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Review

State of the art in copper hydrometallurgic processes control

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Abstract

A review of the state of art and trends in automation and control of hydrometallurgic processes is presented. Besides the great expansion of hydrometallurgic processes world-wide, there are a number of unsolved problems related to lack of instrumentation, lack of process knowledge, odd operating practices, and in general, lack of use of data management and processing. In general, process control of local objectives are frequently achieved, however, application of mature and new techniques, successfully adopted in other mineral processing plants, are seldom reported. In the near future it is expected that intelligent techniques will be incorporated to solve a large variety of problems. © 2001 Elsevier Science Ltd. All rights reserved.

Keywords:

Automation; Process control; Modelling; Data management; Data processing

1. Introduction

Leaching, solvent extraction and electrowinning (LX–SX–EW) processes have become increasingly important to concentrate, purify and separate metal ions and inorganic salts. The most common commercial application of these processes is in the copper industry (Kordosky, 1992). Although oxide ore is preferred in leaching mineralisation, many operations also leach sulphide ores as well. A large number of commercial SX/EW plants have been successfully commissioned all over the world in the last two decades (Arbiter, Fletcher, & Copper, 1994), and over 90% of them are located in North and South America. For example, in Chile, the total SX/EW copper produced reached 1400 thousand tons during 1999, representing almost one half of the total electrolytic copper produced (Pezoa, 1999). This paper is focused on the control practices and trends in LX–SX–EW copper plants.

Typically, the process starts with the crushing and grinding of ore. Since these processes are classified as mineral processing operations, its discussion can be found in (Hodouin, Jämsä-Jounela, Carvalho, & Bergh 2000). The ground material is collected in large heaps, which are sprayed with an acid solution to dissolve out

the metal from the ore. The metal is transferred to the aqueous phase, called the pregnant leach solution (PLS). After the leaching stage, the solution contains impurities, which have to be removed. A simplified flow diagram of the process is shown in Fig. 1.

The solvent extraction stage decreases the proportion of impurities and concentrates the solution. The metal ions are selectively removed from the aqueous PLS via the organic phase and pass back into the aqueous phase. The flow is divided between several parallel SX trains. Extraction and stripping, i.e. the transfer of metal ions into the organic phase and back into the aqueous phase are performed within the mixer-settlers. In the mixer, the organic and aqueous phases are brought into close contact with each other by dispersing the organic or aqueous phases into droplets, a few millimeters in size within another phase. After mixing, the two phases are separated in large settlers by gravity. To improve the overall efficiency of the transfer of metal from the aqueous solution, the solvent extraction process has internal recycling and some material is returned to the leaching stage.

2. Control objectives in copper hydrometallurgy

The aim of an LX–SX–EW process is to obtain high purity commercial copper cathodes at low cost by

Fig. 1. Flow diagram of an LX-SX-EW process.

treating liberated ore, previously prepared by comminution and size separation processes. The process to be controlled in LX-SX-EW can thus be classified into four different categories:

- minerals liberation processes (crushing, grinding and size classification),
- metals separation processes by reaction and mass transfer (leaching, solvent extraction),
- metals separation processes by electrolysis (electrowinning),
- peripheral processes (feeding systems, pumping, filtering, material handling, etc).

The overall control objective of an LX-SX-EW plant is to produce high-quality commercial cathodes, which meet some standards, while maximising the net revenue of the plant. Usually, these objectives require some trade-off between the concentration and flow of PLS, the flow and concentration in the organic phase of copper and contaminants, the degree of entrainment of organic in aqueous, the aqueous carryover in organic, the consumption of reagents, the electric current stability and distribution, the time scheduling of cathodes and anodes changing, among others. Ideally, real-time plant-wide optimisation should be the right approach to LX-SX-EW plant control, as in other processes (Herbst, Pate, Flores, & Zarate 1995), i.e. the adjustment of the operating conditions of the various units as a function of the raw ore properties and feed rate, metal market prices and energy and reagent costs.

However, a first major problem with such an optimal approach is that the major disturbances of the plant, which are the variations of the raw ore properties, are extremely difficult to predict as well as their effects down to the final products. These almost unpredictable and unmeasurable properties of the feed ore continuously change the steady-state and dynamic behaviours of the plant as well as the location of the optimal operating targets.

