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Model based decision support system for the heap leaching process ⋆

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Abstract: As one of the copper recovery processes, hydrometallurgy has gain impact due to its ability to process ore with average low grades at competitive prices compared with other metallurgical processes. Among hydrometallurgical processes the leaching stage, a process that is characterized by its significant temporal and spatial scale of operation, is critical. In spite of extensive developments in instrumentation in pyrometullurgical and concentrators plants, developments in heap leaching instrumentation has not reached the required level for a fully automated control system and furthermore for a stable operation. Computational tools, such us dynamic simulators, can help operators achieve the best performance of the heap using the available instrumentation. This paper presents the development and implementation of an integrated dynamic simulator and a decision support system (DSS) for hydrometallurgical processes with emphasis in heap leaching process. The dynamic simulator uses two dimensional models of fluid transport, transport of solutes and dissolution of copper in the leaching heap, to analyse the effects produced in the variables of interest, such as the consumption of acid, copper concentration in the PLS (Pregnant Leach Solution) and leaching times. The DSS, which is connected to the real time plant information system, gathers the information by sensors and laboratory analyses to perform an automatic on-line parameter estimation of the process and makes predictions to recommend to the operator both curing and leaching rates. Results show that the DSS achieves the identification and prediction with less than 6% of error, allowing the metallurgist to predict the leaching behaviour and take decisions with better information.

Keywords: dynamic simulation, decision support system, hydrometallurgy, heap leaching

1. INTRODUCTION

As an alternative to pyrometallurgy, hydrometallurgy is being used in an increasing number of copper mining operations extracting copper from average low grades ores. This recovery process represents 20% of the primary copper production, and has experienced high use intensity and a significant impact. The main reason is due to the ability to extract mineral at low cost, mainly due to the use of the leaching process, in which the previously crushed and agglomerated ore is stacked to be irrigated with an acid solution to extract the copper from the ore. Although, the leaching process has lower extraction efficiencies than more conventional methods, mostly because its high temporal and spatial extent.

The operational difficulties has forced the need for automated tools for improving productivity. In dynamic systems with distributed, time-varying and uncertain parameters such as heap leaching, usage of simulators becomes a powerful tool for predicting the system behaviour and optimising the operation. Although optimization driven by simulators often is a time consuming process, in this case the system evolves slowly and samples are taken every 12 hours. Therefore, sufficient time is available to perform the optimization by simulation. The optimization results are shown in the Decision Support System (DSS) to assists the operator in daily decision making.

Dynamic simulators are tools that facilitate the study of complex processes. This allows the study of the interaction between process variables and the assessment of their impact on the final product. Examples of simulators are listed in Nikkhah and Anderson (2001), which shows how each simulator is useful in various stages of completion of the projects. In general ore preparation process and leaching have been studied separately, omitting the interactions that occur between processes. The developed simulator

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allows the dynamic simulation from the crushing process to the leaching stage in an integrated manner.

According to Nof (2009), a DSS is an auxiliary system that is intended to help human decision-makers, while a control system makes the decision and implements it by itself using actuators. The main characteristics of a DSS are: 1) designed specifically to facilitate decision processes, 2) should support rather than automate decision-making and 3) should be able to respond quickly to the changing needs of decision-makers. DSS can be categorized in communication-driven, data-driven, document-driven, knowledge-driven and model-driven depending on their capabilities and components. This paper presents a model-driven DSS which uses real time data and both dynamic and optimization models to assist operators in their decisions. An example of a model-driven DSS is presented by Kozan and Liu (2012). They developed a demand-responsive DSS that solves the transport problem for coal. The system integrates, using simulation, coal shipment, coal stockpiles and coal railing providing better decision making on how to assign rail rolling-stocks and how to upgrade infrastructure. Dengiz et al. (2006) developed a DSS that uses a simulator for the optimization of a process using a meta-model Monte Carlo simulation and the optimization methodology presented in Madu (1990).

This paper is structured as follows: Section 2 describes the plant under study. Section 3 describes the dynamic simulator for hydrometallurgy, with emphasis in the leaching modeling. Section 4 describes the DSS for hydrometallurgy and its implementation. The results are presented in Section 5 and conclusion remarks and future work avenues are summarized in Section 6.

