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Strategic evaluation of concentrator operational modes under geological uncertainty

Alessandro Navarra^{a,*}, Andrew Menzies^b, Adam Jordens^c, Kristian Waters^c

^a Department of Industrial Engineering, Universidad Católica del Norte, Antofagasta, Chile

^b Department of Geology, Universidad Católica del Norte, Antofagasta, Chile

^c Mining and Materials Engineering Department, McGill University, Montreal, Canada

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ABSTRACT

Mineral concentrators can be designed to support several modes of operation, which can be optimized for different geometallurgical units. Nonetheless, alternative modes often require additional equipment and processing capacity, hence an associated capital expenditure. Moreover, the concentrator designs are often based on preliminary geological data, and are therefore subject to uncertainty. The current paper describes how stochastic mine planning algorithms may be extended to quantify the net present value (NPV) of alternative operational modes in mineral processing plants, under geological uncertainty. In particular, the Variable Neighbourhood Descent method of Lamghari et al. (2014) was originally developed for open-pit mine planning, and has now been adapted to evaluate concentrator operational modes. Sample computations are presented.

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1. Introduction

A mineral concentrator is a major capital investment that is designed largely at the beginning of the mine life, along with a strategic mine plan. Indeed, concentrator designs may be based on the same preliminary geological data as the mine plan. The utilization of the concentrator and related infrastructure is thus subject to geological uncertainty, which should be reflected in engineering methodologies.

The class of techniques used to incorporate ore variability into metallurgical process design is referred to as geometallurgy and consists of three broad steps: (1) appropriate sampling of the orebody, followed by (2) metallurgical testing of the resultant samples to map the empirical metallurgical data (e.g. Bond Work Index, flotation recovery) throughout the block model using geostatistics, and (3) predicting process outcomes from the block model using a process model (Wills and Finch, 2016). The term "geometallurgical unit" is used to describe a class of ores that are predicted to have similar metallurgical performance due to their comparable composition and morphological features (Lotter et al., 2011).

Geometallurgical approaches have been used to predict grinding circuit throughput (Alruiz et al., 2009), industrial flotation kinetics (Suazo et al., 2010), and heavy mineral sand separations (Philander and Rozendaal, 2014), and has influenced total process design (Lotter et al., 2011). One stream of research in this field seeks to take this process

* Corresponding author. E-mail address: anavarra@ucn.cl (A. Navarra). engineers [to] modify the mining sequence of metallurgical units... in order to ensure a certain level of throughput" or other metallurgical outcome (Alruiz et al., 2009). However, the successful application of these models depends on the accuracy of the geological inputs. In particular, the design (or expansion) of a concentrator has long-term consequences, and would demand that the models be extrapolated over several years, possibly decades; such a long outlook typically implies geological uncertainty, as the sampling points may be sparse for the deepest zones. As such, the economic justification for additional mineral processing equipment requires a systematic incorporation of long-term

one step further by developing statistically reliable particle breakage models (Van der Wielen and Rollinson, 2016) so that fewer samples

need to undergo metallurgical testing (Lund et al., 2015). In this ap-

proach, the input to the geometallurgical model is the behaviour of par-

ticles (based on their composition, size, shape, etc.) rather than sample-

associated quantities such as Bond Work Index or flotation recovery

(Lund et al., 2015). Readers interested in the history and development

link between mine planning activities and final concentrator outcomes.

Accurate prediction of downstream process outcomes allows "planning

Geometallurgy leads to predictive models, which are an essential

of geometallurgical techniques are directed to Lotter et al. (2011).

geological uncertainty. This uncertainty is already addressed by stochastic strategic mine planning algorithms (Ramazan and Dimitrakopoulos, 2005; Ramazan and Dimitrakopoulos, 2013), as they simultaneously consider several geological scenarios (Fig. 1). Each of the scenarios is obtained through conditional simulation (Ravenscroft, 1992), which is a form of Monte





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Fig. 1. Strategic stochastic mining planning considers several equally likely geological scenarios to construct a single long-term mine plan, which is likely to perform well for the entire distribution of possible scenarios.

Carlo simulation (Raychaudhuri, 2008). In this sense, "conditional" implies that the scenarios must match the available geostatistical data, including local spatial averages and variances (first and second order conditions, respectively). Conditional simulation uses appropriate random data to fill in the areas between the sampling points. In principle, each of the scenarios is equally likely. However, they are notably different from one another, as they are each generated from a different set of random numbers. A greater variation between the scenarios corresponds to a greater degree of geological uncertainty. In practice, ten to twenty scenarios have been found to provide a sufficient representation of this uncertainty (Albor and Dimitrakopoulos, 2010), as each additional scenario has a diminishing impact on the resulting mine plan.

