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Isolating the impact of rock properties and operational settings on minerals processing performance: A data-driven approach

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ABSTRACT

Mining operations record a large amount of data from multiple sources (such as block model and online processing data) which is neither effectively nor systematically used to understand and improve operational performance. This paper proposes a generic semi-automatable data analytics method, the Integrated Analysis Method (IAM), that addresses the disconnection between disparate datasets. IAM enables evidence-based understanding of rock and machine parameters, laying the foundation for a potentially more sophisticated way to model and predict mining processes to deliver financial value. IAM systematically combines and analyses both rock characteristics and operational data to isolate the impact of the variability in rock characteristics and operational settings on key performances. Insights extracted from IAM allow one to narrow down key operating conditions, specific to a particular plant, that are correlated to, for example, significant differences in daily throughput while processing batches of ore with similar metallurgical characteristics. Such insights can be used for multiple purposes, for instance, to learn optimal processing recipes for a given set of rock properties. We applied IAM to a combined data set recorded at a Chilean ore deposit and evaluated our findings with domain experts.

1. Introduction

Increasing processing costs and declining ore body grades have called for the global mining industry to focus on improving productivity and energy efficiency in order to stay competitive and to meet the increasing demand for resources (Napier-Munn, 2015; Hesse et al., 2016; Prior et al., 2012; Bearman, 2013; Carrasco et al., 2016b). State-of-the-art operating mechanisms that aim at improving the efficiency of mineral processing, such as flexible circuits (Powell et al., 2014; Foggiatto et al., 2014) and Grade Engineering (Walters, 2016; Carrasco et al., 2016a), have been proposed and incorporated into some mine sites. Flexible circuits manipulate the design of comminution circuits such that they balance the comminution work across different comminution units as the distributions of the particle size of feeds change, allowing plants to handle rock variability. Grade Engineering maximises feed grade by removing low-grade materials as early as possible in the process such that resources (such as energy) are targeted towards processing valuable material as much as possible.

While these state-of-the-art techniques can, and should, be incorporated into practice, their outcomes can be further improved by making use of currently under-exploited knowledge buried within many sources of historical data collected in today's minerals processing plants. In particular, the *uniqueness of the setups of each plant and the geometallurgical characteristics of materials being processed* need to be taken into account. Gaining such information may be challenging due to uncertainties in the geo-metallurgical characteristics of materials being processed, variations in operating conditions, and a lack of knowledge on *how* different types of materials react to different operational settings.

Fortunately, we can attempt to learn this information by analysing historical data, from which we can extract patterns of various operating strategies and quantify their impacts on rock processing performance. Through the application of data analysis techniques, one can learn better operating strategies to maximise outcomes in light of various factors, such as energy, throughput,[2] and materials characteristics such as the hardness of rocks. This extracted information can thus be applied

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[1] Now present at BHP.
[2] Throughput in tonnes per day (TPD).

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Short-term Mine Plan Data

Stockpile Date	Oreto Stockpile	CuS (%)	Fe (%)	As (ppm)	BWi	SPI	...	...
1-Jul-10	140,848	0.09	1.83	56.34	13.21	50.21	...	...
2-Jul-10	141,619	0.08	1.68	65.34	13.96	52.36	...	...
3-Jul-10	142,995	0.09	1.94	50.63	12.08	42.30	...	...
4-Jul-10	153,938	0.08	2.19	49.50	12.47	45.40	...	...

Processing (sensors) Data

Process Date	KWh	SAG IV KWh/TON	Power Utilization SAG IV (%)	Operating Hours Day Shift	Operating Hours Night Shift	Balls Reload (Tons)	Bearing Pressure (psi)	...
	SAG IV	SAG IV	SAG IV	SAG IV	SAG IV	SAG IV	SAG IV	
1-Jul-10	15281.50	2.73	78.77	12.00	12.00	24.29	5332.83	...
1-Jul-10	15459.49	2.78	79.69	12.00	12.00	30.64	5332.70	...
1-Jul-10	15316.14	2.62	78.95	12.00	12.00	32.25	5327.98	...
1-Jul-10	15803.94	2.87	81.46	12.00	12.00	33.39	5337.18	...
1-Jul-10	15589.85	2.82	80.36	12.00	12.00	45.66	5330.39	...