2. PLANT DESCRIPTION

Mantoverde Operation is part of Anglo American Copper Business Unit. Mantoverde hydrometallurgical operation is located 900 meters above sea level and 56 kilometers close to Chañaral port, III region, Chile. It includes an open pit mine, crushing plants and processing facilities for oxidized copper. In 2012 it produced 62,239 tons of copper as high grade cathodes, approx. 6% more in comparison with 2011, and has an approximated staff of 800 workers, considering own personal and contractors for main operations and projects. Figure 1 shows a simplified flowsheet from primary crushing to heap leaching.

The ore extracted from the pit is carried directly to the primary crusher by trucks of 90 tons capacity. The primary crusher circuit consist of one Fuller Traylor crusher with 1,380 T/h design capacity and its product size is 92% under 12.7 cm. One variable speed feeder and a fixed speed conveyor belt carries the product to the fines crushing plant.

The fine crushing plant includes the secondary and tertiary crushing circuits in a traditional recycle configuration. The secondary crusher circuit consists in one primary screen and a secondary crusher (Nordberg Corp Standard, 800 T/h, close side setting 25 mm). The tertiary circuit includes 4 screens (same model as primary screens, different deck opening) and 3 Norberg shorthead crushers (close side setting of 8 mm). The secondary screen undersize is sent to the two fine silos. The ore from the fines silos is conveyed through two belts, which feed two agglomerating drums operating in parallel arranged with an inclination of 7.3 degrees and variable speed. In the agglomeration process the curing begins adding sulphuric acid and raffinate solution, depending on the amount of carbonate present in the ore.

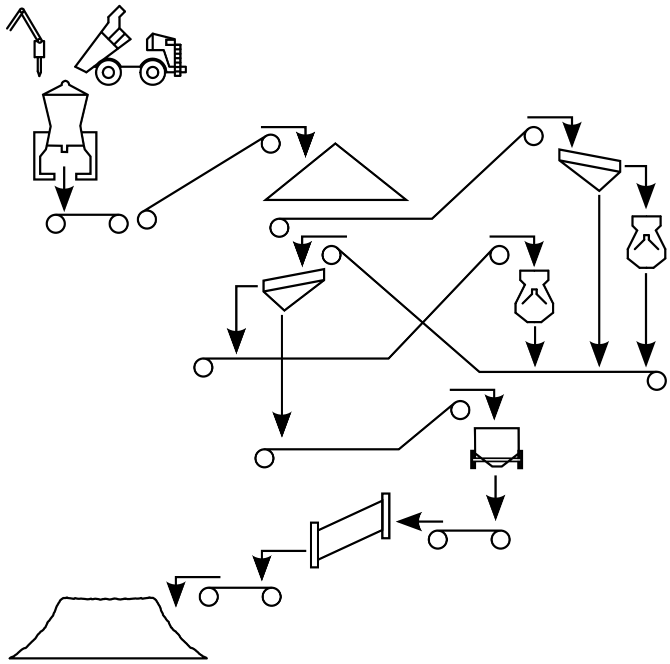

Fig. 1. Plant flowsheet: Primary crushing, secondary and tertiary crushing, agglomeration, and heap leaching.

The agglomerated ore that has an average p_{80} of 15 mm, is carried by a conveyor belt followed by several moving belts towards a radial stacker to build up the heap. The leaching process uses seven areas, whose dimensions are 90 m wide and 900 m long, for the assembly of heaps. Each heap is divided into ten modules and each module is irrigated independently first with ILS to generate PLS and then with Raffinate (from SX process) to generate ILS. The heap drainage flow is capture in two separate piping systems (one for the first 4 modules and the other for the remaining 6 modules). The Pregnant Leach Solution (PLS) is delivered to the next stage (solvent extraction, SX) and the Intermediate Leach Solution (ILS) is used to irrigate the heaps. After the appropriate leaching time (around 170 days), the heap is disassembled with a bucket wheel excavator, and the material disposed through a train of conveyor belts into a dump.

