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EXPERT CONTROL AND FAULT DIAGNOSIS OF THE LEACHING PROCESS IN 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 from 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.

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 safety. 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. 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; Yamaguti 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,

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Nakano & She, 1999b). However, that system did not include any 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 in the control 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. The optimal pHs mentioned here mean that the composition of the zinc sulfate solution obtained meet the given standards, and as much of the soluble zinc in zinc-bearing material is dissolved as possible. This paper describes an expert control and fault diagnosis scheme based on the model-based expert technique developed by Wu, Nakano & She, 1999a, to improve control performance and ensure safe operation. The scheme employs an expert controller to determine the optimal pHs and a fault diagnosis module that performs 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 to 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.

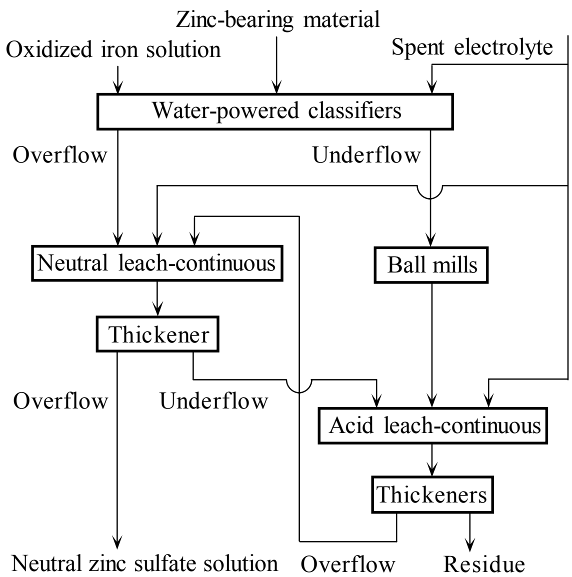

Fig. 1. Leaching process.

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.

An expert control and fault diagnosis scheme based on the hierarchical configuration shown in Fig. 2 was derived to solve the key problems in the control and fault diagnosis of the leaching process. The scheme employs an expert controller, three single-loop controllers, a fault diagnosis module and measurement equipment. The pHs of the overflows of the neutral and acid leaches are adjusted by adding spent electrolyte to the 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 computes the target flow rates of the spent electrolyte that correspond to 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 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 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. The measurement equipment is used for the on-line measurement of process parameters for fault diagnosis.

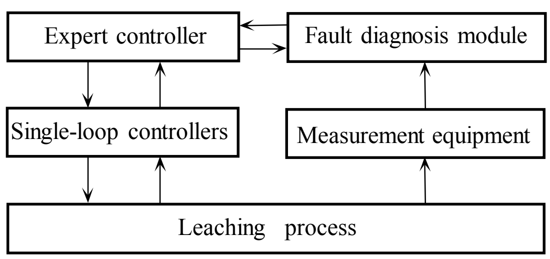

Fig. 2. Hierarchical configuration.

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, computes the target flow rates through a combination of steady-state mathematical models and rule models.

3.1 Determining the optimal pHs

Empirical knowledge and data revealed that the optimal pHs are mainly related to the following factors: the composition and particle size of the zinc-bearing material, the temperature of the solution, and the concentrations of zinc and impurities in the overflows from the neutral and acid leaches. However, it is difficult to express the exact relationships among the optimal pHs and these factors by mathematical models alone.

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

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 optimal pHs are determined in two steps. The first is to select the initial pHs based on f_c, f_{ps} and f_t. The second is to adjust the initial and optimal pHs based on the concentrations of zinc and impurities. The rule models for determining the optimal pHs are constructed based on those two steps and empirical knowledge and data on the process. Some typical rule models for the neutral leach are shown in Table 1.

In Table 1, f_{Ncz} and f_{Nci} denote the concentrations levels (large, medium or small) of zinc and impurities, respectively, in the overflow from the neutral leach; C_{Nopt} is the optimal pH of the overflow from 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.

Table 1. Some rule models for determining optimal pHs.

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 $C_{Nopt} = C_{Nopt} + \Delta C_{Nil}$

The rule models for the acid leaches are similar to those for the neutral leach. The following algorithm determines the optimal pHs.

Step 1: Compute 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: Compute the concentration levels of zinc and impurities in the overflows (f_{Ncz} and f_{Nci}).

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

Leaching can be considered to be a steady-state chemical process because it is generally run within a specific operating range. Based on this supposition, the target flow rates corresponding to the optimal pHs are computed 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.

$$\varepsilon_N V_N \frac{\mathrm{d}x_{Nh}}{\mathrm{d}t} = F_{Co}(x_{Ch} - x_{Nh}) + F_{Ne}(x_{Nhe} - x_{Nh}) + \sum_{i=1}^{2} F_{iAo}(x_{iAh} - x_{Nh}) - \int_0^{V_N} r_{Nh}\mathrm{d}V_N , \quad (1)$$

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, r_{Nh} is the steady-state reaction rate. Let f_{Nzo} denote the steady-state particle reaction rate of zinc oxide with sulfuric acid. The principle of steady-state mass balance for the zinc oxide in the neutral leach and a simple calculation yield

$$F_{Ne} = \frac{1}{x_{Nhe} - x_{Nh}} \left[K_{Nh} \frac{F_{Co}}{1 + k_{Co}} f_{Nzo} - F_{Co}(x_{Ch} - x_{Nh}) \right.$$

$$-\sum_{i=1}^{2} F_{iAo}(x_{iAh} - x_{Nh})\Bigg], \tag{2}$$

where

$$K_{Nh} = \frac{M_{\mathrm{H_2SO_4}}}{M_{\mathrm{ZnO}}}\eta_{Czo}\mu_{Czb}V_N\,; \tag{3}$$

k_{Co} is the ratio of liquid to solid in the overflow from the classifiers; $M_{\mathrm{H_2SO_4}}$ and M_{ZnO} are the molecular weights of zinc oxide and sulfuric acid, respectively; η_{Czo} is the zinc oxide content of the zinc-bearing material; and μ_{Czb} is the specific gravity of the zinc-bearing material.

f_{Nzo} can be estimated based on the experience of experts and operators and accumulated empirical knowledge on the neutral leach process. This estimate is denoted by $\hat{f}_{Nzo}$.

