Mineral Process Design for Sustainability

Luis A. Cisternas
CICITEM - Research Center for Mining
and
Department of Chemical Engineering
Universidad de Antofagasta
Antofagasta - Chile

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PASI 2011: Process Modeling and Optimization for Energy and Sustainability
Motivation

• The minerals industry is looking for progress in the reduction of the impacts of its mining and mineral processing operations.
• They have several challenges for sustainable mineral operation with lower environmental and social impact, but keeping profitable operations.
• These challenges must be addressed in the design, operation and post-closure phases, but the design phase give us the biggest opportunity for reducing the impact of operations and increasing profit (McLellan et al. 2009).

Balance between global consumption and the available production

With continuing rapid economic growth and industrial expansion, high population growth and urbanization, both key metals consumption and GDP are expected to grow in Asia. Asia will have a strong impact on the global trends in key metals consumption.

Takashi Nishiyama, The roles of Asia and Chile in the world copper market, Resources Policy 30 (2005) 131–139
• Several design tools are available that incorporate sustainability elements, but usually these had not been applied to mineral process
• The principal social factors considered are health and safety and the reduction in emissions of toxic waste products.
Design for Environment (DfE)

- The emphasis on reducing the environmental impact, both in per tonne of product and on total amount of emissions and reduction.
Challenges in Metal and Mineral Industry*

- Limited availability of thermodynamic information covering the full spectrum of chemical conversions embodied in minerals technologies.
- Low grade of mineral ores (and as a result, the myriad of impurities which must be removed typically).
- The variability and non-homogeneity of ores resulting in significant variation between ore bodies, as well as over the life of a single mine.

Challenges in Metal and Mineral Industry

• The large energy demand for physical transformation.
• The significant role of poorly understood particulate processes in beneficiation and refining.
• The relative conservation of the industry for technological change, itself captured in the dominance of vendor-driven design solution.
• The environmental impacts of minerals processing.
Core Research Activities

Motivation

PSE at CICITEM

Models for Design

Methods for Process Synthesis

Planning & Operation

Optimization & Modelling

Water & Energy

Process Retrofit & Design

Heap Leaching

Mineral Processing

Crystallization
## Core Research Activities

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<td><strong>Mineral Processing</strong></td>
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</table>
Models for Design

Empirical Models (based in to adjust a curve to experimental data)

Phenomenological Models (Based in the physics equations which describe the system)

Hybrid Models (Based in the combination of the two latter approaches)
Knowledge Map

Motivation

PSE at CICITEM

Models for Design

Methods for Process Synthesis
Knowledge Based Empirical Model

- Data (Information)
- First Principles (Knowledge)
- Knowledge Based Empirical Model
- Post Modelling Activities
Heap Leaching

Motivation

PSE at CICITEM

Models for Design
Data & Information

Motivation
PSE at CICITEM
Models for Design

\[ \frac{dy}{dt} = -k_t \ y^{n_t} \]

constant kinetic

order kinetic

delay

\[ y = R^\infty - R_t \]

\[ R_t(\omega) = 0 \]
Knowledge: Dixon and Hendrix Model

\[ \frac{3}{v \omega} \frac{\partial \chi_t}{\partial \theta} = \frac{\partial \chi_t}{\partial t} = \frac{\partial^2 \chi_t}{\partial x^2} + \frac{2}{x} \frac{\partial \chi_t}{\partial x} + k_p \sigma_p \alpha, \]

\[ \chi_t(x, 0) = 0, \]

\[ \chi_t(1, t) = \chi_b, \]

\[ \frac{\partial \chi_t}{\partial x}(0, t) = 0. \]
Knowledge

\[ \tau = \frac{D_{Ae}t}{\varepsilon_o R^2} \]

particle level

\[ \theta = \frac{u_s t}{\varepsilon_b Z} \]

heap level

\[ E(\theta) = \beta \nu \int_0^\theta \chi_{ib}(1, t) dt \]

\[ \bar{\omega} = \frac{D_{Ae} \varepsilon_b Z}{r^2 \varepsilon_0 u_s} \omega \]