3. HYDROMETALLURGICAL DYNAMIC SIMULATOR

The simulator considers dynamic first principles models to describe in general terms the behaviour of the real plant. The following section briefly describes the models used and indicates the simulated variables in the leaching process. For more information of the other simulated processes the reader is referred to Reyes et al. (2013).

The leaching process has long temporal and big spatial scales. The temporal scale makes decision making difficult (results are obtained days later) and the spatial scale needs the use of partial differential equations models (Cariaga et al., 2005). In Equation 1, θ represents the water content of the heap, D is the diffusion tensor, K is the hydraulic conductivity in the z-axis (unity vector $\hat{k}$). In Equation 2, C_i stands for the concentration of solute i (copper or acid) in the leaching solution and ϕ_i represents the rate of solute added or removed from the solution and q is the Darcy's velocity of the solution.

$$\frac{\partial}{\partial t}\theta = \nabla \cdot \left(D\nabla\theta + K\hat{k} \right) \qquad (1)$$

$$\frac{\partial}{\partial t}C_i = \nabla \cdot \left(D\nabla C_i - q\nabla C_i \right) + \phi_i \qquad (2)$$

An unsolved problem in mineral processing simulation is the interconnection between the processes of ore preparation and operation of the heap leaching plant. The simulator uses assembling and dismantling algorithms for the operation of dynamic heap leaching process of oxide coppers, which allows the output variables of the agglomeration process to take effect on the construction and operation of the heaps. The leaching process simulation and modeling considers the following operation variables and parameters, as shown in Table 1.

Table 1. Input and output variables in leaching process model

Name	Unit	Parameter / Variable
Initial Copper concentration	%	Parameter
Initial Solute copper concentration	%	Parameter
Initial Carbonate concentration	%	Parameter
Hydraulic conductivity	m/h	Parameter
Copper extraction	m^3/kg h	Parameter
Acid consumption	1/h	Parameter
Mean feed size distribution	mm	Input
Mean humidity in heap	%	Output
ILS irrigation rate	L/h/m^2	Input
ILS copper concentration	gr/L	Input & Output
ILS acid concentration	gr/L	Input
Raffinate irrigation rate	L/h/m^2	Input
Raffinate copper concentration	gr/L	Input
Raffinate acid concentration	gr/L	Output
PLS flow	m^3/h	Output
PLS copper concentration	gr/L	Output
PLS acid concentration	gr/L	Output
Copper recovery	%	Output
Leaching rate	m^3/ton	Output

The hydraulic balance between irrigation and drainage flows is important to the heap leaching operation (HL) because it guarantees the future availability of irrigation flow. Figure 2 shows an interconnection diagram between the flows to the Dump operation (Dump N and S), Agglomerators (AGL) and ponds of PLS, ILS and raffinate. Solvent extraction (SX) simulation is carried out using a simplified model based on copper extraction efficiency (Komulainen et al., 2006).

4. HYDROMETALLURGICAL DECISION SUPPORT SYSTEM

This section describes the main and specific objectives, as well the implementation of the heap leaching DSS.

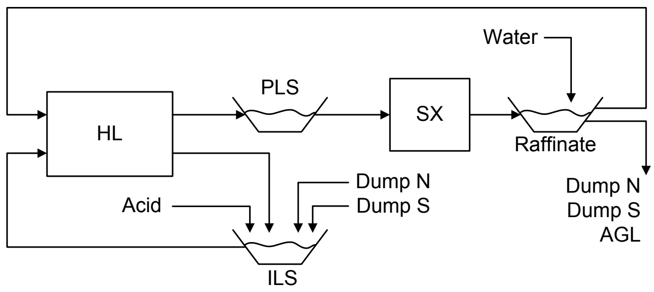

Fig. 2. Hydraulic flows and pools simulation diagram. The Heap Leaching (HL) process generates PLS and ILS flows, the first one is transferred to the Solvents Extraction (SX) process to generate Raffinate and the second one is used to irrigate the heaps in a recycle configuration.

