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.

Third, real-time adjustment of processing plant parameters requires information about the anticipated feed characteristics of incoming ore. A predictive model is needed is to achieve this adjustment. While many models are available [3], finding one that accurately captures the spatial and temporal variation in the underlying material tracking data is challenging. Additionally, these predictions must be available in real-time before a new batch of ore is processed by the plant. Without timely predictions, it is impossible to optimise plant parameters in-time. Real-time predictions are difficult because model computation time must be minimized, and a robust mechanism for integrating these predictions with the existing systems must be established.

Addressing these complexities requires a holistic approach that acknowledges the interconnectedness of mining operations and processing plant performance. In this paper, we introduce a new concept named Closed-loop Real-time Ore Control System (CROCS), which facilitates a direct correlation between plant responses and product specifications with ore source locations in real-time. CROCS is a real-time ore control solution designed to enable quick identification of problematic-ore and facilitates timely operational adjustments. CROCS features a live material tracking system that models ore flow from the mining face through the processing plant to the product stockpile. The system is equipped with a real-time data processing and storage component that handles live material tracking efficiently. CROCS is also capable of predicting incoming ore characteristics based on real-time localized data (from the material tracking system) on a truck-by-truck basis. These predictions can be integrated into a feedforward controller in the processing plant's control system to enable proactive processing parameter adjustment to incoming ore.

To demonstrate the benefit of the CROCS framework, we present a case study of its industry application at the Rio Tinto's Amrun bauxite operation in Far North Queensland, Australia. This study highlights how CROCS can be successfully integrated into a real-life mining operation, yielding significant improvements in operational efficiency and productivity.
The need to address material handling challenges presented by problematic ore (and/or variations in orebody characteristics) is not unique to the Amrun operation but extends to many surface mining operations. Many operations are seeking real-time solutions to manage these issues [4]. A holistic approach that integrates online sensing technologies, comprehensive material tracking, and predictive analytics is essential to manage this complexity. An integrated approach is preferred because it produces the data necessary to identify variations in orebody characteristics and simultaneously supports the creation of optimal response strategies using data analytics.

The remainder of the paper is organized as follows. In the next section, we introduce the concept of CROCS and its main building blocks. In Section 3, we delve into the development and implementation of the CROCS technology at Rio Tinto's Amrun operation. The results and relevant discussions are elaborated upon within this section. Lastly, Section 4 encompasses the conclusion and outlines avenues for future research.

2. Methodology

In this section, we introduce the theoretical framework of CROCS and its building blocks.

2.1 CROCS Theoretical Framework and Building Blocks

CROCS consists of four fundamental building blocks to create a closed-loop system that enhances ore processing efficiency and ensures optimal plant performance. These four building blocks are real-time data collection and integration, real-time material tracking system, real-time prediction of material characteristics, and feedforward controller (Figure 1).

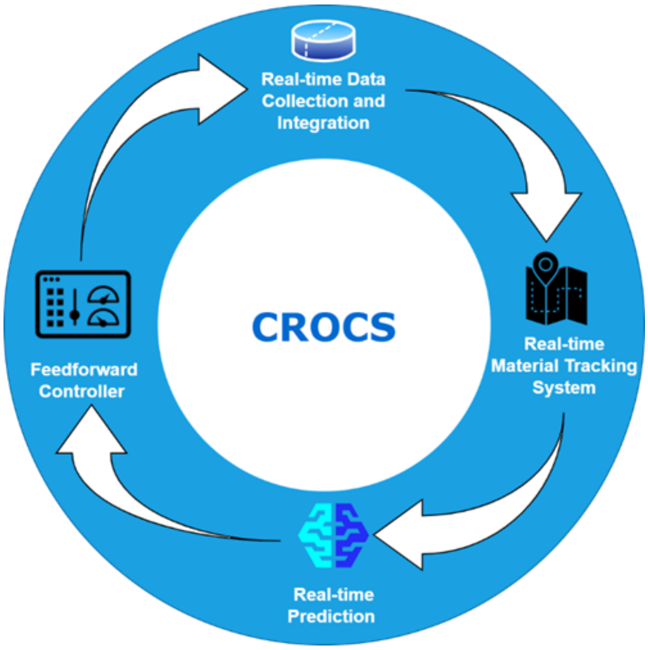

Figure 1. CROCS building blocks: real-time data collection, material tracking, predictive modelling, and feedforward controller.

Real-time data collection and integration refers to CROCS's ability to collect live sensor or online instrument generated data from the processing plant and integrating it with various other sources of data in real-time. Examples of other sources of data include orebody drilling data acquired through resource definition and grade control programs, and information of active mining faces from fleet management systems.