An essential feature of classical control and optimisation strategies is the availability and effectiveness of a mathematical model that accurately describes the steady-state and dynamic characteristics of the process in the whole operating range, including its non-linear behaviour. This leads to a second major problem for LX-SX-EW control, since satisfactory mathematical models are not frequently available for the following reasons: (a) the physics and chemistry of the subprocesses involved are poorly understood, and (b) the relevant information about the state of the subprocesses are quite difficult to measure and describe. Some empirical modelling has been reported (Aminian, Bazin, Hodouin, & Jacob, 1997; Muñoz, Barlett, & Bazzanella, 2000) but usually the validity of such models is so restricted and particular to a specific plant, and its use requires information not commonly available on-line in industry.

LX-SX-EW optimisation and control cannot be performed without a minimum amount of information on the input disturbances, the process states, and the final product quality. This is in fact, the bottleneck of LX-SX-EW control. The efficiency of the operating strategies is totally dependent upon the quality of the information which is used, because on the one hand, it is used to build the knowledge encapsulated in the models which the control strategy is based upon, and on the other hand, it is the input to the real-time optimisation and control algorithms. Therefore, due to both instrumentation and modelling problems, the usual approach is to separate the optimisation and control problem for each unit operation. This control hierarchy is widely accepted in the LX-SX-EW industry and is a mature technology. Most of the times, only the regulatory control of the low level is implemented, the setpoints being manually selected. Decentralised SISO stabilising control is thus a mature technology widely used in the LX-SX-EW industry.

However, for time variant and non-linear LX-SX-EW processes that undergo large unknown disturbances, these multiple SISO control loops sometimes exhibit poor performances. Three types of avenues are used to cope with these problems: MIMO regulatory and supervisory optimising control based on mathematical models, AI techniques based on empirical or heuristics process models, and finally the application of operating rules in expert systems. Studies or application of multivariable regulatory control, adaptive, non-linear and robust control theory to the LX-SX-EW processes are not reported in the literature. A similar situation prevails for the promising alternatives of AI techniques and expert systems.

Since comminution and classification are processes discussed in (Hodouin, Jämsä-Jounela, Carvalho, & Bergh, 2000), this paper will focus only on leaching, solvent extraction and electrowinning processes. Peripheral processes control strategies are not discussed here.

3. Leaching process

To obtain and maintain a close steady-state operation, it is necessary to have good control of the solution flow through the operations. The leaching operation is usually controlled using pumps and through programmable logic controllers (PLC). In general, the leaching stage is governed by three factors: recirculated raffinate flow from solvent extraction, PLS dam level, and PLS pump flow from the collector tank into the solvent extraction feed pool.

The magnetic flow meters, pond level controls, alarm system in the control room, variable speed motors in the raffinate pumping, and operator visual inspections are some of the main tools utilised to reach a solution balance within the plant. The pond levels are usually controlled by the number of pumps operating at one time in the heap PLS pond. PLS stacking on the heaps is periodically utilised to eliminate PLS overflows from the PLS feed pond to the raffinate pond.

Depending on the complexity of the leaching processes, the PLS may be formed from several leaching outputs. In this case an appropriate managing of the streams mixing is crucial to minimise disturbances (both copper concentration and pH of PLS) coming into SX.

4. Solvent extraction process

The combination of flows and their control in the solvent extraction stages are important to maintain satisfactory production levels. The control of every entering extraction and re-extraction flow is performed by the following flow control loops: pregnant leach solution entering the first extraction stage; organic solution entering the second extraction stage; poor electrolyte entering the re-extraction stage and recirculation from the aqueous launder to the re-extraction stage mixer box.

The operator-defined organic/aqueous ratio determines the proportions of the organic flow in the first extraction stage and the re-extraction stage feed of the poor electrolyte.

The four factors governing the solvent extraction stage are poor electrolyte, PLS, organic and recirculated rich electrolyte flows. Each of the flows are controlled. An orifice plate measures the organic flow, while in the other stages, a magnetic flowmeter is applied.