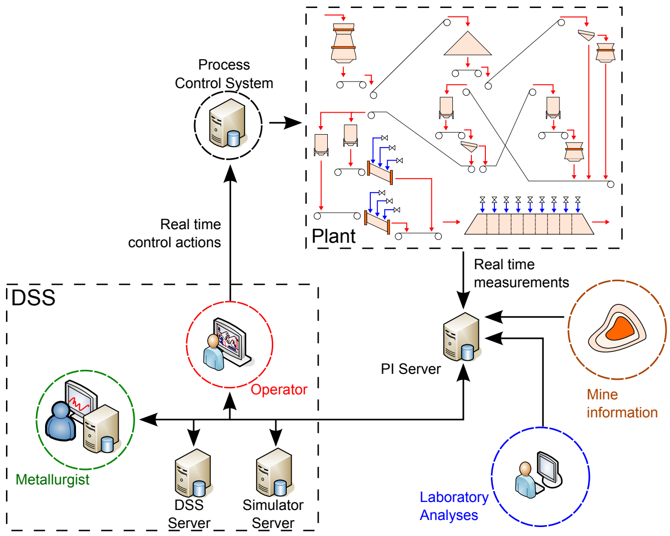

Fig. 3. DSS implementation flow diagram

For more information about the DSS for crushing and agglomeration the reader is referred to Tejeda et al. (2013). The first objective of the DSS is to assist metallurgical personnel defining cure rates and acid concentration for heap leaching irrigation.

The implementation diagram is shown in Figure 3. Each user (operator or metallurgist) has a Human Machine Interface (HMI) connected to the plant information network. These interfaces show the key performance indicators (KPI). Having read the new measurements, the DSS generates KPIs based on predictions made with the dynamic simulation, optimization models and expert systems. After reviewing the DSS predictions the metallurgist can decide with better information how to irrigate the heaps and then communicate to the operators to enter the action through the automation system.

A correct characterization of heap ore enables appropriate selection of acid concentration for agglomeration and heap irrigation. However, this characterization varies among heaps, and differs from the mineralogical and metallurgical studies by problems of representation and scalability. To overcome this, the DSS characterizes the heap by parameter identification methods, and generates predictions of recovery and other variables of interest. These predictions support, through economic analysis based on water and acid consumption and copper extraction, the actions that has to be taken.

Data measurement Measured variables in each heap are the PLS or ILS acid concentration, copper concentration and flow. Furthermore, the irrigation acidity is measured and laboratory measurements are performed every 12 hours to obtain the copper concentration in the irrigation. Mineralogy information is also obtained at the laboratory and used by the dynamic simulator.

Model identification Following Moving Horizon Estimation (MHE) with a square error minimization algorithm, the identification module uses the measurements of input and output variables to adjust the model parameters of the simulator, these and other parameters are listed in table 2.

Table 2. Heap parameters to be calibrated

Parameter	Units	Measured/Calculated
Irrigation area	m^2	Measured
Heap mass	ton	Measured
Total copper content	%	Measured
Soluble copper content	%	Measured
Calcium carbonate content	%	Measured
Hydraulic conductivity	m/h	Calculated
Copper extraction	m^3/kg/s	Calculated
Acid consumption	1/s	Calculated

Moving Horizon Estimation (MHE) raises the state estimation of a system as a problem of optimization to be solved at each iteration and seeks to minimize errors between the measurements and model outputs. The estimation optimization occurs in a backward time span (horizon) of N steps. Equation (3) shows the structure of a problem of MHE applied to a system where x are the state variables, y are the measurements and w and v are the disturbances that affect the system and the measurements, respectively. $J(x_t)$, where x_t refers to $x(t)$, is a quadratic function that penalizes the model's output error and the variations in the estimated variables, ensuring the system observation and the stability of the optimization problem. In the specific case of the leaching process the measurements are the ones mentioned in the previous subsection and the state variables are the heap humidity, acid concentration in the solute, copper concentration in the solute and solid state. The horizon length is a tuning parameter, a long horizon generates a more stable estimation with smooth variations in the parameters and a short horizon allows the detection of fast changes in the parameters. By trial and error a value of 10 measurements, 5 days of operation, was chosen.

