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Expert control and fault diagnosis of the leaching process in a zinc hydrometallurgy plant[$]

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Abstract: This paper concerns a real-world application of an expert system to the automation of a zinc hydrometallurgy plant. The leaching process in zinc hydrometallurgy involves dissolving zinc-bearing material in dilute sulfuric acid to form a zinc sulfate solution. The key problems are to determine and track the optimal pHs of the overflows of the neutral and acid leaches, and to ensure the safe running of the process. This paper describes an expert control and fault diagnosis scheme that solves those problems. The expert control is based on a combination of steady-state mathematical models and rule models, and the fault diagnosis employs rule models with certainty factors and a Bayes representation. A real-world application of this scheme showed that it not only improved the control performance, but also correctly diagnosed faults.

Keywords: zinc hydrometallurgy; leaching process; expert control; fault diagnosis; mathematical models; rule models.

Running title: Expert control & fault diagnosis for zinc leaching

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1. Introduction

Leaching, purification and electrolysis are the three basic processes in zinc hydrometallurgy. Leaching, which is the first process, involves complex chemical reactions for dissolving zinc-bearing material in dilute sulfuric acid to form a zinc sulfate solution (Mathewson, 1959; Zhuzhou Smeltery, 1973). To obtain high-purity metallic zinc and reduce costs, the composition of the zinc sulfate solution must meet the given standards, and as much of the soluble zinc in zinc-bearing material must be dissolved as possible. On the other hand, because even a small fault in the leaching equipment may lead to changes in flow rates and temperatures, which can be quite hazardous, it is important to limit the influence of faults that occur and ensure that the process runs safely. This requires a method not only of effective control, but also of fault diagnosis for the leaching process.

Conventional methods are mainly based on manual operation and mathematical models. It is difficult to obtain the desired performance by such methods because of the complexity of the chemical reactions involved_(Gui & Wu, 1995). On the other hand, the field of expert systems is growing rapidly, and its extensive application to engineering problems has provided effective means of process control and fault diagnosis (Efstathiou, 1989; The Society of Chemical Engineers, 1993; Yamaguchi 1987; Patton, Frank & Clark, 1989). Expert systems use the empirical knowledge of human experts in a specific domain to solve a problem. They have recently been applied in the control of a hydrometallurgical zinc process, and distributed and model-based expert control techniques have been developed that achieve the control objectives of high quality and low costs (Wu, Nakano & She, 1998; 1999a). More specifically, an expert control strategy using neural networks was developed to control the electrolytic process, and the real-world application of that strategy showed that using neural networks can significantly improve control performance (Wu, Nakano & She, 1999b). However, that system did not consider the problem of fault diagnosis.

This paper concerns a combination of expert control and fault diagnosis for the leaching process. Empirical knowledge and data on the process show that the key control problems are to determine and track the optimal pHs of the overflows of the neutral and acid leaches, and that the key fault diagnosis problem is to provide information about the cause and location of any fault that occurs as well as the appropriate countermeasure. Empirical knowledge and statistical data show that there exist pHs for the overflows of the neutral and acid leaches under certain operating conditions such that, when the overflows have those pHs, the resulting zinc sulfate solution meets the given standard and a maximum amount of the soluble zinc in zinc-bearing material is dissolved. These pHs are called optimal pHs in this paper. This paper describes an expert control and fault diagnosis scheme employing the model-based expert technique developed by Wu, Nakano & She, 1999a, to improve control performance and ensure safe operation of the process. The scheme employs an expert controller to determine the optimal pHs and a fault diagnosis module to perform on-line and off-line fault diagnosis. It is based on a combination of steady-state mathematical models and rule models for expert control, and rule models with certainty factors and a Bayes representation for fault diagnosis. The models are constructed from empirical knowledge, statistical data and chemical reactions for the process. A conventional single-loop control technique provides tracking control of the optimal pHs. This paper mainly describes the scheme and a real-world application.

2. Basic scheme

The leaching process considered in this paper is shown in Fig. 1. It uses neutral and acid continuous-leach technology, and consists of one series of neutral leaches and two identical series of acid leaches (Zhuzhou Smeltery, 1973). Each series has four tanks and a thickener. Fig. 2 shows the neutral leach series, and Fig. 3 shows the 1st acid leach series, which is the same as the 2nd.

The zinc-bearing material is delivered to a flotation cell and mixed with an oxidized iron solution and spent electrolyte containing sulfuric acid that is returned from the electrolytic process. The solution is delivered to four water-powered classifiers. The overflow is pumped to the 1st neutral leach tank, and the underflow is milled by four ball mills and pumped to the 1st tank of each acid leach series. The spent electrolyte is also added to the neutral and acid leaches.

The chemical reactions are carried out in the tanks. The solution is then sent to thickeners to settle. The overflow from the neutral leach is sent to the purification process in the form of a neutral zinc sulfate solution, and the underflow is added to the 1st tank of each acid leach series. The overflows from the acid leaches are pumped to the 1st tank of the neutral leach, and the residues are sent to the residue treatment process.

The concentrations of zinc and the major impurities in the neutral zinc sulfate solution from the neutral leach should satisfy the standards shown in Table 1.