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

$$F_{Ne}^g(k) = \alpha_N(k)F_{Ne}(k) + \sum_{l=0}^{k}\beta_N(l)\left[x_{Nh}^g - x_{Nh}(l)\right], \tag{4a}$$

$$F_{Ne}(k) = \frac{1}{x_{Nhe}(k) - x_{Nh}^g}\Bigg\{K_{Nh}(k)\frac{F_{Co}(k)}{1+k_{Co}(k)}\hat{f}_{Nzo}(k) - F_{Co}(k)\left[x_{Ch}(k) - x_{Nh}^g\right] - \sum_{i=1}^{2}F_{iAo}(k)\left[x_{iAh}(k) - x_{Nh}^g\right]\Bigg\}, \tag{4b}$$

where $\alpha_N(k)$ and $\beta_N(l)$ are empirical coefficients determined from empirical knowledge.

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

The following algorithm computes the target flow rate corresponding to the optimal pH for the neutral leach.

Step 1: Select f_{Nzo}, $\alpha_N(k)$ 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, it is set to an allowable value by firing suitable rule models.

An algorithm similar to the one of 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 partial process data are on line measured such as the flow rates of the spent electrolyte, zinc-bearing material, oxidized iron solution, and the overflows and underflows of the classifiers, leach tanks and thickeners; the temperatures of the solutions in the neutral and acid leaches; and the pHs of the overflows and underflows of the classifiers, leach tanks and thickeners, by the E+H electromagnetic flow meters, temperatures meters, and industrial pH meters, etc.

They are stored in the database, which also holds the quality requirements for the neutral zinc sulfate solution, measured and 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 structure of the fault diagnosis module is similar to that of the expert controller. The knowledge base stores the rule models and Bayes representation for fault diagnosis, the causes and locations of faults and associated actions to be taken, etc. The data input by operators are also stored in the database. The inference engine uses forward chaining and backward chaining to perform fault diagnosis. The user interface gives off fault alarms and is used to send commands to the expert controller to correct faults.

4.1. Fault diagnosis procedure

The main functions of fault diagnosis mainly 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 the unusual states, such as excessive flow rates or temperatures and pHs that are too low, 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 or off-line fault diagnosis. Then it outputs the diagnostic results, which indicate the cause and location of the fault as well as the 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 on past fault countermeasures. The construction procedure contains 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 concern the current states of the flow regulation valves and pumps. Unusual states are generally represented by +1 (above the allowable range) and −1 (below the allowable range), but for flow 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 (Yamaguti, 1987; Patton, Frank & Clark, 1989). The unusual states from the basis for constructing fault trees, which connect these states to hypotheses in the middle and fault causes at the top. Moreover, 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.

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 the rule models for fault diagnosis based on the unusual states, fault modes and certainty factors. Based on the unusual states, fault modes and certainty factors thus obtained, rule models for fault diagnosis are represented in the If-Then form.

Some typical rule models are shown in Table 2, 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: first, select the fault mode based on the unusual state; and then extract the cause and location of the fault and a suitable countermeasure.

Table 2. 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 far enough or the valve is broken (0.15)

A backward chaining strategy is used for off-line fault diagnosis, which is based on the fault facts and data input by operators. The inference procedure contains 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

$$P(Y/X_i) = \frac{P(Y/X_i)P(X_i)}{\sum_{j=1}^{n} P(Y/X_j)P(X_j)} \quad (5)$$

The possible fault modes are the ones that satisfy $P(Y/X_i) \geq \beta$, 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.

The optimal pHs and the corresponding target flow rates were determined by the expert controller, and the target flow rates were tracked by the single-loop controllers. 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. More specifically, the concentration of zinc is kept in the range of 140-170 g/l, and that of Cu, Cd and Co are less than 450 mg/l, 1000 mg/l and 25 mg/l, respectively, which means that high-purity metallic zinc is obtained. Statistical data shows that costs are considerably lower. Compared with conventional control, the leach rate of the zinc-bearing material is much higher, and the consumption of zinc-bearing material is dramatically lower. 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 and suitable countermeasures are taken before the fault occurs.

6. CONCLUSSIONS

This paper has described an expert control and fault diagnosis scheme for the leaching. Expert control involves determining the optimal pHs and the corresponding target flow rates, and is implemented in an expert controller based on a combination of steady-state mathematical models, rule models, forward chaining and model-based chaining, and the tracking of target flow rates, which is achieved by means of conventional single-loop controllers. Fault diagnosis ensures the safe running of the process, and is performed by a fault diagnosis module that employs rule models with certainty factors, a Bayes representation, forward chaining and backward chaining. A real-world application demonstrates the effectiveness of the scheme.

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