The next component of CROCS is the material tracking system where ore flow is tracked from the orebody to the product stockpiles through the processing plant. A single-use Tracking ID is used for monitoring each truck load of ore being transported and processed. The Tracking ID also allows the real-time data collected in the first component to be contextualized and aggregated to a truck level, so that all data captured is at the same unit of analysis. This makes correlation analysis amongst plant operating parameter, performance, online instrument measurements and orebody data straightforward. In addition, a processing plant typically consists of several key pieces of equipment such as crushers and screens. The material tracking system is configured to track material flow through all key ore processing locations. This comprehensive tracking allows end users of the system to gain a clear picture of material movement throughout the entire process and opens the possibility for live identification of which batch of ore is causing material handling issues. Furthermore, the wealth of real-time information collected enables development of a precise understanding of how the plant responds to each truckload of ore. This enables the operation to proactively adjust its processing strategy or even short-term mine plans to better respond to varying ore characteristics.

Another component of CROCS is the predictive models. Real-time data collected from the system is of spatiotemporal nature. CROCS features models that can analyze the spatial and temporal correlations in the underlying data to predict likely feed material characteristics for the next truckload. These predictions can be integrated into the processing plant's control system to live fine-tune the plant's parameters for optimal performance.

The feedforward controller is the last key component of the CROCS system. It provides information or predictions about the type of ore carried by a truck before it dumps its load at the plant. This feedforward signal enables the plant to adjust operations, enhancing throughput and stability.

The entire process operates as a closed loop, as it is repeated for every truckload of ore being processed. Each time the plant responds to a truckload of ore, its response is captured and recorded in CROCS's database. This feedback can then be used to adjust and improve the plant's response for processing the next truckload of ore. By continuously capturing and utilising this feedback, the system operates as a closed loop with interactive learning capability, progressively enhancing the plant's performance with each cycle. Moreover, each element within this loop occurs in real-time. There is no need to wait for hours to obtain the necessary information for decision-making. This real-time capability defines CROCS as a dynamic and responsive system (Figure 1).

2.1.1 Real-time Data Collection and Integration

Processing plants are typically equipped with sensors capturing production performance and online material characterization instruments measuring ore characteristics in real-time. This is an enormous source of information, alternative to and in addition to exploration data. CROCS features a spatial database that can be used to store such information. With the support of the material tracking system (discussed in Section 2.1.2), all process signals captured in the database can be contextualized by a single-use Tracking ID. This means for every truck load of ore that the plant has processed, the database can capture the precise plant response against that batch of ore, and information can be uniquely identified by the Tracking IDs.

Data generated by the plant (such as crusher motor performance, moisture, product grade, and amount and size of timber contamination in the ore stream) and collected through the material tracking system could prove to be extremely useful when combined with other sources of information. For example, by combining real-time plant response with ore source location data (from fleet management system) and in-situ material characterisation data (such as elemental concentration, mineralogy information) obtained from orebody drilling and mapping, end users can develop a precise understanding of how plant performance is correlated and impacted by ore characteristics, enabling them to set up best processing strategies. The CROCS database can be configured in a way to also store information from other source systems, enabling plant data to be further enriched to include essential attributes for analytics. (see Table 1).

By establishing the CROCS database, operations can achieve a deeper understanding of the end-to-end ore behaviour and processing efficiency, leading to more informed decision-making.

Table 1. Example dataframe generated by CROCS integrating pit, plant, and orebody data. Please note that the information presented here is not actual operational data but serves as an illustrative example.

ID	Tracking point	Timestamp		Plant responses			Ore source location			Ore in situ attributes		
	Equipment	Start	End	Attribute	value	…	X	Y	Z	Geology	Al_2O_3 (%)	…
# 1	Crude ore conveyor	22/08/2022 21:08	22/08/2022 21:11	Moisture	8.81	…	87419	88654	327	2	38.5	…
# 1	Crusher	22/08/2022 21:11	22/08/2022 21:12	Motor current	96.46		…	…	…	…	…	…
# 1	…	…	…	…	…	…	…	…	…	…	…	…
# 2	Crude ore conveyor	22/08/2022 21:20	22/08/2022 21:23	Moisture	10.31	…	…	…	…	…	…	…
# 2	…	…	…	…	…	…	…	…	…	…	…	…

2.1.2 Real-time Material Tracking System

The CROCS material tracking system is a full end-to-end ore tracking system where material movement is tracked from extraction through to processing. Once the ore is mined, it is transported to the processing plant by haul trucks. Several technologies such as onboard Global Positioning Systems (GPS) and Radio Frequency Identification (RFID) scanners can be leveraged for tracking [5, 6]. Most haul trucks are equipped with GPS systems to track their movements in real-time. Alternatively, RFID readers can be placed at loading and unloading locations to ensure the ore's journey from the pit to the processing plant is continuously monitored. Most operations today utilize fleet management systems to track the location of haul trucks, typically using GPS to locate their whereabouts. Important information such as precise ore loading location is usually available from these fleet management systems. In CROCS, every haul cycle is tracked, and a single-use Tracking ID is assigned to monitor material movement.