In addition, an important consideration in process control is to dissolve as much of the soluble zinc in the zinc-bearing material as possible. This requires optimal conditions for the chemical reactions. Generally speaking, these conditions are influenced by many factors, such as the pH and temperature of the solution, the duration of the reaction, and the composition and particle size of the zinc-bearing material, etc. However, for steady-state operation, the main factors are the pHs of the overflows of the neutral and acid leaches. So, the key to process control is to determine the optimal pHs, and to track them. Empirical knowledge and data on the process show that the pHs of the overflows have to be in the range of 4.8~5.2 for the neutral leach and 2.5~3.0 for the acid leaches to guarantee the optimal conditions.

An expert control and fault diagnosis scheme based on the hierarchical configuration shown in Fig. 4 was derived to solve the key problems in the control and fault diagnosis of the leaching process.

The scheme employs an expert controller, a fault diagnosis module, three single-loop controllers and measurement equipment.

The expert controller optimizes and coordinates process control. It determines the optimal conditions for the chemical reactions involved in the process and obtains the corresponding optimal values of the control parameters of the process. Coordination means that the optimal values of the control parameters must be in accord with the actual states of the chemical reactions involved in the neutral and acid leaches.

Empirical knowledge and statistical data on the process show that the pHs of the overflows of the neutral and acid leaches are the main factors influencing the chemical reactions. They are considered to be the main control parameters in the proposed scheme. The optimal pHs can be achieved by adjusting the amount of spent electrolyte added to the leaches. So, the main control inputs are the flow rates of the spent electrolyte added to the neutral and acid leaches, and the main control outputs are the pHs of the overflows of those leaches.

The expert controller employs a reasoning strategy that combines steady-state mathematical models and rule models of the process and uses forward chaining and model-based chaining to determine the optimal pHs; and it computes the target flow rates of the spent electrolyte that yield the optimal pHs, so that the composition of the neutral zinc sulfate solution meets the given standards, and as much of the soluble zinc in the zinc-bearing material is dissolved as possible.

The fault diagnosis module monitors the process. It sends information to the expert controller that restricts the control activities to the safe range, for example, by ensuring that the pHs of the overflows of the neutral and acid leaches are not abnormally high or low. These limitations are also used as constraints in the optimization and coordination of process control.

The fault diagnosis module uses an expert reasoning strategy based on rule models with certainty factors and a Bayes representation, and combines forward and backward chaining to perform on-line and off-line fault diagnosis, so as to ensure safe operation.

As shown in Fig. 4, the expert controller receives process data and control commands from the fault diagnosis module to perform control optimization and fault recovery. At the same time, the fault diagnosis module also receives the data from the expert controller that is collected by the three single-loop controllers.

The three single-loop controllers track the target flow rates by means of PI control algorithms to ensure that the actual pHs match the optimal values.

The variables controlled in the single-loop controllers are the flow rates of the spent electrolyte to be added to the 1st neutral leach tank and the 1st tanks of the two series of acid leaches. The single-loop controller controls the amount that the valve is opened to adjust the flow rate of spent electrolyte.

Measurement equipment is used for the on-line measurement of process parameters such as pHs, concentrations, flow rates, etc.

3. Design of expert controller

The design of the expert controller is based on the model-based expert technique developed by Wu, Nakano & She, 1999a. The controller determines the optimal pHs by means of rule models, and computes the target flow rates through a combination of steady-state mathematical models and rule models.

3.1. *Determining the optimal pHs*

There exist optimal pHs in the leaching process that ensure that as much of the soluble zinc in zinc-bearing material as possible is dissolved on condition that the concentration standards of the zinc sulfate solution are met. The values of the optimal pHs vary with time. Conventional control methods choose fixed pHs in the allowable ranges in advance and track them. So, they cannot guarantee that the resulting pHs of the overflows are optimal. To solve this problem, it is indispensable to determine the optimal pHs in the given ranges at every moment to obtain the optimal chemical reaction conditions.

Empirical knowledge and data revealed that the optimal pHs are mainly related to the following factors:

1. The composition and particle size of the zinc-bearing material;
2. The temperature of the solution; and
3. The concentrations of zinc and impurities in the overflows of the neutral and acid leaches.

However, it is very difficult to express the exact relationships among the optimal pHs and these factors with mathematical models.

To obtain the optimal pHs, production rule models of the If-Then form (Efstathiou, 1989) are used, and a number like $R^{\#}$ is assigned to each rule model.

The If part contains the zinc content (f_c) on a scale of 1 to 10 and the particle size (f_{ps}) on a scale of 1 to 8 of the zinc-bearing material, the temperature of the solution (f_t = high, medium or low), and the concentrations of zinc and impurities in the overflows from the neutral and acid leaches. The Then part contains instructions to select and adjust the initial and optimal pHs.

The rule models for determining the optimal pHs are constructed based on empirical knowledge and data on the process. Some typical rule models for the neutral leach are shown in Table 2. The rule models for the acid leaches are also constructed in the same manner.

In Table 2, f_{Ncz} and f_{Nci} denote the concentration levels (high, medium or low) of zinc and impurities, respectively, in the overflow of the neutral leach; C_{Nopt} is the optimal pH of the overflow of the neutral leach; C_N is the initial value of C_{Nopt}; and C_{N84m}, C_{N101h}, C_{N18l}, ΔC_{Nzl} and ΔC_{Nil} are empirically determined values.

The rule models for the acid leaches are similar to those for the neutral leach. The algorithm that determines the optimal pHs is divided into two stages as follows:

Stage 1. Select the initial pHs based on f_c, f_{ps} *and* f_t.

Step 1: Find f_c, f_{ps} and f_t from the zinc content and particle size of the zinc-bearing material, and the temperature of the solution, respectively.