delay
Knowledge Based Empirical Model

\[
R_\tau = R_\tau^\infty \left( 1 - e^{-k_\tau \left( \frac{D_{Ae}}{r^2} \left( t - \omega \right) \right)} \right),
\]

\[
R_\theta = R_\theta^\infty \left( 1 - e^{-k_\theta \left( \frac{u_s}{\varepsilon_b} \left( t - \omega \right) \right)} \right),
\]

\[R = R_\theta + R_\tau.\]

\[
R = R^\infty \left[ 1 - \alpha \ e^{-k_\theta \frac{u_s}{\varepsilon_b} \left( t - \frac{\varepsilon_b Z}{u_s} \omega \right)} - (1 - \alpha) \ e^{-k_\tau \frac{D_{Ae}}{r^2} \varepsilon_0 \left( t - \frac{\varepsilon_b Z}{u_s} \omega \right)} \right].
\]
Leaching tests with copper minerals from northern Chile in heaps measuring 3, 6 and 9 m in height
Results versus Dixon & Hendrix

Motivation

PSE at CICITEM

Models for Design
Post Modelling: Optimization of flow rates

\[
\frac{\partial E}{\partial u_s} = E_\infty \left[ \lambda k_t \left( \frac{w}{u_s} + \frac{(t - \bar{w})}{Z\epsilon_b} \right) e^{-\psi_1} + \Lambda k_g \frac{D_{Ae\bar{w}}}{R^2\epsilon_0u_s} e^{-\psi_2} \right].
\]
Remark on Modelling in Mineral Process

- Designers and operators of minerals process have traditionally had to rely on empirical methods and field experience for design and troubleshooting.
- Empirical methods limit the options for engineers to improve the performance of process relative to the properties of ore and variation in design/operation conditions.
- Phenomenological models can be developed, however, they are more difficult to apply in industry applications due it is necessary to deal with rather complex mathematics or suppose an ideal behaviour, and need information that is difficult or impossible to measure (bulk particle systems).
- A third modelling approach is also possible. It consists in the combination of the two latter approaches. This approach leads to rather simple models but enough accurate for some applications (e.g. optimization, sensitivity analysis) and easy to transfer to practice.
References on Heap Leaching Modelling

Flotation Structural Optimization

Profit vs Residence time graph

Introduction  Crystallization  Flotation Design  Flotation Analysis
Cryssallization Structural Optimization

Temperature vs. Cost graph

- Introduction
- Crystallization
- Flotation Design
- Flotation Analysis
Dimensional Representation

Roberto Matta
Chilean 1911-2002

Mujer Desnuda de Pie y Hombre Sentado con Pipa,
Pablo Picasso (Spanish)
Introduction

Crystallization

Flotation Design

Flotation Analysis
Crystallization is extensively used in different industrial applications (fertilizers, detergents, foods, pharmaceutical products, treatment of waste effluents).

The crystallization stages are usually accompanied by other separation techniques. Leaching.

Various types of crystallization exist: cooling, evaporation, reactions, and drowning-out.

The characteristics of the product affects a series of other associated operations. filtration & washing.

The separation is limited by multiple saturation points.
### Equilibrium data for MgSO₄+Na₂SO₄+H₂O system.