The current work presents an extension of strategic mine planning algorithms that addresses the performance of different geometallurgical units. In particular, the new approach considers alternate modes of operation for mineral concentrators, which are designed to address the distinct geometallurgical units that may be present in the ore. Therefore, each geological scenario assigns randomly generated grade values, as well as other randomly generated mineralogical attributes, which affect the processing of these blocks under the different operational modes. Ultimately, the approach can be used to create confidence intervals to project economic returns, with and without the implementation of additional operational modes, thus providing a statistical basis to compare plant designs, and justify plant expansions.

2. Concentrator modes within a two-stage optimization framework

Given a set of geological scenarios (Fig. 1), strategic mine planning considers two or more decision-making stages (Ramazan and Dimitrakopoulos, 2013; Navarra and Waters, 2016):

- Possibly one or more stages to determine the design and/or position of main shafts, processing plants, and other auxiliary equipment
- The block combinatorial stage to determine which combination of blocks to mine in each period
- The downstream stage to determine the expected economic return that is obtained from the downstream processing of the mined material (concentration, transportation, etc.)

The decisions that are made in early stages serve to parameterize and constrain the later stages.

Following previous work, the block combinatorial and downstream stages have been integrated into a two-stage stochastic optimization framework (Ramazan and Dimitrakopoulos, 2005; Navarra and Waters, 2016), which considers a set of feasible mine plans *X*. A mine plan *x* is feasible (i.e. $x \in X$) if it respects the mine tonnage capacity for each period, as well as structural mechanic constraints, e.g. a maximum pit slope in the case of open-pit mining. The economic value that can be extracted from each block depends on the processing technique that is applied, which in turn depends on the grade and rock type of the block, and is thus subject to geological uncertainty. Indeed, a strategic

(long-term) evaluation of a plan x must allow processing decisions to be determined on a tactical (short-term) basis, as more geological data becomes available. As will be described below, these processing decisions constitute an optimization within an optimization, i.e. a twostage optimization.

The objective is to construct a feasible mine plan $x \in X$ that maximizes the expected net present value (NPV) of the operation,

$$\mathbb{E}[NPV(x)] = -\sum_{t=1}^{n_T} c_t(x) + \frac{1}{n_S} \sum_{t=1}^{n_T} \sum_{s=1}^{n_s} v_{ts}(x)$$
(1)

in which $c_t(x)$ is the expected discounted mining cost incurred in period $t, v_{ts}(x)$ is the recovered value in period t and under scenario s. The number of time periods and scenarios under consideration are denoted n_T and n_S , respectively. The time periods typically correspond to 0.5 or more years of operation.

In general, $v_{ts}(x)$ is itself an optimization

$$v_{ts}(x) = \max_{y \in Y_{ts}(x)} v_{ts}(x, y)$$
⁽²⁾

in which $Y_{ts}(x)$ is the set of feasible downstream parameterizations for period *t*, under geological scenario *s*, given a mine plan *x*. Increasingly realistic models of downstream operations correspond to increasingly complex definitions of $Y_{ts}(x)$; a relatively simple definition is sufficient to represent alternate concentrator modes, as will be described below. The objective of the framework can be written as $\max_{x \in X} \mathbb{E}[NPV(x)]$, or more explicitly,

 $\max\left(-\sum_{r=1}^{n_T} c_r(\mathbf{y}) + \frac{1}{2}\sum_{r=1}^{n_T} \sum_{r=1}^{n_S} \max_{\mathbf{y}} \mathbf{y}\right)$

$$\max_{\mathbf{x}\in\mathbf{X}}\left(-\sum_{t=1}^{L}c_t(\mathbf{x})+\frac{1}{n_S}\sum_{t=1}^{L}\sum_{s=1}^{L}\max_{\mathbf{y}\in\mathbf{Y}_{ts}(\mathbf{x})}v_{ts}(\mathbf{x},\mathbf{y})\right)$$

which is indeed a two-stage stochastic optimization. This type of framework has been applied in open-pit mining for well over a decade (Ramazan and Dimitrakopoulos, 2005; Dimitrakopoulos, 2011), and has recently been adapted to underground mining (Carpentier et al., 2016).

Particular implementations of the two-stage optimization framework consist of the following:

- A procedure to obtain and evaluate an initial feasible solution $x \in X$
- A combinatorial algorithm that modifies the incumbent solution *x* in search of altered solutions *x*' that may be superior to *x*
- A procedure to evaluate $c_t(x')$ for all periods t
- A downstream optimization that evaluates $v_{ts}(x')$, for all periods t and scenarios s

When the combinatorial algorithm encounters a feasible candidate $x' \in X$ such that $\mathbb{E}[NPV(x')] > \mathbb{E}[NPV(x)]$, x' becomes the new incumbent solution, $x \leftarrow x'$. The combinatorial algorithm continues searching until no more improvements can be reached.

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