Step 2: Determine the initial pHs, such as C_N, by rule models R^{EC1} - R^{EC3}.

Step 3: Find the concentration levels of zinc and impurities in the overflows (f_{Ncz} and f_{Nci}).

Stage 2. Adjust the initial pHs based on the concentrations of zinc and impurities to obtain the optimal pHs.

Step 4: Determine the optimal pHs, such as C_{Nopt}, by rule models such as R^{EC4} - R^{EC5}.

3.2. Computing the target flow rates

The pHs of the overflows are adjusted by controlling the flow rates of the spent electrolyte added to the leaching process. So, it is crucial to determine the target flow rates of spent electrolyte that yield the optimal pHs. In the calculation, conventional control methods are based solely on mathematical models obtained from the main chemical reaction equations. However, those models do not consider other chemical reactions, variations in the reaction conditions, or the incompleteness of the reactions.

Leaching can be considered to be a steady-state chemical process because it is generally run within a specific operating range. Based on this observation, this paper proposes a method for determining the target flow rates that yield the optimal pHs by a combination of steady-state mathematical models and rule models describing the process.

The chemical reactions occur mainly in the leach tanks. The steady-state mathematical models are based on the assumptions that the zinc-bearing material and the solution in the tanks are agitated and completely mixed, and that the temperature of the solution is uniform. The mass balance principle (e.g. Inugita & Nakanishi, 1987) yields the following dynamic balance equation for the sulfuric acid in the neutral leach.

$$\varepsilon_N V_N \frac{\mathrm{d}x_{Nh}}{\mathrm{d}t} = F_{Co}(x_{Ch} - x_{Nh}) + F_{Ne}(x_{Nhe} - x_{Nh})$$

$$+\sum_{i=1}^{2} F_{iAo}(x_{iAh} - x_{Nh}) - \int_0^{V_N} r_{Nh} \mathrm{d}V_N \,, \tag{1}$$

where x_{Nh}, x_{Ch} and x_{iAh} are the concentrations of sulfuric acid in the solution after the neutral leach, the classifiers and the *i*th acid leach series, respectively; x_{Nhe} is the concentration of sulfuric acid in the spent electrolyte added to the neutral leach; F_{Co} and F_{iAo} are the flow rates of the overflows from the classifiers and the *i*th acid leach series, respectively; F_{Ne} is the flow rate of the spent electrolyte added to the neutral leach; V_N is the total volume of the neutral leach tanks; ε_N is the ratio of liquid to solid in the solution in the neutral leach; and r_{Nh} is the reaction rate of sulfuric acid.

For steady-state operation, $dx_{Nh} / dt = 0$ and r_{Nh} is the steady-state reaction rate. So, Equation (1) becomes

$$F_{Ne}(x_{Nhe} - x_{Nh}) = r_{Nh}V_N - F_{Co}(x_{Ch} - x_{Nh}) + \sum_{i=1}^{2} F_{iAo}(x_{iAh} - x_{Nh}) \,. \tag{2}$$

Let f_{Nzo} denote the steady-state particle reaction rate of zinc oxide with sulfuric acid and x_{Czo} denote the concentration of zinc oxide in the overflow from the classifiers. Then,

$$\frac{M_{\mathrm{ZnO}}}{M_{\mathrm{H_2SO_4}}} r_{Nh} = F_{Co} x_{Czo} f_{Nzo} \tag{3}$$

is obtained for the zinc oxide in the neutral leach by the principle of steady-state mass balance, where M_{ZnO} and $M_{\mathrm{H_2SO_4}}$ are the molecular weights of zinc oxide and sulfuric acid, respectively. x_{Czo} can be computed from

$$x_{Czo} = \eta_{Czo} \mu_{Czo} \frac{1}{1 + k_{Co}} \,, \tag{4}$$

where η_{Czo} is the zinc oxide content of the zinc-bearing material; μ_{Czb} is the specific gravity of the zinc-bearing material; and k_{Co} is the ratio of liquid to solid in the overflow from the classifiers.

Combining Equations (2), (3) and (4) yields

$$F_{Ne} = \frac{1}{x_{Nhe} - x_{Nh}} \left[K_{Nh} \frac{F_{Co}}{1 + k_{Co}} f_{Nzo} - F_{Co}(x_{Ch} - x_{Nh}) - \sum_{i=1}^{2} F_{iAo}(x_{iAh} - x_{Nh}) \right], \tag{5}$$

where

$$K_{Nh} = \frac{M_{\mathrm{H_2SO_4}}}{M_{\mathrm{ZnO}}} \eta_{Czo} \mu_{Czb} V_N \,. \tag{6}$$

f_{Nzo} can be estimated based on the experience of experts and operators and accumulated empirical knowledge on the neutral leach process. Using this estimate, $\hat{f}_{Nzo}$, in Equation (5) yields

$$F_{Ne} = \frac{1}{x_{Nhe} - x_{Nh}} \left[K_{Nh} \frac{F_{Co}}{1 + k_{Co}} \hat{f}_{Nzo} - F_{Co}(x_{Ch} - x_{Nh}) - \sum_{i=1}^{2} F_{iAo}(x_{iAh} - x_{Nh}) \right]. \tag{7}$$

