations of zinc and sulfuric acid should be 45 - 60 g/l and 150 - 200 g/l, respectively, and the ratio of the hydrogen ion concentration to the zinc ion concentration should be 3.0 - 3.8.
(2) The temperature should be 30 - 38 °C.
(3) The current density should be 450 - 600 A/m^2.

Constraints (2) and (3) have been satisfied by an air cooling system established for the spent electrolyte cycled back into this process, and by a hierarchical control system designed to control the current density (Wu, *et al.*, 1993), respectively. So, it is clear that, from the standpoint of process control, satisfying constraint (1) is the key to obtaining high-purity metallic zinc.

On the other hand, the current efficiency is mainly affected by process parameters, such as the temperature of the electrolyte, that influence the electrolysis conditions. To improve the current efficiency as much as possible, we need to optimize the concentrations of zinc and sulfuric acid under the condition that constraint (1) is satisfied. Therefore, the key problem in process control is to determine the optimal concentrations of zinc and sulfuric acid for the given temperature and current density, and to track them, so as to satisfy constraint (1) and yield the maximum current efficiency.

The control input of this process is the flow rate of new electrolyte that is mixed with spent electrolyte. Adjusting the flow rate of new electrolyte provides control of the concentrations of zinc and sulfuric acid in the electrolyte. Thus, it is necessary to compute and track the target flow rate of new electrolyte to achieve the optimal control of the concentrations of zinc and sulfuric acid.

2.2. Control strategy and system architecture

An expert control strategy using neural networks is described that achieves the control objectives of the electrolytic process. It uses an expert controller to determine the optimal concentrations of zinc and sulfuric acid within specific ranges for the measured temperature and current density and to compute the target flow rate of new electrolyte added to the process. A single-loop control scheme is employed in this strategy to track the target flow rate of new electrolyte.

Based on this expert control strategy, ECSNN was designed, yielding the architecture shown in Fig. 2. The main components are an expert control computer system containing an expert controller, three 761 series single-loop controllers made by the Foxboro Company and an automatic measurement system for on-line measurement. The expert controller is connected to the 761 controllers by means of a special wiring concentrator and voltage converter, and communicates with the automatic measurement system by means of a manufacturing automation protocol. The three control loops consist of the 761 controllers, inverters, pumps and flow meters.

[Insert Fig. 2 about here]

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

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

The automatic measurement system uses automatic concentration analyzers, temperature meters, flow meters and current meters, to measure the concentrations, temperatures, flow rates, and current density.

3. Neural networks and rule models

To determine the optimal concentrations of zinc and sulfuric acid, the relationships among the current efficiency and the process parameters must be established. However, the relationships have very strong nonlinearity, which make them difficult to describe using mathematical models alone. In the proposed expert control strategy, they are described using backpropagation networks and rule models based on the chemical reactions involved, empirical knowledge and statistical data on the process.

3.1. Neural networks and training

Among the process parameters influencing the electrolysis conditions, the temperature of the electrolyte is critical. The statistical data show that the of the process can be described very well by dividing the range of operating temperatures into four smaller ranges centered at $31\,°C$, $33\,°C$, $35\,°C$ and $37\,°C$. Those data also show that the electrolysis characteristics are different in each range. To describe these different characteristics, we construct four backpropagation networks based on statistical data for the four ranges.

The four backpropagation networks use the three-layer structure shown in Fig. 3. The input layer, hidden layer and output layer have three neurons, nine neurons and one neuron, respectively. x_I is the current density, x_Z and x_S are the concentrations of zinc and sulfuric acid, respectively, and η_I is the current efficiency.

[Insert Fig. 3 about here]

Another reason for using four backpropagation networks instead of just one is to approximate the nonlinear relationships among the current efficiency and the process parameters using the smallest possible number of neurons and a simple formula, so as to enable quick computation of the current efficiency.

Let x_T be the temperature of the electrolyte. To simplify the construction of the backpropagation network and the determination of the optimal concentrations of zinc and sulfuric acid, the four temperature ranges are crisply specified as $30 \le x_T < 32$, $32 \le x_T < 34$, $34 \le x_T < 36$ and $36 \le x_T \le 38$. The corresponding four backpropagation networks, which are denoted by BP3L1, BP3L2, BP3L3 and BP3L4, are constructed based on statistical data captured from experimental data and historical data for the four temperature ranges.