In general, the most critical problems found in SX plants are related to (Farías, Reghezza, & Vergara, 1994):

- pH of PLS,
- copper concentration in PLS,
- crud formation,
- aqueous carry over in organic,
- organic entrainment in aqueous,
- phase separation times

In many cases, the copper concentration and pH are regulated from samples that are taken manually and spread. Chemical assays are known each for four or more hours. Thus, i.e. the average desired value of 10 g/l of Cu varies from 9.8 to 12 g/l while pH varies from 1.6 to 2.8. It must be noticed that important losses of efficiency and selectivity are observed under deviations of ± 0.3 g/l and ± 0.2 in pH.

Some problems are associated with entrainment from one phase into the other, leading to plant instability, low quality of copper cathodes, excess consumption of reagents, increased anodic corrosion, transport of undesirable elements to the electrolyte, and extra losses of organic. Some problems may be partially solved with the help of filters, settlers, column flotation, separators, coalescers, flocculants, etc. However, part of these problems may be avoided with a high quality process information and appropriate control strategies and operating practices. Presently, in most operations the level of the interface is not measured directly, and the level is regulated manually. This condition favours the entrainment of organic phase into the aqueous phase to be processed in the EW plant. The problem here is the loss of organic (expensive) and the loss of capacity of the EW cells, the need to sacrifice some banks of cells because of contamination. Furthermore, the usual lack of coordination of the flowrates and mixing of different process streams cause disturbances and increases the organic losses. Another problem is the chloride contamination of the electrolyte, that has an important impact on the life of permanent cathodes.

5. Electrowinning process

The control loop for the rectifier is usually designed to maintain the direct current consistent with the setpoint. The aim is to protect the rectifier from overheating and to prevent the major consequences like unbalanced Cu in the plant, accelerated corrosion of anodes, increase in cathodes noduling, generation of short circuits and decrease of cathode purity.

The electrolysis cells have two important automation applications: operation of the baths, and voltage monitoring and accounting. The bath operation includes a schedule for anode changing, cathode changing and cleaning intervals for each cell. All the bath voltages and currents are scanned at predetermined intervals. The lower limit value is used to check for short circuits. Values higher than the upper limit indicate passivity of the electrodes. Temperature measurement is carried out by means of an infrared camera installed on the handling crane. An imminent short circuit can be seen from locally increasing temperatures. The supervision of cell voltage and temperatures allow traceability of short

circuits on the basis of cell location information (Siemens, 1998; Spitzlei, 1994).

Electrolyte treatment is managed with the goal of maintaining a predetermined constant temperature. Sensors, e.g. for temperature, level, flow, pressure and conductivity are used. The main task is to control the flow of hot water or steam to the heat exchanger. All motors, stirrers, pumps and valves are controlled. The levels in vessels and tanks are kept within acceptable limits.

Anode and cathode preparation machines are equipped with their own PLC controllers. They handle the internal logic sequences of the preparation processes and monitor the input and output conveyors.

Current maldistribution and shortcircuiting in EW cells are the main cause for cathodes rejection. The electrolyte temperature and its relation with the proper current density is also controlled. Low temperature causes crystallisation.

6. Information acquisition

6.1. Instrumentation

In comparison with other mature mineral process, a rather slow incorporation of instrumentation and control systems has been observed. pH meters, conductometry (to measure phase continuity in mixers) and flowmeters can be considered as mature instrumentation.

On-line analysers for monitoring and control purposes are reported lately. A number of applications exist with Outokumpu's Courier system (Hughes & Saloheimo, 1999; 2000) and Amdel stream analysers, however these techniques are still active in the sense that their availability is very sensitive to maintenance and calibration programs.

Even when mature sensors for detecting interface position are available in the market, the application of these sensors in SX plants to control the organic/aqueous interface position is rarely found, and is not reported in the literature.

The lack of process knowledge and accurate on-line information on relevant process variables has largely contributed to little developments in information and control systems.

6.2. Data management and communications

Real-time and historical information is useful for global plant optimisation. Smart data management systems are required for efficient communication between the business staff (information on metal inventories, costs, production objective, equipment availability, etc.), the process engineers (information

for production optimisation and control), the laboratory (quality control), the environment department, and the operators of the various units. In addition to the data exchange facilities, the format of the information must be easily adapted to the various objectives of data processing (local control, loop tuning, mass balance calculation, process modelling, maintenance and trouble-shooting, performance indicator display, real-time optimisation, etc.). Bascur and Kennedy, (1999) describe extensively, the availability of the data management architectures and their benefits. Innovative communication systems between remote locations are emerging. In general, actual data managements and communication facilities are not frequently used in LX-SX-EW plants.