To continue tracking ore movement through the processing plant, it is essential to integrate the Tracking IDs from the fleet management system into the plant control system (Figure 2). This integration ensures continuity and seamless data flow between the two systems, preventing any disconnects that could disrupt the end-to-end tracking. When haul trucks arrive at the dump bridge of the processing plant, weight sensors or other types of instruments such as ultrasonic sensors can be used to detect truck arrival and unloading. Belt-weighers measure the weight of the ore as it moves along the conveyor belts, this information can be used by the plant control system to track the flow rate, volume, and speed of material movement through the processing facility (Figure 2). It is also important to arrange the control system to produce timing data indicative of the time at which ore is located at each processing component within the plant.

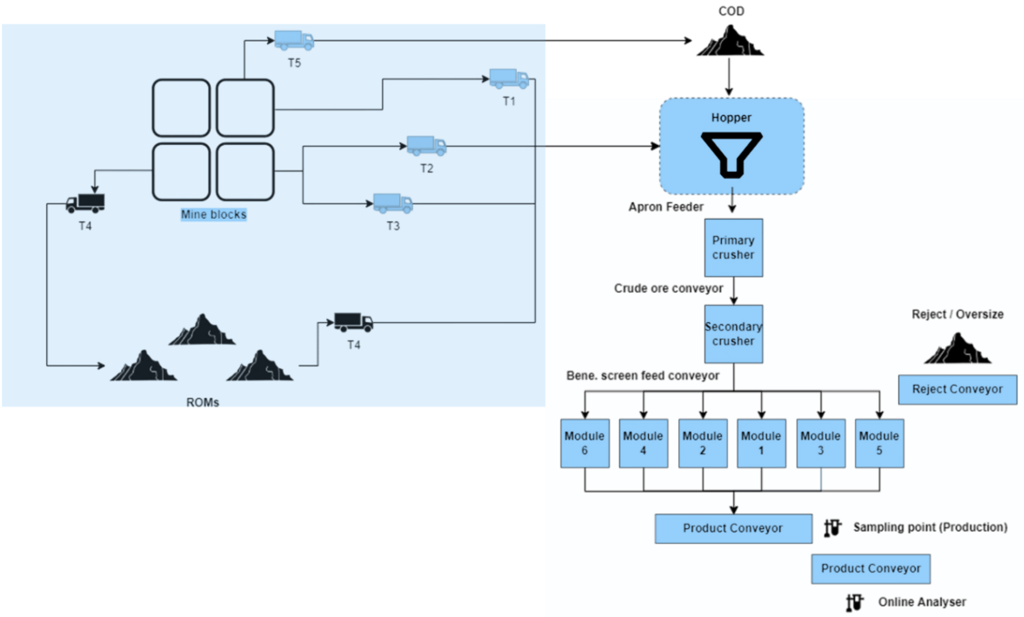

Figure 2. CROCS real-time material tracking system featuring a typical processing plant.

As discussed in earlier sections, modern processing plants are equipped with sensors for measuring plant response and characterizing material characteristics online. These readings can be contextualized and summarized for each Tracking ID, and at each key ore processing point within the plant. This data is then stored in the spatial database discussed in the previous section. The Tracking IDs can be used to link up to ore source location, which can then be further linked to ore characteristics obtained from drilling.

In summary, ore characteristics, source location (from fleet management) and plant response data are now stored in a database and can be linked via the Tracking ID for further analysis. In addition, end users (such as operational personnel) of the system can start live identifying problematic ore based on immediate plant behaviours as material is processed through the plant.

2.1.3 Real-time Predictive Models and Feedforward Signals

Data generated from CROCS exhibit both spatial and temporal correlations. The spatial attributes of the data refer to the precise source location information of each parcel of ore that is mined and processed. Whereas the temporal correlations are reflected in the timing and sequence of ore movement events, which is crucial in understanding the changes in ore characteristics and plant responses over time. These correlations make it possible to predict future plant responses for upcoming trucks, as they reveal the dynamic changing relationships between the plant and the ore.