Let x_{Nh}^{g} denote the target concentration of sulfuric acid in the solution after the neutral leach, which corresponds to the optimal pH. From empirical knowledge, the target flow rates of the spent electrolyte added to the neutral leach during the *k*th period are given by

$$F_{Ne}^{g}(k) = \alpha_N(k) F_{Ne}(k) + \sum_{l=0}^{k} \beta_N(l) \left[x_{Nh}^{g} - x_{Nh}(l) \right], \tag{8a}$$

$$F_{Ne}(k) = \frac{1}{x_{Nhe}(k) - x_{Nh}^{g}} \left\{ K_{Nh}(k) \frac{F_{Co}(k)}{1 + k_{Co}(k)} \hat{f}_{Nzo}(k) - F_{Co}(k) \left[x_{Ch}(k) - x_{Nh}^{g} \right] \right.$$

$$\left. - \sum_{i=1}^{2} F_{iAo}(k) \left[x_{iAh}(k) - x_{Nh}^{g} \right] \right\}, \tag{8b}$$

where $\alpha_N(k)$ and $\beta_N(l)$ are empirical coefficients determined from empirical knowledge. $\alpha_N(k)$ is used to take other reactions into account, and the term $\sum_{l=0}^{k} \beta_N(l) \left[x_{Nh}^{g} - x_{Nh}(l) \right]$ is used to compensate for the error between the target and actual values.

The rule models for determining $\hat{f}_{Nzo}(k)$, $\alpha_N(k)$ and $\beta_N(l)$ are constructed by a method similar to those for the optimal pHs.

The following algorithm computes the target flow rate that yields the optimal pH for the neutral leach.

Step 1: Select $\hat{f}_{Nzo}(k)$, $\alpha_N(k)$ and $\beta_N(l)$ based on f_c, f_{ps} and f_t as well as the concentrations of sulfuric acid in the overflow of the neutral leach and in the solutions added to the neutral leach by rule models.

Step 2: Obtain $x_{Nhe}(k)$, $x_{Ch}(k)$, $x_{iAh}(k)$, $k_{Co}(k)$, $F_{Co}(k)$ and $F_{iAo}(k)$ from the measurement equipment.

Step 3: Compute x_{Nh}^{g} corresponding to the optimal pH, and $K_{Nh}(k)$ based on process data.

Step 4: Compute the target flow rate $F_{Ne}^{g}(k)$ from steady-state mathematical model (4). If the value is outside the allowable range, set it to an allowable value by firing suitable rule models.

An algorithm similar to the one for the neutral leach computes the target flow rates for the acid leaches.

3.3. Structure of expert controller

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

The characteristics-capturing mechanism captures the characteristics of the process data from the measurement equipment and the three single-loop controllers. These characteristics are matched up with the conditional parts of rule models.

The database stores process data from on-line measurement. It also stores the quality requirements for the neutral zinc sulfate solution, statistical data on the process, reasoning results from the inference engine, etc.

The knowledge base stores the rule models, steady-state mathematical models, empirical data, calculation laws, etc.

The inference engine acquires data from the database, and then uses both the knowledge in the knowledge base and a reasoning strategy that combines forward chaining (Efstathiou, 1989) and model-based reasoning (Ishizuka & Kobayashi, 1991) to determine the optimal pHs and compute target flow rates. The target flow rates are sent to the single-loop controllers.

The user interface is used to configure and edit the knowledge base, and to display and print data, graphs, reasoning results, etc.

4. Design of fault diagnosis module

The basic structure of the fault diagnosis module is similar to that of the expert controller. It is shown in Fig. 5.

The knowledge base stores the rule models, Bayes representation and empirical data for fault diagnosis; the causes and locations of faults; the corresponding actions to be taken; etc. The database stores data from measurement equipment and input by operators, statistical data, reasoning results, etc. The inference engine uses forward chaining and backward chaining to perform fault diagnosis. The user interface displays reasoning results and gives off fault alarms, and is also used to send commands to the expert controller to remove faults.

4.1. Fault diagnosis procedure

The main functions of fault diagnosis are to detect and diagnose faults in important equipment, such as the leach tanks, pumps, etc., and to indicate the causes and locations of faults as well as suitable countermeasures. The fault diagnosis module is designed to provide support for the safe running of the process. It monitors the process in real time to detect any unusual states, such as excessive flow rates or temperatures, abnormally low pHs, etc. In addition, it also accepts fault facts and data input by operators. Based on unusual states and fault facts and data, the module performs on-line and off-line fault diagnosis. Then it outputs the diagnostic results, which indicate the cause and location of the fault as well as suitable actions to be taken.

The module uses rule models with certainty factors and a Bayes representation, and combines forward chaining and backward chaining. The procedure is as follows.

Step 1: Obtain data on the process from the measurement equipment and the expert controller to capture any unusual process states, and accept fault facts and data input by operators through the user interface.

Step 2: Store the unusual states and fault facts and data in the database.

Step 3: Based on data in the database, select either a fault mode for on-line fault diagnosis using rule models in the knowledge base and a forward chaining strategy, or possible fault modes for off-line fault diagnosis using a Bayes representation.

Step 4: For off-line fault diagnosis, select one of the possible fault modes using a backward chaining strategy.

Step 5: Display the reasoning results with certainty factors on the screen, and/or give off an alarm through a bell and lights.

Based on the diagnosis, the operators find the cause and location of the fault by checking the site, and take suitable countermeasures to correct the fault. According to type of the fault, operators can also send commands through the user interface to the expert controller to correct it.