It is clear that, for a given temperature, using the appropriate backpropagation network for that temperature yields a good estimate of the current efficiency from the given current density and concentrations of zinc and sulfuric acid.

The expressions for describing each backpropagation network have the same structure. In the input layer, the inputs of the three neurons are x_I, x_Z and x_S, and the outputs are the same as the inputs. In the hidden layer, the input and output of the *i*-th neuron are defined to be

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

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, 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

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

This function maps the input to the interval (-1, 1) (Hagan, *et al.*, 1996). In the output layer, the input and output of a 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, and b_O is the bias of the neuron of the output layer.

Expressions (2) and (4) can be combined into the following form:

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

It express the relationship among the current efficiency, the concentrations of zinc and sulfuric acid, and the current density for a given temperature range. 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 the weights and biases of BP3L1, BP3L2, BP3L3 and BP3L4, a number of statistical data are acquired from experimental and historical data on the process corresponding to the four temperature ranges. The data for each range are used to train the corresponding backpropagation network. 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 output and the *j*-th target output, respectively, and *N* is the total number of target outputs used in training.

A basic backpropagation training algorithm (Rumelhart, *et al.*, 1986; Hagan, *et al.*, 1996) is used to determine the weights and biases of a backpropagation network. It employs the gradient of *J* to adjust the weights and biases during training, so as to minimize *J*. 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. A batch training method is used to implement the above gradient descent algorithm. In this training, the weights and biases are updated only after all the training data have been fed to the network. The gradients calculated during each training session are added together to determine the changes in the weights and biases.

The weights and biases of each backpropagation network are determined by off-line training. When the environment and operating conditions of the process are changed, it is necessary to determine the weights and biases afresh. The weights and biases thus obtained are input into ECSNN through an on-line man-machine interface.

3.2. Rule Models

In the electrolytic process, there is an interaction between the concentrations of zinc and sulfuric acid in the electrolyte because they are determined in part by the flow rate of new electrolyte. This interaction makes it 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 obtained 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 empirical knowledge on the process.

All rule models use the following production rule form (Hayes-Roth, *et al.*, 1983; Jackson, 1986; Liebowitz, 1988; Mockler & Dologite, 1992)

$$R^{\#}: \quad \text{If} \quad condition \quad \text{Then} \quad action, \tag{8}$$

where $R^{\#}$ is the number of the rule model, *condition* is the operating state of the process or a logical combination thereof, and *action* is the conclusion or operation.

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 of the concentrations are first determined from the temperature of the electrolyte and the current density at the cathode. Next, an initial concentration of zinc is selected from the optimal range, and the appropriate target flow rate is computed for the new electrolyte. Then, the concentration of sulfuric acid in the electrolyte is estimated under the assumption that new electrolyte is supplied at the computed target flow rate. If the estimate is in the optimal range of sulfuric acid concentrations, then 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.

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

$$Q_N = \frac{k_Z x_{ZS} - x_{OZ}}{x_{NZ} - k_Z x_{ZS}} Q_O, \tag{9}$$

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 using the following empirical expression:

$$x_{SS} = \frac{Q_N x_{NS} + Q_O x_{OS}}{k_S (Q_N + Q_O)}, \tag{10}$$

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 added, and k_S is an empirically determined coefficient.

Rule models are used to select the backpropagation network, determine the optimal ranges of the concentrations of zinc and sulfuric acid, select the initial concentration of zinc from the optimal range, and adjust the concentration of zinc in the optimal range. Table 2 shows some typical rule models used to determine the optimal concentrations of zinc and sulfuric acid in the electrolyte. $\tilde{U}_Z$ and $\tilde{U}_S$ 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. Δx is an empirically determined value.