The foundation of the predictive modelling framework lies in these spatial and temporal correlations [7]. When predicting future plant responses at a new loading location, values observed at nearby locations (both spatially and temporally) can be combined to produce a forecast. Although several types of models are available, after experimentation, we identified spatially aware machine learning models [8–10], especially eXtreme Gradient Boosting (XGBoost) regression models [11] as the best approach. These models are typically known for their stability and simplicity while achieving accurate predictions. Moreover, XGBoost is highly flexible in handling multi-type, multi-resolution, and high-dimensional data, which is the inherent nature of the CROCS data. A limitation of typical XGBoost machine learning model is their difficulty in understanding spatial information. However, this can be addressed by engineering spatial features into the data, enabling the model to become spatially aware during both training and prediction phases [12].

To optimize plant parameters in real-time, the predictions must be made available just-in-time before the plant processes a new truckload of ore. A just-in-time prediction ensures that the model is always trained on the latest data, capturing changes in the orebody patterns as soon as possible. If we activate the model as soon as a truck is loaded, it will not have access to the latest observations from the plant to train on, thus reducing the accuracy of the prediction. However, if the model is activated too late, it will be rendered useless as the ore will have already been processed. Therefore, finding a solution to automatically trigger the predictive model in real-time is an important practical challenge.

One solution is to utilize road beacons that are commonly found on haul roads. As soon as a truck drives past a road beacon that is sufficiently close to the processing plant, a signal can be obtained and used to activate the predictive model. Careful selection of road beacons is essential, aiming for the shortest travel time from the selected beacon to the dump area. It is important to ensure there is enough time to train the model and provide prediction results to the control system before a truck arrives at the hopper. In practice, we also recommend that the model be retrained and tuned frequently to sustain optimal performance. However, retraining the model for every incoming truck prediction is not necessary. Retraining should be done at intervals that fit the nature of the data, balancing performance maintenance with operational efficiency. For highly volatile data, frequent updates may be required, whereas for more stable data sources, less frequent retraining may suffice.

Once a prediction becomes available, it is integrated into the plant's control system as a feedforward signal. This signal helps to control the downstream processing equipment's response to the ore. With a better understanding of the anticipated material properties, the control system can proactively adjust processing parameters to achieve optimal performance, enhancing plant throughput and stability.

It is important to realise that CROCS utilizes the most immediate data collected from material tracking system to make predictions. These predictions are then used to optimize the plant's response in real-time. Additionally, the responses are captured in CROCS's database, allowing the operation to analyze the plant's behaviour from recent activities. This information aids in making future adjustments to the plant, ensuring the desired performance is achieved.

3. Results, Discussion and Case Study

CROCS has recently been introduced at Rio Tinto's Amrun bauxite operation in Far North Queensland, Australia. In this section, we present a summary key results and findings observed at Amrun.

3.1 Rio Tinto Amrun Bauxite Operation

Rio Tinto's Amrun mine (Figure 3) is a large bauxite production asset located on the Western Cape York Peninsula in Far North Queensland [13]. In Amrun, the extraction process involves mining crude bauxite ore, which undergoes crushing and washing in a processing plant to enhance its handleability and quality before shipment to customers. Most of the processing plant's feed originates directly from the orebody (in-situ, approximately 75–80 %), with the remainder sourced from Run of Mine (ROM) stockpiles.