4.2. Rule models for fault diagnosis

An important aspect of the design of the fault diagnosis module is the construction of rule models, which are based on the empirical knowledge of engineers and operators as well as on empirical data and statistical results of past fault countermeasures.

The procedure for constructing rule models is shown in Fig.6. It has four steps.

Step 1: Collect all unusual states that are useful for fault diagnosis. The unusual states are mainly collected through on-line measurement and off-line data input, and also include the current states of the flow-controlling valves and pumps.

The main variables that can be measured on-line are as follows:

1. The flow rate of the spent electrolyte, zinc-bearing material, oxidized iron solution, and overflows and underflows of the classifiers, leach tanks and thickeners;
2. The temperatures of the solutions in the acid and neutral leaches;
3. The pHs of the overflows and underflows of the classifiers, leach tanks and thickeners; and
4. The operating states of the flow regulation valves and the pumps.

Unusual states are generally represented by +1 (above the allowable range) or −1 (below the allowable range), but for valves and pumps they are represented by +1 (closed for a valve and stopped for a pump).

Step 2: Establish fault modes using the fault tree analysis method (Yamaguchi, 1987; Patton, Frank & Clark, 1989). As shown in Fig. 7, the unusual states form the basis for constructing fault trees, which connect these states to hypotheses in the middle and fault causes at the top. The fault modes are captured from the hypotheses. The cause and location of a fault as well as suitable countermeasures are contained in a fault mode extracted from empirical knowledge and statistical data on past fault countermeasures. A name and a number are assigned to each fault mode. An example is given in Table 3.

Step 3: Determine the certainty factors that represent the probability of fault causes. It is desirable to assign a probability to each fault cause because there might be several causes for one fault mode. The probability is given by a certainty factor that depends on the failure rate of the equipment, and empirical knowledge and statistical data on past safe recovery.

Step 4: Construct rule models for fault diagnosis based on the unusual states, fault modes and certainty factors. Rule models for fault diagnosis are represented in the If-Then form.

Some typical rule models are shown in Table 4, where the values in parentheses are certainty factors.

4.3. Reasoning strategy for fault diagnosis

A two-step forward chaining strategy is used for on-line fault diagnosis:

1. First, select a fault mode based on information about the unusual state; and
2. Then extract the cause and location of the fault and a suitable countermeasure from the knowledge base.

It follows from the above two steps that fault diagnosis using forward chaining requires a method of selecting the rule models and related data in the knowledge base according to the unusual state. The procedure from choosing a rule model to executing it has three steps: marching, clash resolution and action. In our case, a clash-resolution strategy (Efstathiou, 1989) in which the rule model with the most complex conditions is fired first is used to select the fault mode.

A backward chaining strategy based on the fault facts and data input by operators is used for off-line fault diagnosis. The inference procedure is shown in Fig. 8. It has four steps.

Step 1: Select possible fault modes from the fault facts by using a Bayes representation.

Step 2: Test each fault mode by checking the data and states of the process.

Step 3: If the test is successful, the fault mode is selected, and the cause and location of the fault and a suitable countermeasure are displayed as reasoning results on a screen. If not, go to the next step.

Step 4: See if all possible fault modes have been tested. If yes, select the most probable fault mode and display the associated reasoning results. If not, select the next fault mode and return to step 2.

Assume that all possible fault modes are selected from among *n* fault modes. Let Y and X_i denote a fault fact and the *i*th fault mode; and let $P(X_i)$ and $P(Y/X_i)$ denote the a priori probability of X_i and the conditional probability of Y with respect to X_i, respectively. Then, $P(X_i/Y)$, which is the a posteriori probability of X_i with respect to Y, can be obtained from $P(X_i)$ and $P(Y/X_i)$ by using a Bayes representation

$$P(X_i/Y) = \frac{P(Y/X_i)P(X_i)}{\sum_{j=1}^{n} P(Y/X_j)P(X_j)}. \tag{9}$$

The possible fault modes are the ones that satisfy

$$P(X_i/Y) \geq \beta, \tag{10}$$

where β is an empirical coefficient. $P(X_i)$ and $P(Y/X_i)$ are determined from the failure rates of the equipment, and empirical knowledge and statistical data on past safe recovery.

5. Real-world application

The designed expert control and fault diagnosis scheme was used in the leaching process of a nonferrous metals smeltery.

As shown in Fig. 9, a distributed computer control system for the leaching process was constructed based on an industrial control computer (IPC 810), three single-loop controllers (761 series by Foxboro), measurement equipment and control algorithms. The expert controller and the fault diagnosis module are in the industrial control computer.

The distributed computer control system runs under the Windows 98 operating system. The functions of the expert controller were implemented using a package of application programs written in the C++ language, while those of the 761 controllers were implemented through the configuration.

It should be pointed out that the package of application programs used in the expert controller was specially developed for the electrolytic process. Compared with programs designed using the development platform of an expert system, our package has the advantages of quick execution speed and high efficiency, but also the disadvantage of a long development time.

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

The distributed computer control system is currently running in a nonferrous metals smeltery. It is an important part of the control of the overall hydrometallurgical zinc process.

The optimal pHs and the corresponding target flow rates are determined by the expert controller, and the target flow rates are tracked by the single-loop controllers. Figs. 11, 12 and 13 show some results of actual runs. The dotted lines indicate the standard limits of the concentrations.

The results show that the pHs are kept in the optimal ranges of 4.8 ~ 5.2 for the neutral leach and 2.5 ~ 3.0 for the acid leaches, and that the concentrations of zinc and the major impurities (Cu, Cd and Co) in the neutral zinc sulfate solution meet the given standards (Table 1).