$$\begin{aligned}
\min_{x_t} \quad & J(x_t) \\
& \text{subject to} \\
& \quad \hat{x}(t+k+1|t) = A\hat{x}(t+k|t) + B_1 u(t+k) + w(t+k) \\
& \quad \hat{y}(t+k|t) = C\hat{x}(t+k|t) + D_1 u(t+k) + v(t+k) \\
& \quad \text{, using } k = -T \ldots -1
\end{aligned} \tag{3}$$

Predictions The DSS uses the calibrated models to make predictions of the heap leaching process behaviour and the hydraulic balance between leaching and solvents extraction processes. The prediction routine uses a predefined leaching cycle (provided by the user) and algorithms to model the stacking and disassembling of the heaps. Also, using statistical analysis the parameters recently calibrated are projected in the future, giving a more reliable prediction.

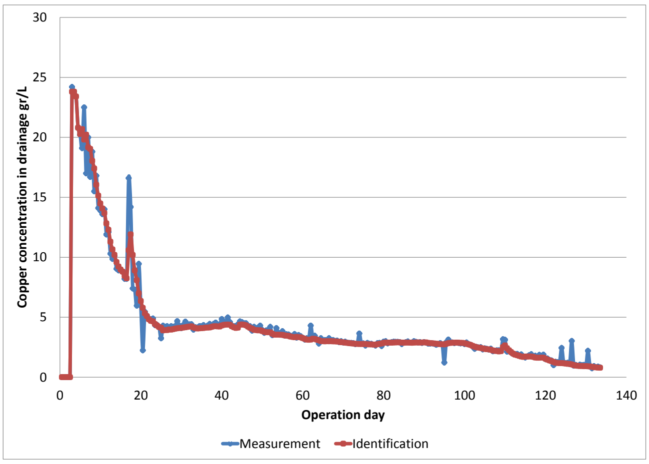

Fig. 4. Example of identification. The dynamic model responds accurately providing a powerful tool to predict the system behaviour.

5. RESULTS

As a first step the dynamic model and its implementation are validated with real industrial data. Figure 4 shows the results for the identification process over the life-cycle of the heap. The identification process achieves the necessary fit to validate the algorithms and therefore the dynamic simulator models.

To validate the prediction stage, input and output data of ended heaps are partitioned in two sets. The first 25 days (inputs and outputs) are used to calibrate the parameters. The rest of the operation days are used to check the goodness of the prediction. To achieve this only the future inputs are passed to the DSS which predicts the future outputs. Figure 5 show the prediction for the copper recovery, a key indicator for metallurgists which normally is available only at the end of the heap operation. Figure 6 show the average Root Mean Square Error (RMSE) of the copper recovery prediction in six heaps. The predictions are made in four different times of the heap operation (days 20,30, 45 and 60) and in each day a prediction of different length is made (3, 7, 15 and 30 days). It must be

Using the prediction routine the metallurgist also has access to the hydraulic balance of the leaching plant and solvents extraction pools. Figure 7 shows an example of the results that are given to the user considering only 45 days of prediction for display purposes. The main information includes a prediction of the level in the ILS, PLS and raffinate pools, which are the main resources metallurgist have to consider. In the example the prediction shows how the ILS pool level is decreasing, while the PLS is increasing. This result indicates to the metallurgist that an action has to be taken, such as transferring PLS to the ILS pool, to avoid future pool imbalance. Also, Figure 7

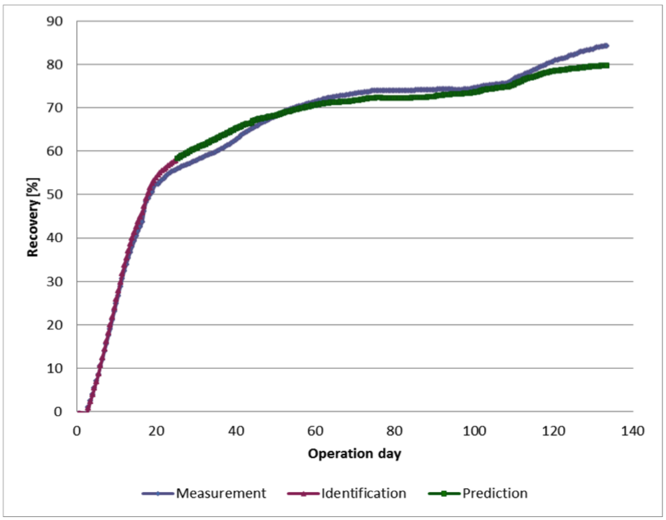

Fig. 5. Prediction of the copper recovery. The dynamic model is calibrated with the first 25 days (red), and then using only the inputs the DSS predicts the future outputs (green).