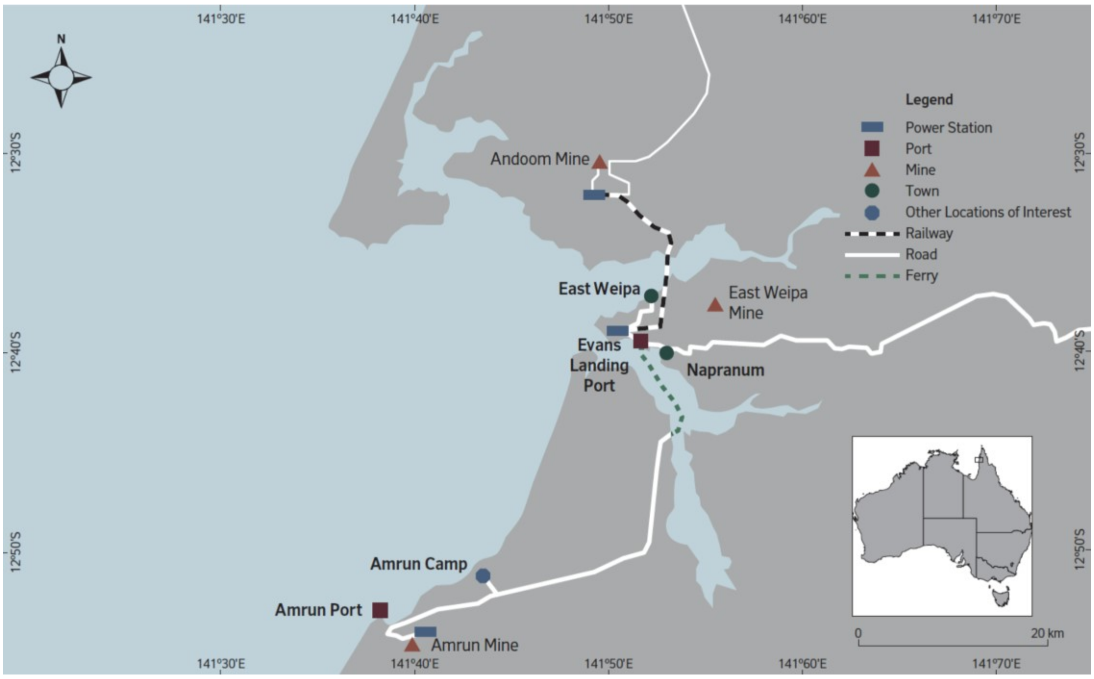

Figure 3. RioTinto's Weipa operations in Far North Queensland, Australia.

In the Amrun mining operation, the highly variable characteristics of mined bauxite ore can pose significant challenges for the processing plant. The presence of problematic ore (see Figure 4) causes material clogging and blockage issues for the processing plant, which, if not addressed, can result in reduced throughput and unplanned downtime. It was initially nearly impossible to quickly identify areas where the problematic ore is from due to the multi-pit mining approach. In addition, there was no mechanism to link plant performance to the source location of the ore in real-time, making it difficult to identify where problematic ore comes from and how ore from different pits is impacting processing efficiency.

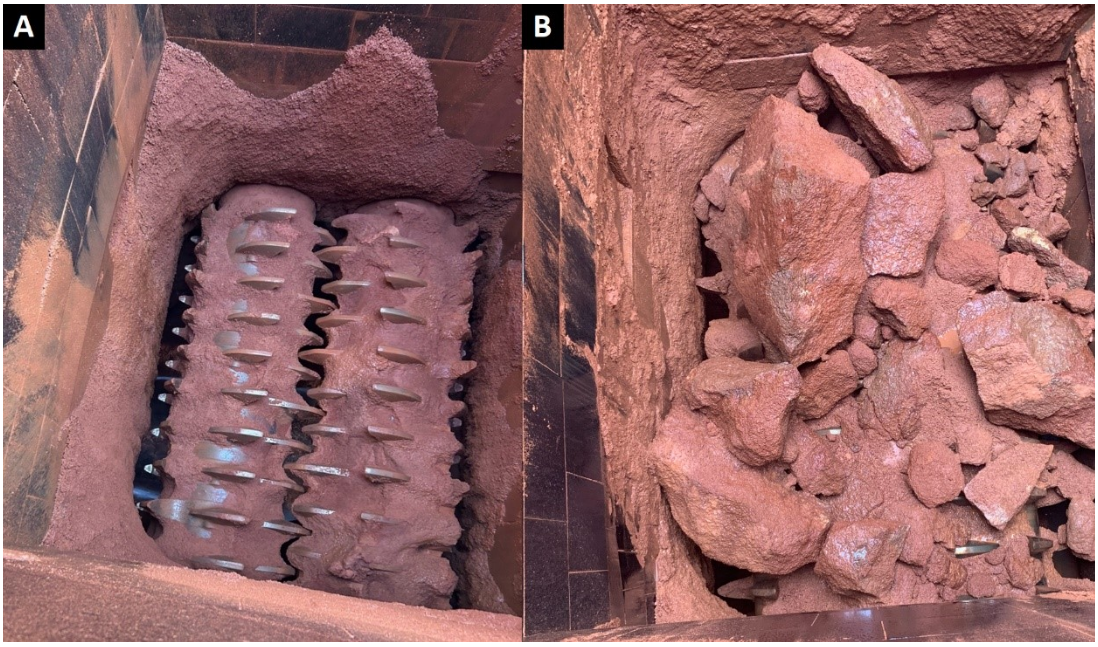

Figure 4. Problematic ore (i.e., A: sticky, B: rocky) in crusher.