In contrast, results for the conventional control show that it could only keep the pHs in the ranges of 4.0 ~ 5.8 for the neutral leach and 2.0 ~ 3.5 for the acid leaches, the concentration of zinc in the range of 120 ~ 150 g/l, and that of Cu, Cd and Co less than 550 mg/l, 1100 mg/l and 35 mg/l, respectively.

For conventional control, it is clear that the pHs could not be kept in the optimal ranges, and that the concentration of zinc was relatively low and those of the impurities were relatively high.

Compared with conventional control, statistical data shows that the expert control method proposed in this paper considerably cuts costs, makes the leach rate of zinc-bearing material 5.0% higher, and dramatically reduces the consumption of zinc-bearing material. This means that much more of the soluble zinc in the zinc-bearing material is dissolved.

Regarding fault diagnosis, actual runs show that the percentage of hits is over 90% for on-line diagnosis and over 95% for off-line diagnosis. Fault diagnosis reduces the frequency of occurrence of actual faults to quite a low level because it pinpoints the cause and location of faults so that suitable countermeasures can be taken before the fault occurs.

6. Conclusions

This paper has described an expert control and fault diagnosis scheme for the leaching process in a zinc hydrometallurgy plant. The results of actual runs show that the scheme not only provides effective control, but also ensures safe operation of the leaching process. The following conclusions can be drawn:

1. The complex behavior of the leaching process can be described using a combination of steady-state mathematical models and rule models. The models are constructed based on the steady-state chemical reactions involved in the process and empirical knowledge and data on the process.
2. Expert control that combines steady-state mathematical models, rule models, forward chaining and model-based chaining can be used to determine the optimal pHs of the overflows of the neutral and acid leaches and the corresponding target flow rates of the spent electrolyte added to the process. The conventional single-loop control technique is used to track the target flow rates.
3. Fault diagnosis that employs rule models with certainty factors, a Bayes representation, forward chaining and backward chaining guarantees the safe running of the process.
4. Expert control and fault diagnosis can be implemented by an expert controller and by a fault diagnosis module, respectively, in an industrial control computer.
5. A real-world application has demonstrated the effectiveness of the scheme.

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Captions of Figures and Tables

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Table 2. Some rule models for determining optimal pHs in neutral leach.

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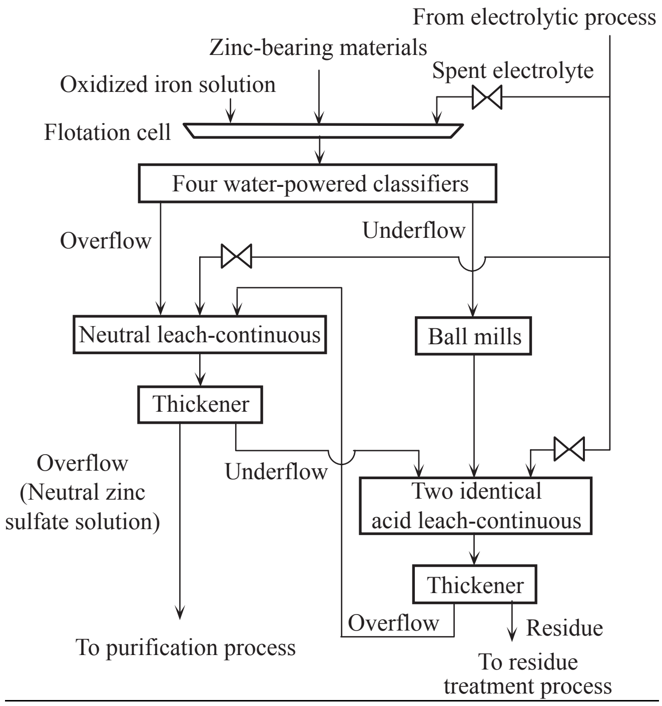

Fig. 1. Leaching process.

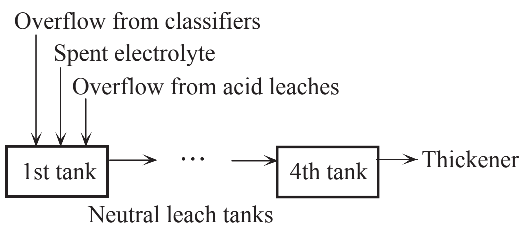

Fig. 2. Neutral leach series.

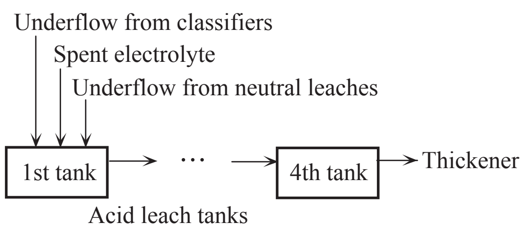

Fig. 3. First acid leach series.

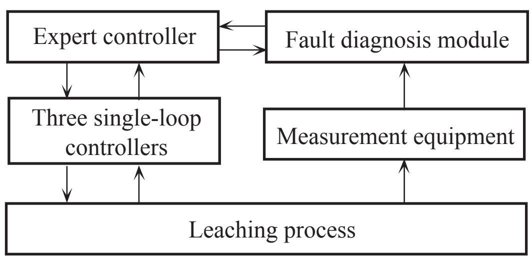

Fig. 4. Hierarchical configuration.