7. Data processing

7.1. Data reconciliation

Due to the inherent inaccuracies of the measurements made, the raw data delivered by the sensors, such as flowrates and chemical assays, contains errors. Data reconciliation procedures are used to correct measurements and make it coherent with prior knowledge about the process. Frequently, mass conservation equations are used as a basic model to reconcile redundant data with prior knowledge constraints (Crowe, 1996). At the same time, data reconciliation techniques may be used to infer unmeasured process variables such as flowrate and composition of internal streams of a complex unit. Applications for LX-SX-EW plants are not reported, but with the consolidation of on-stream analysers it is expected that they will be rapidly adapted.

7.2. Pattern recognition

Historical or real-time sets of measurements on multivariable processes contain massive amounts of information about the behaviour of the operation. However, they are difficult to exploit because of the high number of available variables, their poor reliability and finally the lack of measurements for the most important properties as mentioned above. Statistical or AI techniques are, in general, active or emerging to extract, from these data sets, pieces of information which may be useful for monitoring, predictive maintenance, diagnosis, control and optimisation. Since the work of MacGregor and Kourti (1995) statistical process control has been shown to be less adequate to handle frequently collected and large history databases of process variables. The multivariate projection techniques, principal component analysis (PCA) and partial least squares (PLS), specially have proved to be effective in a number of industrial applications. Taylor (1998), for example, discusses the application of PCA for the

prediction of blast furnace stability. According to Kresta, Macgregor, and Martin (1994) and Kourti, Lee and Macgregor (1996), these methods address the traditional problems encountered in statistical analysis such as collinearity, missing data and large dimensionality. Neural networks has also been applied in process monitoring and analysis, particularly to cases with nonlinearities and unknown mechanisms involved in the process. The use of self organizing maps (SOM) has been successful in various industrial applications (Kohonen, 1990). One example is the estimation of physical quality of copper cathodes discussed in Rantala, Virtanen, Saloheimo, and Jamsa-Jounela (2000). A study to correlate the copper concentration of poor electrolyte with other measured variables was performed by Katajainen (1998) using plant data. Wikström et al. (1998) discussed the application of these techniques to an electrolysis process.

7.3. Process supervision, fault detection and isolation

In general, some methods are emerging to detect either sensor biases or model inadequacy using multi-variable statistical tests on the residuals of material balance constraints (Berton & Hodouin, 2000; Hodouin & Berton, 2000). ANN are also active methods to detect and diagnose faults (Jämsä-Jounela, 2000). Supervision of the control strategy for processes as flotation columns is used to detect sensor or operating problems using data validation and expert systems (Bergh, Yianatos, Acuña, Perez, & Lopez 1999). Wu, Nakano, and She (1998) presented a distributed expert control system for a hydrometallurgical zinc process. Laguitton et al. (1989) described the development of expert systems to assist the operation at a zinc leaching plant. Later Wu, Nakano, and She (1999a) presented a model-based expert system for the zinc leaching process and Wu, Nakano, and She (1999b) discussed the implementation of an expert control strategy using neural networks for the zinc electrolytic process. Recently, expert control and fault diagnosis of the zinc leaching process is discussed (Wu, She, Nakano, & Gui, 2000). In particular, no applications have been reported in copper LX–SX–EW plants. It is expected that they will appear, as soon as the information about the relevant process variables allows the development and implementation of supervisory control, on top of conventional distributed control systems. At Santa María University (Bergh, 2000), a project to automate an SX/EW pilot plant is under development.

8. Conclusions

Since LX–SX–EW processes for copper production are relatively new, most of the operating problems and

process inefficiencies are partially attributed to plant design and reagents selection. However, the information about the relevant variables in these processes are extremely poor and inaccurate, that stabilisation of the plant around a steady state can only be partially achieved by decentralised conventional control of flows, levels and so on.

To improve the process efficiency and quality of the products, the incorporation of reliable instrumentation, as on-stream analysers and automatic titrators, is needed. When this has been achieved, the development and implementation of supervisory control will be possible. This supervisory control will be a hybrid system that will incorporate all the new techniques successfully applied in other fields, as in mineral processing.

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