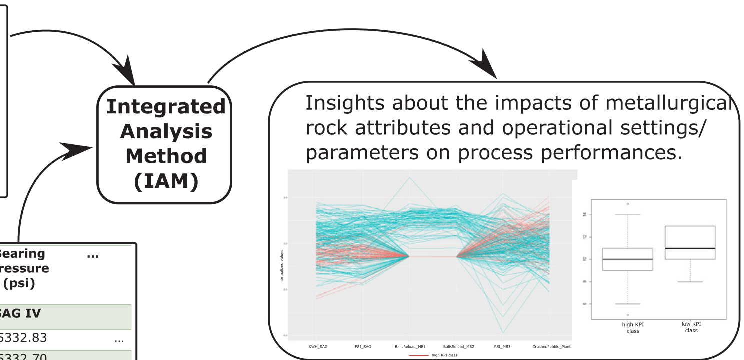

Fig. 1. Data sources for the Integrated Analysis Method (IAM) proposed in this article. IAM facilitates integrated analysis of *both* rock properties and operating parameters to extract insights into the impacts of metallurgical rock attributes and operational settings/process parameters on process performances.

in practice. For example, by understanding how different operational settings affect the throughput of a plant for a given rock metallurgical characteristics, site engineers in a comminution plant can adjust the processing parameters and operational settings to the values which, in the past, have shown to deliver higher throughput.

The main contribution of this paper is a generic semi-automatable data analytics method, called the Integrated Analysis Method (IAM) that can be used to isolate the impact of rock characteristics[3] and operational settings. In particular, IAM provides a systematic way to analyse traditionally-disparate data sets *combined*: short-term mine plan data (that includes information about the characteristics of rocks to be processed on a particular day) and processing data (collected from various sensor readings in a plant) – see Fig. 1. By analysing these disparate data sets in an integrated manner, IAM is able to gain insights into the combined impact of materials variability and processing uncertainty on key performance indicators (KPIs) of a processing plant, such as tonnes per day (TPD).

A key benefit of IAM is its ability to learn better operating strategies, *adjusted* for a given characteristics of rocks to be processed. Given periods when rocks with similar characteristics were processed, IAM identifies those periods that produced optimal results and then learns the operational settings applied during those periods. This knowledge is valuable in enabling adjustments to machine settings that are *customised* to the geo-metallurgical characteristics of materials to be processed to achieve optimal KPIs.

Furthermore, IAM supports a better integration between scheduling and control (Harjunkoski et al., 2009a). Insights extracted from IAM can be used to inform short-term operating strategies of a plant, based on the expected characteristics of rocks that are to be processed within a certain time horizon (such as weekly or monthly) as dictated by short-term plan data.

We acknowledge that the application of data analytics for operational supports in the mining industry has been demonstrated before. For example, as early as the 1970s, there have been attempts to apply machine learning techniques to gain insights into the impact of operational settings on plant performances (Ge et al., 2017; Brittan and van Vuuren, 1973; Mackay and Lloyd, 1975). More recently, Marais and Aldrich (2011) and Aldrich et al. (2010) looked into how online images taken from a flotation process can be used to predict the recovery and grade of the extracted metal. Zhang et al. (2002) looked at how to apply a genetic algorithm to recorded sensor data in the design of a coal mill. Nevertheless, how the geo-metallurgical characteristics of materials being processed influences the choice of operating strategies was not addressed in these works. IAM aims to resolve this.

This paper is organised as follows. Section 2 details IAM. Section 3 describes the data set obtained from a processing plant related to a Cu porphyry deposit in Chile. Section 4 details the application of IAM on this data set to demonstrate its applicability. Section 5 raises issues related to the use of IAM, and Section 6 discusses related work. Conclusions are provided in Section 7.

2. Approach

The process of minerals extraction involves several stages, including blasting, comminution, and flotation (Wills, 2006). The notion of an 'optimal result' varies with the stage of the process. For example, during the comminution stage, an 'optimal' result typically includes high tonnes of rock processed per hour, while during the flotation stage, an 'optimal' result may refer to high recovery rate.

KPIs are influenced by several factors, such as geo-metallurgical properties and operational settings. The operational settings and rock properties both influence KPIs, but in order to study them, their influences on KPIs need to be analysed separately. To separate the influence of these factors, we introduce the Integrated Analysis Method (IAM), a methodology that aims to analyse the influence of these factors on KPIs. For instance, in Section 4, we illustrate IAM with an analysis of the influence of rock properties and operating strategies on the throughput per day of a comminution plant.

In the following sections, we will use the terms X and Y for variables related to rock characteristics and operational settings respectively.

2.1. A pluggable framework

IAM is designed as a pluggable framework whereby a wide range of analysis techniques can be included and applied in the analysis chain as long as the data sets and the chosen analysis techniques satisfy certain constraints (gradually elaborated throughout this section). As a consequence, IAM is agnostic to underlying domain-specific variations, such as the types of plants or mills. Furthermore, IAM is flexible to the KPI used: any KPI can be used as long as its corresponding values are available in the data set being analysed.

Fig. 2 shows a data model for the data sets and configuration parameters that IAM needs, depicted using the Unified Modeling Language (UML) class diagram (Group, 2015). The basic building blocks for the data model are the two data types: `RockMetallurgy` which represents any metallurgical attributes of rocks, such as the Bond Ball Mill Work Index (BWi) and SAG Power Index (SPI), and `ProcessTag` which represents data items captured from a processing plant, such as bearing

[3] We refer to metallurgical properties of rocks with the term 'rock characteristics'.