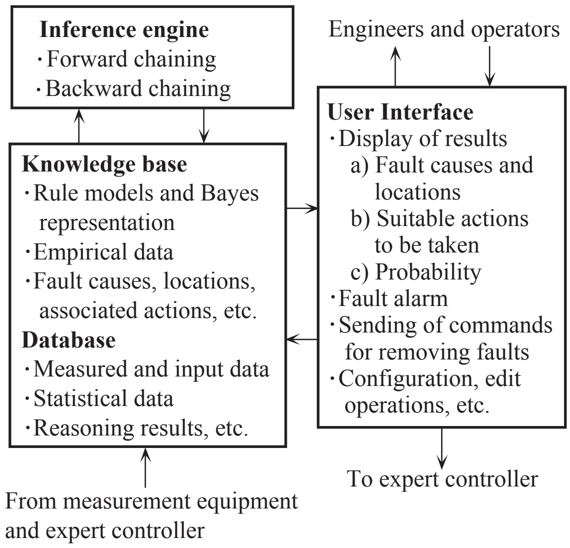

Fig. 5. Fault diagnosis module.

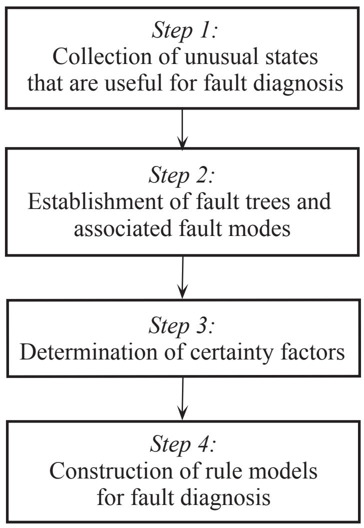

Fig. 6. Procedure for constructing rule models.

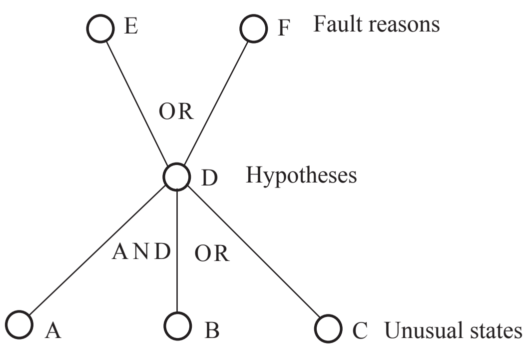

Fig. 7. A fault tree.

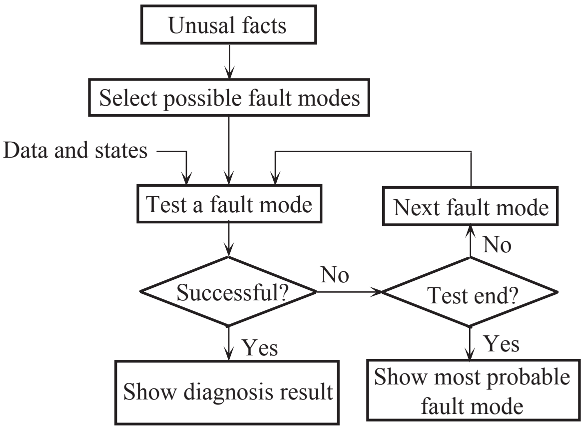

Fig. 8. Flow chart of backward chaining.

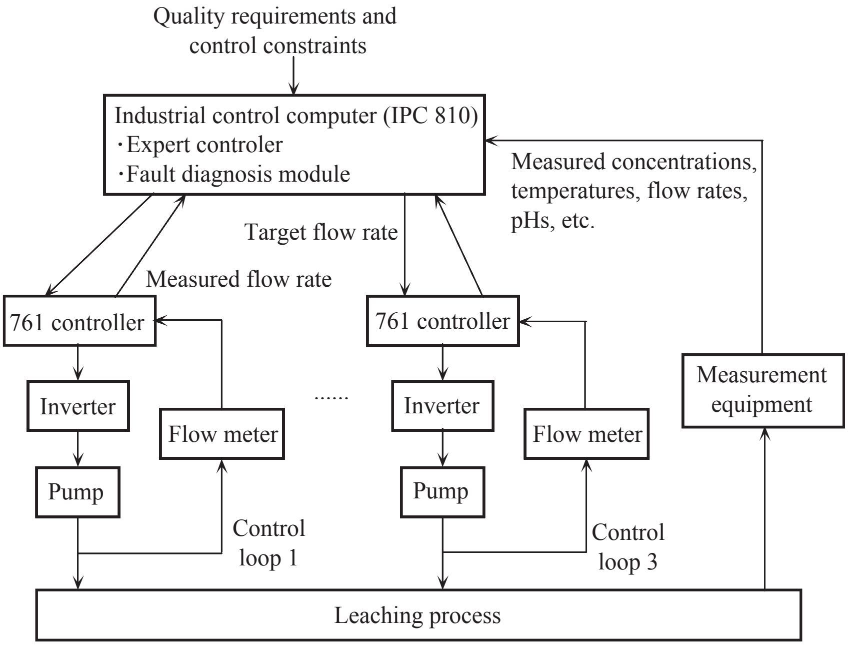

Fig. 9. Architecture of distributed computer control system.