Additionally, the fluctuating bulk density of incoming ore trucks (see Figure 5) presented complexities for optimizing plant feedrate control. A suboptimal feedrate can lead to surging issues and lost tonnes. The previous control schemes were reactive rather than proactive, exacerbating these issues, especially given the absence of predictions for incoming ore characteristics, hindering the plant's ability to dynamically adjust to changing ore properties and maximize operational efficiency.

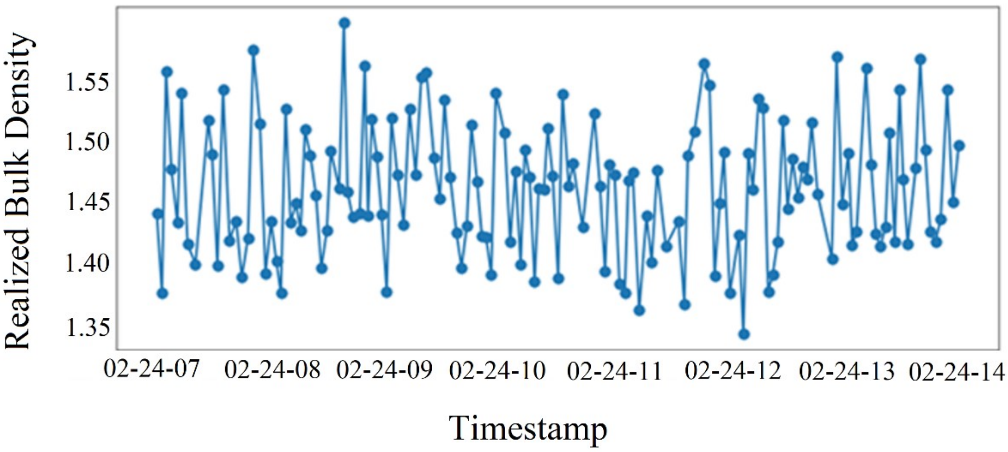

Figure 5. Truck by truck feed characteristics variation.

Furthermore, communication challenges between plant operators and mine services impede effective response strategies, impacting on stability and hindering throughput optimization. These limitations restricted the operation's ability to respond promptly to rapidly changing ore properties. Therefore, there was a clear opportunity for integrated solutions leveraging advanced technologies such as material tracking, machine learning and real-time optimization based on real-time data. These solutions would enable proactive control, improve communication, and optimize plant performance in the face of variable ore characteristics and multi-pit mining operations.

3.2 CROCS Deployment at Amrun Operation

Deployment of CROCS at Amrun followed a multi-phase approach. We deployed an end-to-end real-time material tracking system where Amrun's fleet control management system was integrated with the processing plant's control system. This integration allowed for the processing plant's operating parameters and subsequent performance responses to be correlated with ore characteristics and source location in real-time. In addition, the data generated from the CROCS system were stored in a dedicated spatial database for further analysis. The data generated by CROCS includes sensor readings from various equipment and measurements from online material characterisation devices. Examples of data collected include crusher current, bulk density, crude ore moisture, and elemental composition such as Al_2O_3, SiO_2, Fe_2O_3, and TiO_2. Moreover, other important information such as Tracking ID, loader operating coordinates, product type, ore attributes derived from drilling and the reserve block model are also stored in the same database and linked to plant observations. Lastly, leveraging the advanced predictive models in CROCS, we also rolled out real-time predictive models forecasting feed characteristics for incoming trucks into the processing plant. These predictions can be used as feedforward signals to enable the processing plant's control system to make instantaneous adjustments to operating parameters, facilitating feedrate optimization.

The deployment of the CROCS technology at the Amrun operation has yielded significant findings and improvements across various aspects of the operation.

One key revelation from CROCS is the insight into the fluctuating bulk density of incoming ore trucks, as depicted in Figure 6. It was difficult for the plant to respond optimally to the fluctuating density because the variable was previously perceived to be random and impossible to forecast. However, with the implementation of CROCS, it became evident that the zigzag pattern in bulk density is caused by ore originating from alternately high and low-density pit locations, as illustrated in Figure 6. This understanding enabled the prediction of realized bulk density to be used by the control system for optimal feedrate control.