[Insert Table 2 about here]

4. Design of the expert controller

An expert controller was designed based on the constructed backpropagation networks and rule models. It uses a forward chaining strategy that combines backpropagation networks and rule models to determine the optimal concentrations of zinc and sulfuric acid in the electrolyte, and the corresponding target flow rate of new electrolyte. The forward chaining strategy is implemented in an algorithm that repetitively uses the corresponding backpropagation network and rule models.

4.1. Structure of the expert controller

The structure of the expert controller is shown in Fig. 4. It consists of a characteristics-capturing mechanism, a knowledge base, a database, an inference engine, and a man-machine interface.

[Insert Figure 4 about here]

The characteristics-capturing mechanism manipulates process data to obtain data on characteristics of the process. These data are stored in a working memory, and 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 empirical knowledge and data from the knowledge base and database, and uses a forward chaining strategy (Hayes-Roth, *et al.*, 1983; Jackson, 1986; Liebowitz, 1988; Efstathiou, 1989; Mockler & Dologite, 1992) that combines 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 obtain high-purity metallic zinc and yield the maximum current efficiency.

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

Using the appropriate backpropagation network for the temperature range containing the measured temperature yields a good estimate of the current efficiency based on the selected concentrations of zinc and sulfuric acid and the measured current density and temperature. Through a combination of backpropagation networks and rule models, the optimal concentrations of zinc and sulfuric acid are determined by maximizing the estimated value.

4.2. Algorithm for determining optimal concentrations

A flow chart of the forward chaining strategy used in the expert controller is shown in Fig. 5. The following operations are carried out repetitively.

(1) Fire and execute rule models.

(2) Compute the current efficiency using the selected backpropagation network.

(3) Select or adjust the concentration of zinc in the electrolyte.

(4) Compute the target flow rate of new electrolyte and estimate the concentration of sulfuric acid in the electrolyte.

[Insert Figure 5 about here]

The forward chaining strategy is implemented in an algorithm. The algorithm used to determine the optimal concentrations and compute the target flow rate is as follows:

Step 1: Measure 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 $\widetilde{U}_Z$ and $\widetilde{U}_S$ of the concentrations of zinc and sulfuric acid by computing the current efficiency based on the selected backpropagation network, so as to yield the maximum current efficiency.

Step 4: Set the concentration of zinc to

$$x_{ZS} = \frac{\max(\tilde{U}_Z) + \min(\tilde{U}_Z)}{2}. \tag{11}$$

Step 5: Compute the target flow rate, Q_N, of new electrolyte from expression (9), and estimate the concentration, x_{SS}, of sulfuric acid from expression (10).

Step 6: Check if $x_{SS} \in \tilde{U}_S$. 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 $x_{ZS} = \max(\tilde{U}_Z)$ or $x_{ZS} = \min(\tilde{U}_Z)$. 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 $\tilde{U}_Z$ by rule models such as R^{EC2} and R^{EC3}, and return to Step 5.

Step 8: Determine the optimal ranges $\tilde{U}_Z$ and $\tilde{U}_S$ of the concentrations of zinc and sulfuric acid by computing the current efficiency based on the selected backpropagation 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. System implementation and run results

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

5.1. Implementation of ECSNN

ECSNN was implemented on an IPC 610 type computer system, and three 761 series single-loop controllers. It originally ran under the MS-DOS 6.22 operating system, but a new version runs on the Windows operating system. The functions of the expert controller were implemented in a program written in C language, while those of the 761 controllers were implemented through the controller configuration.

It should be pointed out that the programs used in the expert controller were specially developed for the electrolyte process. Compared to programs designed on a development platform for expert systems, they have the advantages of quick execution and high running efficiency, but also the disadvantage of a long development time.

Special instruments are used to accurately measure different kinds of process data. More specifically, concentrations are measured with an X-ray fluorescence analyzer, flow rates with E+H electromagnetic flow meters, etc.

5.2. Results of actual runs

Some results of actual runs using ECSNN are shown in Fig. 6. The dotted lines indicate the constraints on the process parameters given in Section 2.1. When the concentrations of the constituents of the new electrolyte fall within the standard allowable ranges shown in Table 1, 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 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.