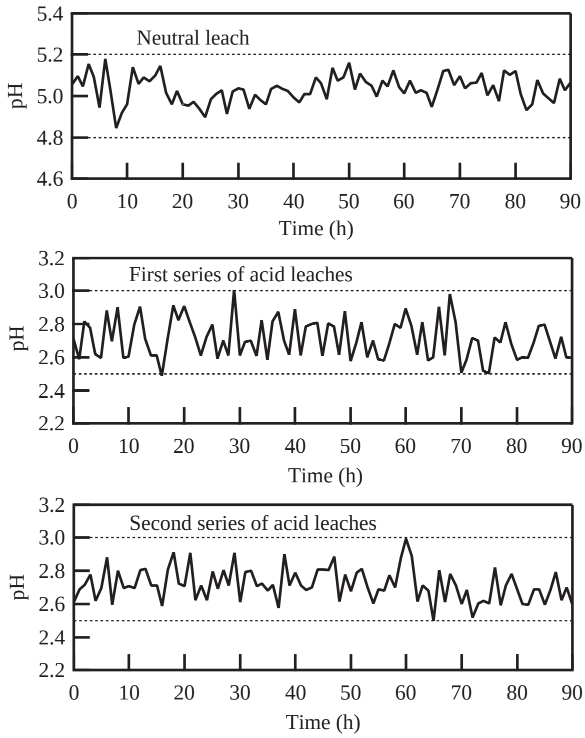

Fig. 10. pHs of overflows.

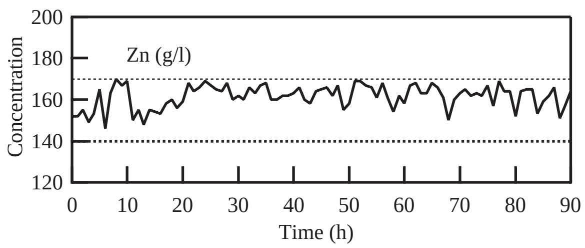

Fig. 11. Concentration of zinc in overflows.

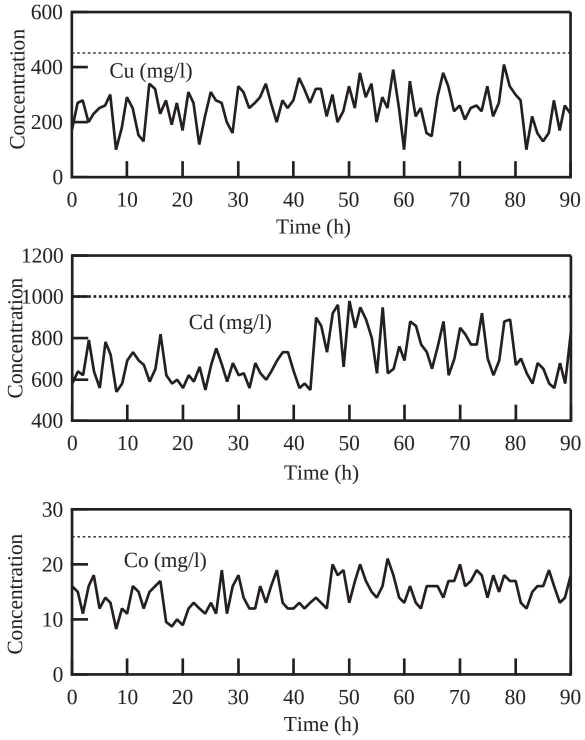

Fig. 12. Concentrations of major impurities in overflows.

Table 1. Standard allowable ranges of concentrations of zinc and major impurities in neutral zinc sulfate solution (mg/l).

Zn	Cu	Cd	Co
140000 ~ 170000	< 450	< 1000	< 25

Table 2. Some rule models for determining optimal pHs in neutral leach.

R^{EC1}: If $f_c = 8$ and $f_{ps} = 4$ and $f_t =$ medium
Then $C_N = C_{N84m}$
R^{EC2}: If $f_c = 10$ and $f_{ps} = 1$ and $f_t =$ high
Then $C_N = C_{N101h}$
R^{EC3}: If $f_c = 1$ and $f_{ps} = 8$ and $f_t =$ low
Then $C_N = C_{N18l}$
R^{EC4}: If $f_{Ncz} =$ large Then $C_{Nopt} = C_N - \Delta C_{Nzl}$
R^{EC5}: If $f_{Nci} =$ large Then $C_{Nopt} = C_{Nopt} + \Delta C_{Nil}$

Table 3. An example of a fault mode.

Number: Y106
Name: First neutral leach tank is blocked
Fault causes:
a) There is too much residue at the bottom.
b) The pipe at the bottom is blocked.
c) The flow opening at the bottom is too small or broken.
Location: First neutral leach tank.
Suitable actions to be taken:
a) Remove the residue at the bottom.
b) Clean the pipe at the bottom.
c) Open the flow valve at the bottom more or repair the flow valve.

Table 4. Some typical rule models for fault diagnosis.

R^{FD1}: If the underflow from the classifier is −1 and the overflow from the classifier is +1
Then the fault mode is J101 (0.95)
R^{FD2}: If the fault mode is J101
Then there is too much residue at the bottom of the classifier (0.85), or the classifier is broken (0.10)
R^{FD3}: If the underflow of the neutral leach tank is −1
Then the fault mode is Y100 (0.95)
R^{FD4}: If the fault mode is Y100
Then there is too much residue at the bottom of the neutral leach tank (0.60), or the pipe at the bottom of the neutral leach tank is blocked (0.20), or the valve is not open enough or the valve is broken (0.15)