Enhancing Efficiency in Mining Operations through Closed-loop Real-Time Ore Control System (CROCS)

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Abstract

Efficient mining operations and ore processing are vital for maximizing productivity in the mining industry. However, the inherent spatial variability in ore characteristics presents significant challenges, including material rehandling, excessive stockpiling, suboptimal plant throughput, and plant downtime. These challenges necessitate a proactive approach to ore control, as issues observed in processing and mining operations are often linked to ore characteristics. Presently, the lack of real-time forecasting of orebody characteristics entering processing plants hampers proactive adjustments, exacerbating operational inefficiencies.

In this paper we introduce the Closed-loop Real-time Ore Control System (CROCS), an innovative solution designed to revolutionize ore control in the mining industry. CROCS includes an orebody-to-product stockpile tracking system, contextualization of tracking data, and feedforward control models for predicting and optimizing mining operations and plant parameters. By seamlessly integrating pit and plant data, CROCS establishes a comprehensive ore-tracking system that monitors ore movement from extraction to processing in real-time. This enables quick identification of problematic ore and facilitates timely adjustments to operational parameters, thus mitigating material handling issues, disruptions, and suboptimal throughput. CROCS also offers opportunities for real-time reconciliation against existing plans and enhances short-term planning capabilities for material delivery strategies, ultimately optimizing resource utilization and reducing operational costs. This study presents the application of CROCS at Rio Tinto’s Amrun bauxite operation in Far North Queensland, Australia.

Keywords: Mining operations, Ore control system, Ore processing, Geometallurgy, Bauxite.

1. Introduction

Mining techniques encompass a diverse array of methods tailored to the geological characteristics and economic considerations of mineral resources. Among these techniques, surface mining, commonly referred to as open-pit mining, is a prominent method for extracting near-surface mineral resources. Open-pit mining involves the excavation of open pits, exposing the orebody for extraction. This method is favoured for its efficiency in accessing shallow deposits and its ability to facilitate high-volume production rates [1]. The operation typically employs heavy machinery, including excavators, bulldozers, and haul trucks, to remove overlying material and transport extracted ore to processing facilities [2].

In surface mining, a key challenge is handling the inherent variabilities in the ore. These variabilities can affect many aspects of a surface mining and mineral processing operation, making it difficult to maintain operational efficiency. For example, variations in ore hardness and fines content can affect the flowability of the material. Typically, high rockiness and fines content in ore cause issues such as material clogging, blockages, and poor flow in chutes and conveyors. These characteristics disrupt the material handling process, causing inefficiencies in crushing and grinding, increasing wear and tear on machinery, and ultimately leading to unplanned downtime. Moreover, variations in ore grade and moisture can lead to inconsistent product quality and yield, resulting in fluctuating production levels, and directly impacting the stability of the operation. Lastly, variations in ore density can cause fluctuations in the flow rate of the material through a processing plant. This inconsistency can lead to throughput challenges, as equipment (such as conveyors and crushers) may not operate optimally under varying loads. Sub-optimal flow rates can also cause surging and material spillage issues, which disrupts the consistent feed of ore into the processing plant.

A further complication is the multi-pit mining approach utilized in many surface mining operations. Multi-pit mining refers to the practice of operating multiple loaders or excavators simultaneously within a single mining operation. Whilst a multi-pit mining approach improves mine productivity by allowing equipment to distribute workload across different pits, it also complicates troubleshooting ‘problematic ore’ due to the increased complexity of operations. Problematic ore refers to ore types that cause issues for mining operations and mineral processing plants. These issues can arise from the ore texture, such as excessively rocky or very fine ore types, the mineralogy, including the presence of problematic minerals, or the chemistry, involving an abundance of deleterious elements. When multiple pits are open for extraction, it often becomes challenging to pinpoint specific areas that are delivering the problematic ore to the processing plant.

Addressing these material handling challenges requires the mining operation to establish a comprehensive understanding of how ore from different mining locations affects the processing plant’s operation in real-time. To develop this understanding, it is important to study the correlation amongst ore characteristics, processing plant operating parameters and corresponding performance responses. Understanding this correlation opens up the possibility for operational personnel to accurately identify which mine area is delivering the problematic ore, and enables the development of targeted intervention strategies. Moreover, a well-understood relationship between ore characteristics and plant performance enables real-time optimisation of processing parameters. This can include adjusting the feedrate or modifying water addition, leading to higher recovery rates and ultimately more efficient operation.

In practice, it is challenging to link ore characteristics to the processing plant responses, because of several factors.

First, tracking material flow from the orebody through the processing plant is difficult. Ore is fungible because individual batches of ore are largely indistinguishable from one another when being processed through the plant. Developing a tracking logic is hindered by the need for in-depth process knowledge and expertise in plant design to model the continuous ore stream and link it to the ore source location. Existing material tracking tools that are widely available in the market often focus on monitoring material movement from pit to plant, neglecting the critical aspect of tracking ore movement through the processing plant.

Second, there are challenges associated with selecting suitable data-processing and hosting solutions for storing material tracking data and information related to the source location of ore. Processing plants are equipped with sensors for monitoring equipment behaviour and online material characterization (such as mineral composition). These data are often high-frequency time-series in nature. Live-processing this information for each batch of ore as material is processed (and tracked) through the plant is a resource-intensive task, requiring appropriate processing and storage solutions to handle it effectively.

material handling issues, enabling collaborative problem-solving and real-time reconciliation against existing plans and models.

Looking towards the future, CROCS holds significant potential for further optimization and sustainability in mining operations. The best operator vision aims to break down silos and achieve a fully integrated system for optimizing the mining value chain. Smart and proactive mine planning based on real-time data and predictive models will enhance operational efficiency. Additionally, the green mining vision focuses on reducing the mining footprint through enhanced understanding of ore characteristics and proactive mine planning, thus maximizing energy efficiency and sustainability.

Despite challenges such as sensor reliability and integration complexities, the transformative impact of CROCS in enhancing efficiency and sustainability in mining operations is undeniable. Continued research and development in closed-loop real-time ore control systems like CROCS will be crucial for further advancing the mining industry's efficiency and sustainability.

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