[Insert Figures 6 about here]

As mentioned above, the conventional method only tracks fixed concentrations of zinc and sulfuric acid and makes adjustments by adding new electrolyte to the process. The concentrations often selected are 50 g/l for zinc and 180 g/l for sulfuric acid. The flow rate of new electrolyte is determined solely by mathematical models obtained from the chemical reaction equation (1). This method cannot ensure that the process parameters are always kept within the given ranges. It is also difficult to maintain the optimal electrolysis conditions. In contrast, with ECSNN, the optimal electrolysis conditions are always maintained. This results in high-purity metallic zinc and low electrical power consumption.

Statistical data on the electrolytic process show 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.

It should be pointed out that the proposed expert control strategy only optimizes the concentrations of zinc and sulfuric acid in the electrolyte under the conditions that the temperature and current density are kept within the given ranges. From this point of view, it is not a global optimization and hence the effect of using ECSNN is limited. In addition, if possible, the weights and biases of the backpropagation networks should be updated on line so that they adapt quickly to changes in the process.

6. Conclusions

This paper has described an expert control system using backpropagation networks, which is currently being used to control the electrolytic process of a nonferrous metals smeltery. The system design is based on a combination of backpropagation networks and rule models, and a single-loop control technique. The results of actual runs show that the designed system effectively controls the electrolytic process. The main features are as follows:

(1) Backpropagation networks and rule models that express the complex relationships among the process parameters influencing the electrolysis conditions and the current efficiency influencing electrical power consumption are constructed based on the chemical reactions involved, empirical knowledge and statistical data 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 uses forward chaining and combines backpropagation networks and rule models.

(3) The optimal electrolysis conditions are maintained by tracking the target flow rate of new electrolyte, with the tracking being performed by a conventional single-loop control technique.

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

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Captions of Figures

Captions of Tables

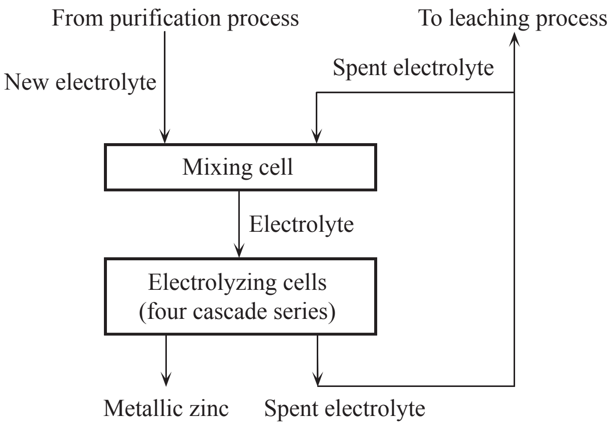

Fig. 1. Electrolytic process.

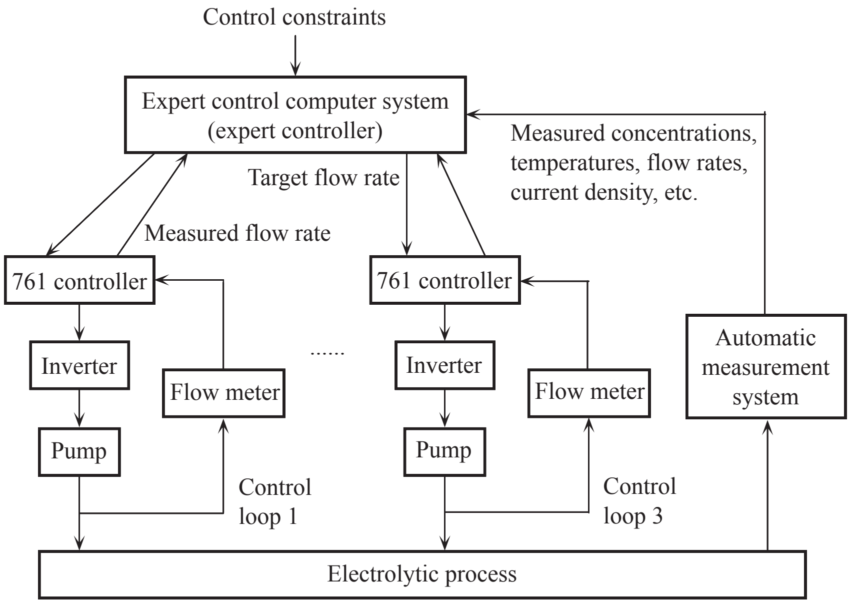

Fig. 2. Architecture of ECSNN.