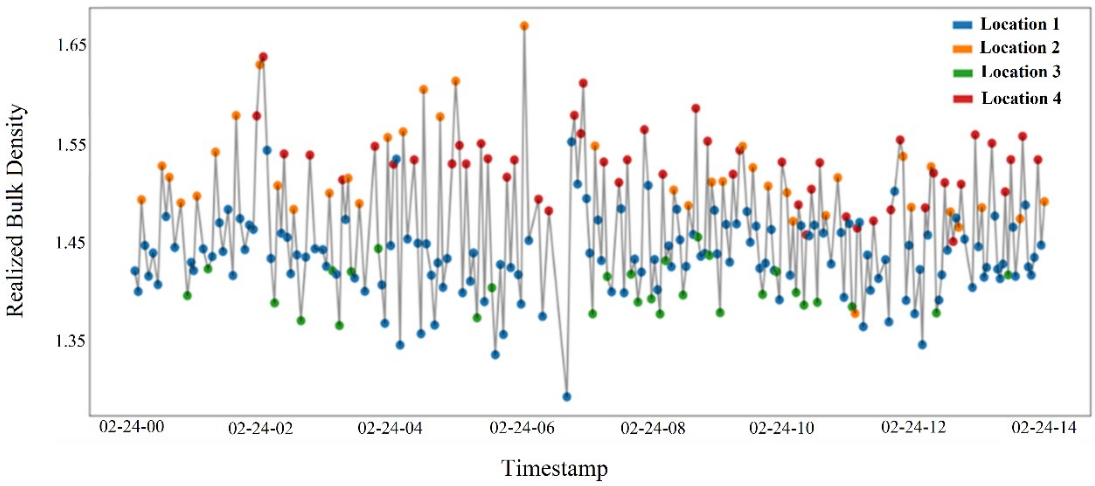

Figure 6. Truck by truck feed characteristics variation color-coded by ore source location.

When we leveraged the predictive model embedded within CROCS, we found the model was able to capture the zigzag pattern observed in the data. Figure 7 compares the predictive performance of CROCS with the orebody block model. The plot clearly shows that the orebody block model lacks the resolution and essential information needed to accurately predict plant performance. In contrast, the CROCS real-time prediction model, which employs a spatial version of the extreme gradient boosting technique, accurately predicts the bulk density of incoming ore at Amrun's beneficiation plant. The predicted average density feed from the CROCS model ($M_y = 1.341$) is much closer to the actual average density feed from the plant ($M_x = 1.342$) compared to the estimate from the reserve block model ($M_y = 1.498$). Additionally, the Root Mean Square Error (RMSE) decreased by 85 % with the CROCS model, dropping from 0.161 for the reserve block model to 0.023 for the CROCS predictive model. The correlation coefficient (ρ) and the slope of regression (SoR) also significantly improved with the CROCS model, increasing from 0.53 to 0.81 and from 0.47 to 0.69, respectively.

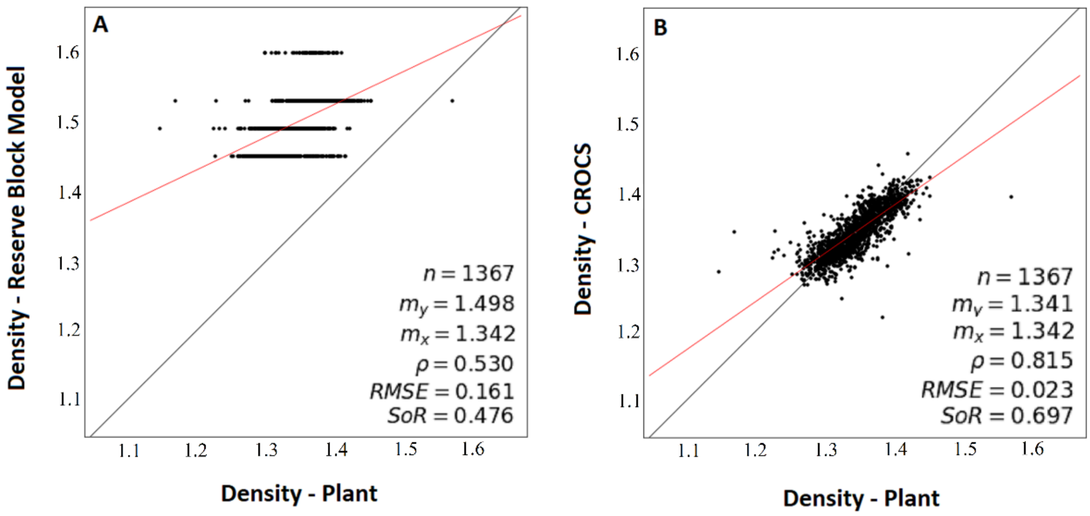

Figure 7. Predicting plant realized bulk density via A) orebody block model and B) CROCS predictive model. In this plot, n represents the number of trucks delivering material to the plant. M_x and M_y are the averages of the data for each axis. ρ is the correlation coefficient, $RMSE$ is the root mean square error, and SoR is the slope of the regression.