<table>
<thead>
<tr>
<th>T °C</th>
<th>keys</th>
<th>MgSO₄</th>
<th>Na₂SO₄</th>
<th>Solid phase</th>
</tr>
</thead>
<tbody>
<tr>
<td>18.7</td>
<td>C</td>
<td>20.57</td>
<td>11.8</td>
<td>Mg₇ + Na₁₀</td>
</tr>
<tr>
<td>25</td>
<td>D1</td>
<td>21.15</td>
<td>13</td>
<td>Mg₇ + SD1</td>
</tr>
<tr>
<td>25</td>
<td>D2</td>
<td>16.6</td>
<td>17.8</td>
<td>SD1 + Na₁₀</td>
</tr>
<tr>
<td>50</td>
<td>E1</td>
<td>31.32</td>
<td>4.74</td>
<td>Mg₆ + SD1</td>
</tr>
<tr>
<td>50</td>
<td>E2</td>
<td>11.98</td>
<td>23.25</td>
<td>SD1 + Na</td>
</tr>
<tr>
<td>97</td>
<td>F1</td>
<td>32.2</td>
<td>5.55</td>
<td>Mg₁ + SD2</td>
</tr>
<tr>
<td>97</td>
<td>F2</td>
<td>14.4</td>
<td>19.15</td>
<td>SD2 + SD3</td>
</tr>
<tr>
<td>97</td>
<td>F3</td>
<td>5.88</td>
<td>26.9</td>
<td>SD3 + Na</td>
</tr>
<tr>
<td></td>
<td>SD1</td>
<td>35.99</td>
<td>42.48</td>
<td></td>
</tr>
<tr>
<td></td>
<td>SD2</td>
<td>45.86</td>
<td>54.14</td>
<td></td>
</tr>
<tr>
<td></td>
<td>SD3</td>
<td>22.02</td>
<td>77.98</td>
<td></td>
</tr>
</tbody>
</table>

Mg₇=MgSO₄.7H₂O; Mg₁=MgSO₄.1H₂O; Mg₆=MgSO₄.6H₂O; Na₁₀=Na₂SO₄.10H₂O; Na=Na₂SO₄; SD1=Na₂SO₄·MgSO₄.4H₂O; SD2=Na₂SO₄·MgSO₄; SD3=MgSO₄·3Na₂SO₄

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**Example: Astrakanite**

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Cake-Washing Superstructure

Solvent

Parallel options

Slurry

Washed cake

\[ y_{e-1} \]

\[ z_e \]

\[ y_e \]

\[ r_e \]

Series stages

Cake-Washing Superstructure

Introduction

Crystallization

Flotation Design

Flotation Analysis
Heat Integration Superstructure
Mathematical Model

State Superstructure

\[
\sum_{l \in Lq \cap S_{in}(s)} w_l \cdot x_{l,i} - \sum_{l \in Lq \cap S_{out}(s)} w_l \cdot x_{l,i} = 0 \quad s \in S_I, i \in I
\]

Task Superstructure

\[
\begin{align*}
\begin{bmatrix}
y_{t,s} \\
FC_{t,s} = \alpha_{t,s} \\
VC_{t,s} = \beta_{t,s} \sum_{l \in S_{in}(s)} G_{l,t}^i \\
Q_{t,s}^C = HQ_{t,s}^C G_{t,l}^o \\
Q_{t,s}^S = HS_{t,s} G_{t,l}^o, l \in S_{out}(s)
\end{bmatrix} & \geq \begin{bmatrix}
\neg y_{t,s} \\
FC_{t,s} = 0 \\
VC_{t,s} = 0 \\
Q_{t,s}^C = 0 \\
Q_{t,s}^S = 0
\end{bmatrix}
\end{align*}
\]

\[t \in T(s), s \in S_M\]

Cake Washing

\[
\begin{bmatrix}
y_{w_{l,e}} \\
\neg y_{r_{l,e}} \\
y_{l,e,i} = y_{mw_{l,e,i}} \\
y_{pw_{l,e,i}} = y_{l,e-1,i}
\end{bmatrix} \lor \begin{bmatrix}
y_{w_{l,e}} \\
\neg y_{r_{l,e}} \\
y_{l,e,i} = y_{mr_{l,e,i}} \\
y_{pr_{l,e,i}} = y_{l,e-1,i}
\end{bmatrix} \lor \begin{bmatrix}
y_{w_{l,e}} \\
\neg y_{r_{l,e}} \\
y_{l,e,i} = y_{l,e,i} \\
y_{mr_{l,e,i}} = 0
\end{bmatrix}
\]

\[
e \in E(Lw), \quad l \in Lw, i \in I
\]

Heat Integration

\[
R_k - R_{k-1} - \sum_{m \in V_k} Q^V_m + \sum_{n \in U_k} Q^U_n = \sum_{l \in H_k} w_l \left( C_p \Delta T \right)^H_{lk} - \sum_{l \in C_k} w_l \left( C_p \Delta T \right)^C_{lk} \quad k \in K
\]