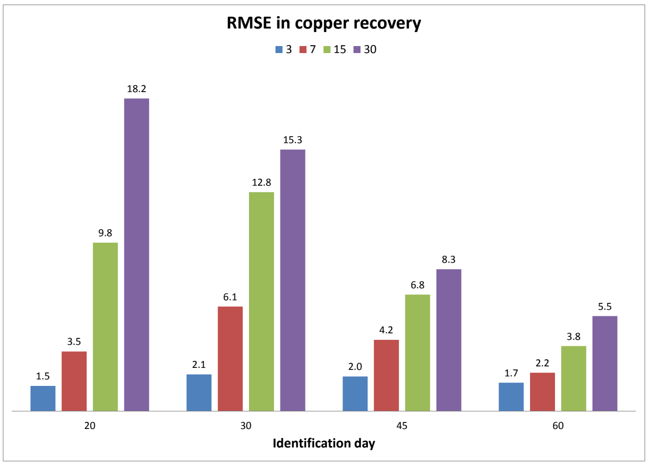

Fig. 6. Prediction errors. the average RMSE in the recovery of six heaps is presented in four different times of the heap operation and four different lengths of prediction. With more information (60 days of operation) the 30 days prediction has an error lower than 6%.

shows the additional information given to the metallurgist, the total drainage and irrigation flow in the heap leaching plant. With this information the metallurgists can analyze how the assembling and disassembling of the heaps, i.e. changes in irrigation flows, affect the hydraulic balance, clearly seen in the sawtooth behavior of the output flows.

6. CONCLUSIONS AND FUTURE WORK

In this paper we have presented the development of an integrated dynamic simulator and a model based DSS for the heap leaching process. We describe the simulated variables and parameters to be adjusted. These developments seek to reduce the technological gap between hydrometallurgical and concentrator operations.

The use of simulation tools allows the study of the relationships between process variables, generating a better

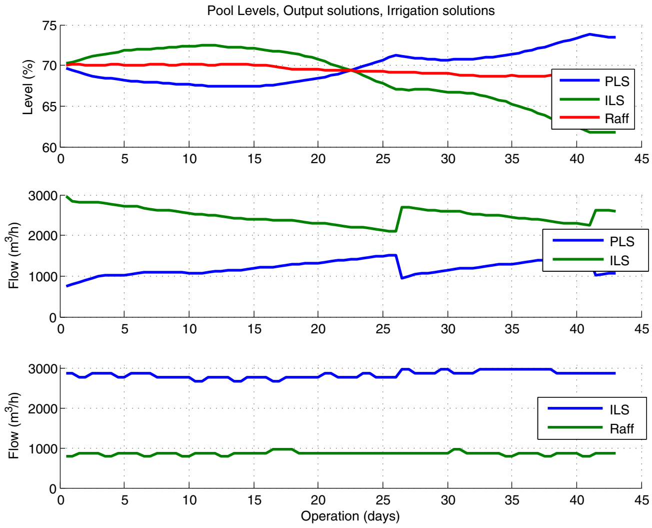

Fig. 7. Example of hydraulic balance. The DSS makes prediction of the pool's level in order to assist the metallurgist in the decision of how to irrigate the heap.

understanding of the process and its behavior. The simulation example presented shows that simulation can be used as a predictive tool for the support of decision making personnel, bringing future key performance indicators to the present.

Future lines of development are related to the validation of the DSS with on-line data. Also, to implement different set of rules for helping the planning of new irrigation cycles. Finally, it is considered the future developments in modelling and assisting-oriented algorithms of the solvents extraction and electrowinning processes.

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