Operationally, CROCS enabled swift identification of problematic ore and consequently reduced plant downtime. When the processing plant is affected by problematic ore, the live visualization tool (known as the mine-to-plant dashboard) we deployed as part of CROCS helped front-line staff to quickly identify problematic areas, and therefore facilitated collaborative problem-solving and communication among various stakeholders involved in day-to-day operations. By leveraging the real-time information from CROCS, it is possible to reduce chute blockage downtime by up to 25%. This reduction can be achieved by timely adjustment of critical operational levers such as appropriate feedrate adjustment and stabilising ore feed into the plant (e.g. redirecting trucks to crude ore support dumps to allow for a more controlled, drip-feed of problematic ore into the plant). CROCS fostered the development of proactive control strategies to enhance plant stability and mitigated material handling risks. This proactive approach minimized the occurrence of downtime or rate losses, and thereby improved overall plant operation efficiency.

Furthermore, CROCS facilitated correlation analysis between ore characteristics and plant behavior, aiding in the identification of issues within the mine or the plant itself. This capability enables the planning and design of mitigating strategies to address challenging ore, thereby enhancing plant recoveries. For instance, by pinpointing the sources of low recovery materials, CROCS allows for informed blending decisions, such as redirecting trucks containing problematic ore to different stockpiles.

The implementation of CROCS has not only streamlined operations but has also led to operational improvements. For example, the quick identification of problematic ore and the facilitation of response strategies have helped reduce downtime and enhance throughput. These outcomes underscore the substantial benefit realized from the deployment of CROCS on the efficiency and performance of the Amrun operation.

Developing, deploying, and maintaining CROCS for a surface mining operation poses several significant challenges alongside its numerous benefits. Firstly, ensuring the reliability and accuracy of sensors within the processing plant presents an ongoing challenge, requiring regular checks to confirm they are all functioning correctly. Additionally, the construction and maintenance of real-time databases and predictive models demand upfront capital investment and ongoing operational costs. This includes the need for dedicated teams to manage and maintain the infrastructure, as well as ensuring robust cybersecurity measures are in place to protect sensitive data. Moreover, while CROCS technology thrives when there is majority single source of ore, integrating it into operations where ore is predominantly sourced from ROM stockpiles introduces complexities. This scenario necessitates advanced material tracking and spatial modelling to accurately monitor and manage material movement through the stockpiles, adding further layers of complexity to system deployment and maintenance. Despite these challenges, the potential benefits of CROCS in optimizing ore processing and improving operational efficiency make overcoming these hurdles worthwhile for surface mining operations.

In summary, CROCS is a generalized concept that can address the broader industry needs because it provides up-to-date information on how the processing plant is responding to ore with varying characteristics throughout the extraction and processing process. CROCS captures material tracking data from the processing plant and integrates this with other sources of information such as orebody and pit data to provide a comprehensive view of the end-to-end mining and processing operation. This capability enables end-users to uncover where problematic ore comes from and develop a precise understanding of how the plant responded to each truck load of ore. The predictive capability for future trucks based on localized geographical information acquired from the CROCS system enables fine-tuning the processing plant for optimal performance. By continuously monitoring this information in real-time, mining companies can make dynamic adjustment to their operations and design tailored processing strategies to maximize ore recovery and minimize dilution, ultimately leading to improved resource utilization and profitability. Additionally, CROCS facilitates real-time spatial reconciliation between planned and actual production, allowing for timely adjustments to mining plans and production schedules. This capability not only enhances operational efficiency but also helps identify areas for improvement in mining processes, leading to overall performance enhancement and cost reduction.

4. Conclusions

Implementing a closed-loop real-time ore control system offers significant benefits for mining operations, particularly in terms of efficiency, cost reduction, and decision-making enhancement. CROCS revolutionizes ore management by providing a comprehensive solution to track ore movement from the pit to the stockpile and throughout the beneficiation process. This enables a direct correlation between orebody characteristics and processing plant responses, enhancing knowledge accumulation and operational efficiency.

The deployment of CROCS at Rio Tinto's Amrun operation has yielded tangible improvements in operational efficiency, with downtime reduction of up to 25 % when the appropriate response levers are pulled. Swift identification of problematic ore, collaborative problem-solving, and proactive control strategies have significantly minimized plant downtime and increased throughput. The system's mine-to-plant production dashboard facilitates quick identification of 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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