Objective Function

\[
\min \sum_{s \in S_M} \sum_{t \in T(s)} (FC_{t,s} + VC_{t,s} + CT_{t,s} Q_{t,s}^C + CS_{t,s} Q_{t,s}^S) + \sum_{m \in V} c_m Q^V_m + \sum_{n \in U} c_n Q^U_n + \sum_{l \in Lw} \sum_{e} (Cf_{l,e} + Cv_{l,e})
\]
Example: Astrakanite (MgSO$_4$·Na$_2$SO$_4$·4H$_2$O)

The MILP formulation contains 1209 equations, 1201 continuous variables, and 145 binary variables. Solution time was 84 s for OSLv2 (GAMS) with a 1.7 GHz Pentium 4 processor.
• Over the last 20 years significant advances have been achieved in methods for the design and improvement of separation processes based on fractional crystallization.
• These advances have addressed the separation of simple systems, systems involving the formation of compounds, drowning-out, metathetic salts, hybrid processes, environmental applications and multicomponent systems.
• Important advances have been made in the use of phase diagrams as design tools, especially with respect to the visualization of multicomponent systems.
• Procedures for the conceptual design of these systems have been divided into two schools of thought. One group of researchers used hierarchical procedures based on rules, whereas others used superstructures that represent different possibilities for processing, applying a mathematical model for identification of the most useful approach to each problem.
References on Fractional Crystallization Design

Flotation Circuit Design Problem

CuFeS$_2$
FeS$_2$
SiO$_2$

CuFeS$_2$
FeS$_2$
SiO$_2$

Flotation Design

Introduction  Crystallization  Flotation Design  Flotation Analysis

40
Mineral flotation processes consist of several units that are grouped into banks and interconnected in a predefined manner in order to divide the feed into concentrate and tailing.

The behavior of these processes depends on the configuration of the circuit and the physical and chemical nature of the slurry treated.

The design of these circuits is carried out based on the experience of the designer, with the help of laboratory tests and simulations.

Some attempts have been described in the literature on automated methods for the design of these types of circuits.

Methods for the design of flotation circuits have not yet progressed to the stage where an optimum circuit configuration can be completely derived automatically.

Estimation of flotabilities of particle classes is probably the most challenging aspect in flotation modelling.
• Stochastic programming is applied to the design of mineral flotation circuits and compared them with results obtained by using deterministic programming (mean values of design parameters).
• In the optimization problem, it is desired to find the optimal configuration, equipment design (cell volume and cell number for each stage) and operational conditions (residence time) of a circuit with three stages: rougher, scavenger and cleaner.
• The problem includes uncertainty in the feed composition and in the metal price. Each uncertain parameter is characterized probabilistically using scenarios with different occurrence probabilities.
• The feed has three mineralogical species: Chalcopyrite (CuFeS$_2$), Tennantite (Cu$_{12}$As$_4$S$_{13}$) and Gangue (SiO$_2$ + Al$_2$O$_3$).
Mathematical Model

MINLP

\[
\max inc_1 - c_1 - c_{As1} - fc
\]

s.t.
• Mass Balance
• Kinetics of flotation
• Arsenic penalization
• Cell volume
• Bounds
• Cost
• Income

stochastic MINLP

\[
\max - fc + \sum_{s \in S} P_s \cdot (inc_s - c_s - c_{As_s})
\]
Variability of uncertainty parameters represented in ten scenarios. \( e_1 \) and \( e_2 \) are chalcopyrite and tennantite feed grade. \( P \) copper price in US$/Ton.

- The average data considered are: Chalcopyrite grade 2.72 %, Tennantite grade 0.3 % and gangue grade 96.96 %, which implies a total copper grade of 1.11 % and arsenic grade of 0.02 % in the feed stream. The average copper price is 4,444 US$/Ton.
The simulation delivers an income of $1.319 \times 10^9$ U.S.$/y.