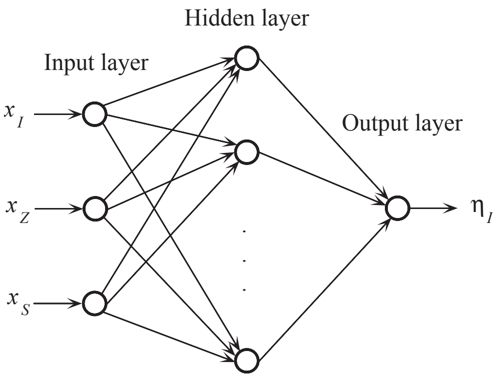

Fig. 3. Structure of a backpropagation network with three layers.

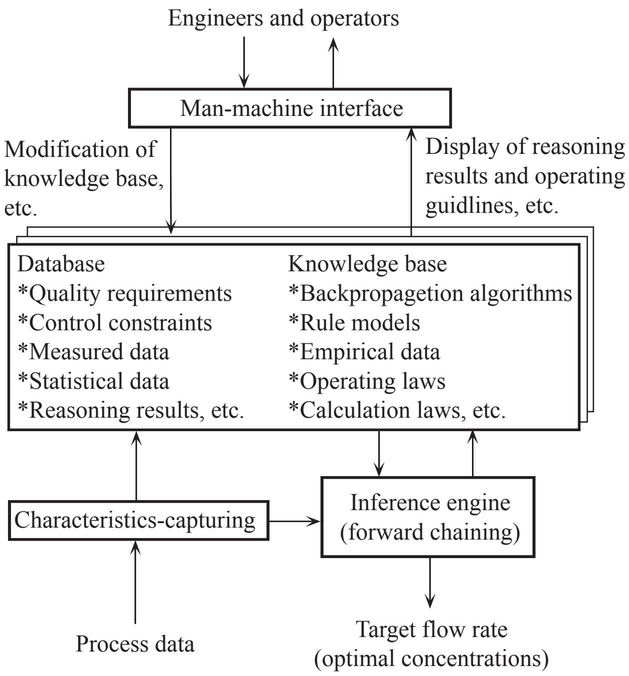

Fig. 4. Structure of the expert controller.

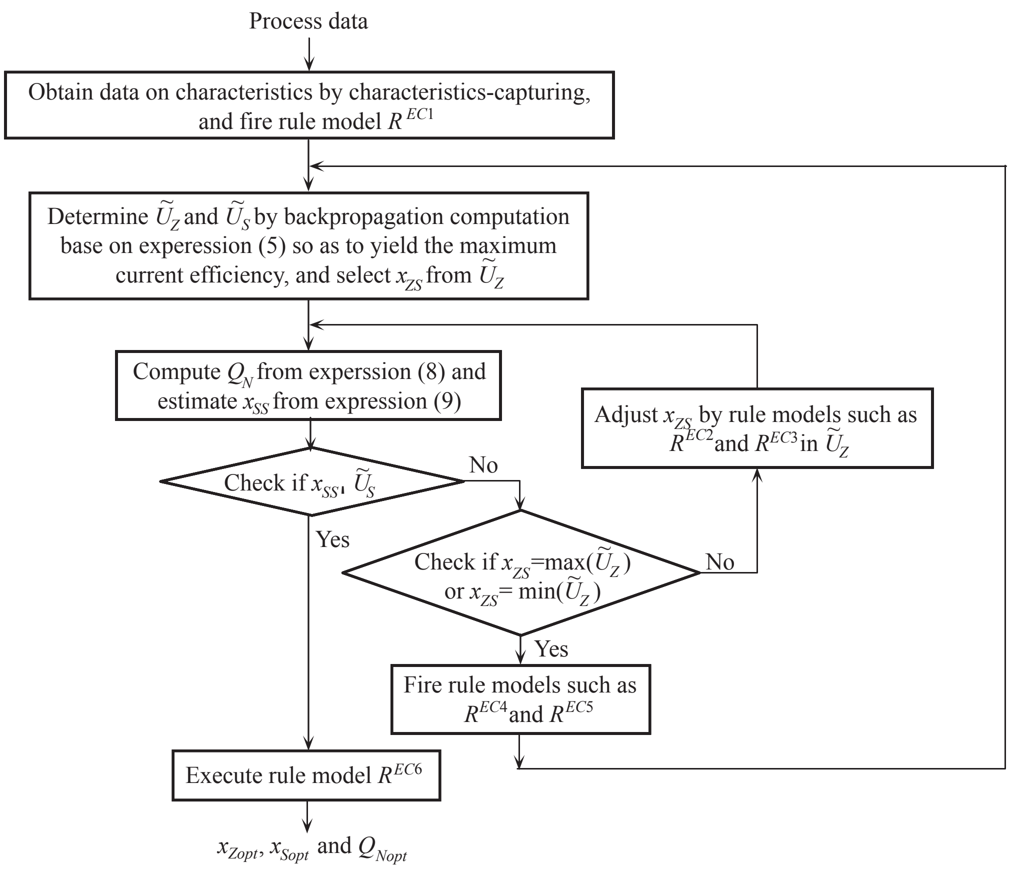

Fig. 5. Flow chart of reasoning using combination of backpropagation networks and rule models.

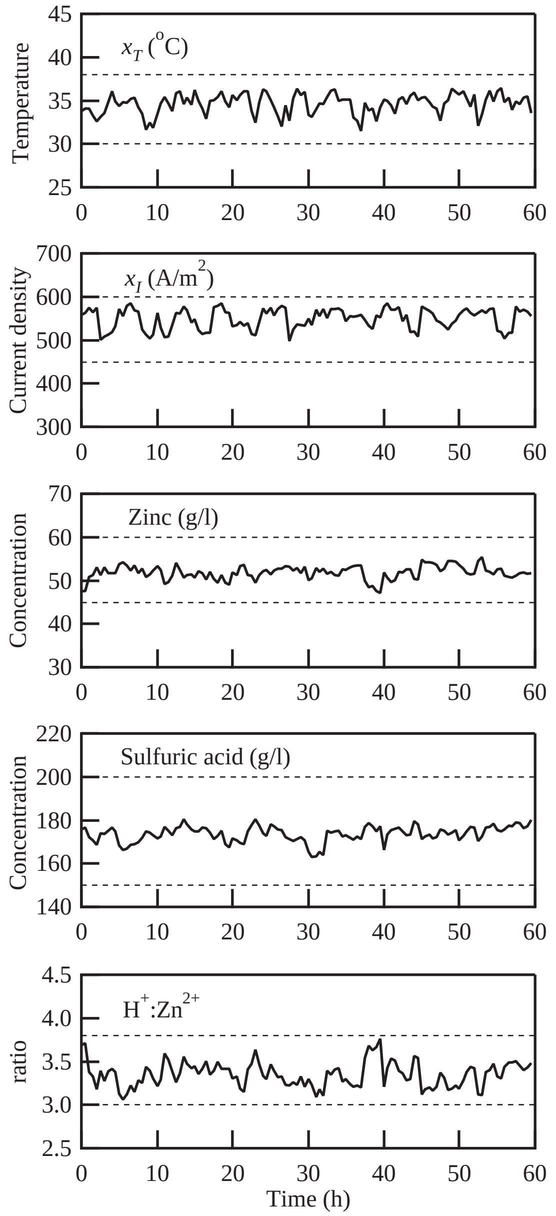

Fig. 6. Some results of actual runs using ECSNN.

Table 1. Standard allowable ranges of constituents of new electrolyte (mg/l).

Zn	Cu	Cd	Co	Ni	As	Sb	Ge	Fe
140000 ~ 170000	< 0.2	< 1.0	< 1.0	< 1.0	< 0.24	< 0.3	< 0.05	< 20

Table 2. Some typical rule models for determining the optimal concentrations.

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