The real expected income is the weighted average of the incomes determined by evaluating on each scenario the design and operational variables. We found that the real expected income is about 4.5% less than given by the simulation, $1.263 \times 10^9$ U.S. $/y.$
Stochastic Model

<table>
<thead>
<tr>
<th>Variable</th>
<th>Scenario</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
</tr>
</thead>
<tbody>
<tr>
<td>$r_{S,R}$ (h)</td>
<td></td>
<td>0.015</td>
<td>0.015</td>
<td>0.015</td>
<td>0.015</td>
<td>0.015</td>
<td>0.012</td>
<td>0.015</td>
<td>0.015</td>
<td>0.015</td>
<td>0.014</td>
</tr>
<tr>
<td>$r_{S,S}$ (h)</td>
<td></td>
<td>0.013</td>
<td>0.013</td>
<td>0.013</td>
<td>0.013</td>
<td>0.013</td>
<td>0.013</td>
<td>0.013</td>
<td>0.013</td>
<td>0.013</td>
<td>0.013</td>
</tr>
<tr>
<td>$r_{S,C}$ (h)</td>
<td></td>
<td>0.047</td>
<td>0.066</td>
<td>0.061</td>
<td>0.047</td>
<td>0.064</td>
<td>0.026</td>
<td>0.066</td>
<td>0.031</td>
<td>0.064</td>
<td>0.066</td>
</tr>
<tr>
<td>$y_{s,1}$</td>
<td></td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
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<tr>
<td>$y_{s,2}$</td>
<td></td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>As grade</td>
<td></td>
<td>1%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cu grade</td>
<td></td>
<td>18.3%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Real Expected Income US$/y</td>
<td></td>
<td>$1.39 \times 10^9$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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</tr>
</tbody>
</table>

- The real expected income is $1.39 \times 10^9$ US. $/y$. This means to increase the income by 10% ($130 \times 10^6$ US. $/y$) if it is compared with the deterministic model.

- Design variables for this case are 20 cells for each stage with a cell volume for each stage of 300 ft$^3$.

- The residence time for the scavenger stages is 0.013 h. for all scenarios. Rougher and cleaner residence times are flexible to each scenario.
• if the price of metal is low, besides having a small operating time for the cleaner stage, it should recycle the cleaner tail and scavenger concentrate to the rougher stage. This is aimed at trying to remove impurities from the pulp that goes to the cleaner stage.

• if the price of metal is high, it is also necessary recirculation of the concentrate from scavenger stage to rougher stage, but the cleaner tail is re-circulated to the rougher stage for cleaning. The increased operating time of the cleaner stage will increase the recovery of both copper and other species, but due to high metal prices, it remains the most convenient option.
ANALYSIS OF UNCERTAINTY IN FLOTATION CIRCUITS

Monte Carlo Simulation

Indicators

Spider Graphics

Post-simulation Analysis
INDICATORS

**Technical**
- Concentrate Grade
- Separation Factor
- Beneficiation factor
- Recovery

**Statistical**
- Mean
- Standard deviation
- Kurtosis
- Skewness

**Indicators**
- Kurtosis
- Skewness
- Standard Deviation
- Mean

**Spider Graphics**
- Multiple goals

**Introduction**
- Crystallization
- Flotation Design
- Flotation Analysis
RESULTS

\[ I_P = \frac{P - P_{\text{min}}}{P_{\text{max}} - P_{\text{min}}} \]
• Analyze the separation of copper and arsenic in the system Chalcopyrite ($\text{CuFeS}_2$), Tennantite ($\text{Cu}_{12}\text{As}_4\text{S}_{13}$), Quartz.

• Process of CSIRO-Australia
Superstructure

55 flotation circuits
Technical Indicators

Global Copper Recovery

Copper Concentrate grade
Environmental Indicators

Arsenic in the product

Fresh water usage
Environmental & Economical Indicators

CO₂ Generated

Income
Multiple goals based on Sumbranches


Final Remark

• There are several tools and methodologies for DfS, but they have not been applied to the metal and mining industry.
• Methodologies for design, analysis and optimization must be adapted to metal and mining industry.
• Limited availability of thermodynamic information, the variability and non-homogeneity of ores, particulate process poorly understood are the main challenges to apply PSE methodologies in DfS.
• To date our group has worked on issues such as crystallization, flotation, leaching, solvent extraction and dewatering.