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Meta-Model Development for Mine-to-Mill Optimisation Using AI and Simulation

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Abstract **-** The current demand for mineral resources is higher than it has ever been, and it is expected that, over time, the quality of future resources will decline, and they will become more difficult to extract. Routinely collected on-site data from various mining stages are often neglected in mining operations and are not being used to improve the value of the mining chain. To address this issue, mining companies need to increase the efficiency of their mining processes to achieve sustainable production by using innovative solutions. The primary purpose of the study presented here is to develop an integrated knowledge-based system using advanced AI techniques to simulate, monitor, assess, and optimise mining processes from blasting to downstream products. In this study, publicly available data from the Barrick Cortez Mine in Nevada, USA, was used to model the entire mining process from blasting to SAG mill by using Orica's Integrated Extraction Simulator (IES) platform. The comparison of real data from the mining site with simulated data on the IES platform demonstrates that the modelled operations closely match the real data. Thirteen parameters related to blasting, screens, crusher, and SAG mill were considered. Given the computational infeasibility of testing all combinations, three million scenarios were simulated to identify key performance drivers. Machine learning models—including linear regression, decision trees, random forest, and XGBoost—were evaluated to determine the most effective for predicting outcomes. The next step involved using input scenarios and outcomes to investigate key features and interpret results using feature importance and SHapley Additive exPlanations (SHAP) techniques, respectively, as powerful tools for determining the influence of individual features of the models. The findings highlight the potential of AI-driven meta-models to enhance decision-making, reduce operational costs, and improve resource usage in mining operations.

Keywords**:** Mine to product, Mining Integration, Optimisation, IES, Artificial Intelligence

1. Introduction

The mining industry, characterised by its complex and interconnected operations, plays a pivotal role in supplying essential raw materials for various downstream products across diverse sectors. From the initial stages of resource exploration and extraction to the delivery of final products, each step in the mining process can significantly impact the overall efficiency, sustainability, and profitability of the entire value chain. However, the traditional approach to managing these operations often involves disparate systems and fragmented decision-making processes, leading to unexpected outcomes and missed opportunities for improvement. Valery et al. [1] discussed a comprehensive optimisation strategy for mining operations that integrates mine and mill processes to maximise profitability. In 1998, Morrison [2] investigated the energy efficiency of different comminution circuits by implementing simulation techniques. The mine-to-mill blasting approach is introduced to optimise rock breakage processes involved in blasting, crushing, and SAG milling. The results indicated that, by careful design and management of intense blasting operations, significant increases in mill throughput and reductions in milling costs would be expected. Furthermore, Scott et al. [3] in another study emphasised the need to quantify the value added by optimising rock breakage tracking processes in mining. Using a combination of case studies, literature reviews, and empirical data, the study analysed the impact of intense blasting on downstream comminution benefits as shown in Figure 1 by Kanchibotla et al.

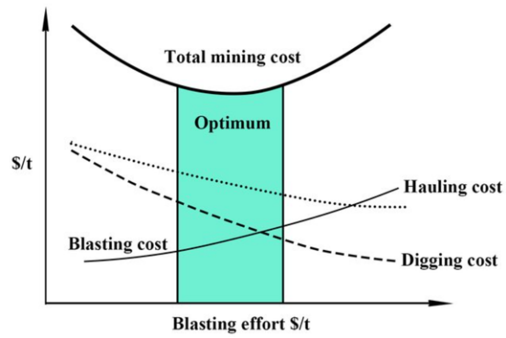

Fig. 1 Blasting Effort versus downstream Costs [4]

On the other hand, a series of studies conducted by different researchers regarding the use of artificial intelligence and innovative techniques to monitor, assess, and optimise mining operations including exploration, blasting, grinding, and milling [5-15].

Despite the comprehensive research on mine-to-mill optimisation mentioned in the previous paragraphs, significant gaps remain that hinder the full potential of efficiency and productivity improvements. The main research gaps that have been discovered from a literature review of books, papers, and reports are the lack of a systematic approach to system design, the lack of use of sophisticated AI techniques, and the disconnection between the characterisation of resources and the mining process. To address these challenges, a systematic, data-driven approach that leverages advanced simulation tools and machine learning techniques is necessary. This research potentially fills these gaps and assists in the mine-to-mill optimisation which will assist mineral producers and companies to be more effective, efficient, and contribute to implementing sustainable mining practices.

2. Methodology

The methodology for this research project involves an approach that includes various aspects aimed at developing an integrated system for linking resources to downstream mining products. The key section of this methodology is the use of real data, simulations, and advanced analytical techniques to monitor and optimise each stage of the mining process, from blasting to SAG mill. The following steps outline the methodology in detail:

2.1. Case study and data Acquisition

The first step is to collect real-world data on various parameters related to resource characteristics, mining processes, and downstream product requirements. This data serves as the foundation for building simulation models that replicate the entire mining system, including exploration, extraction, transportation, and processing stages. In this study, the published data from the Cortez Gold Complex (Wenban mine) and its process flow diagram (in Figures 2 and 3) have been used to simulate processes and validate them.

Fig. 2 Location of Cortez Complex [16]

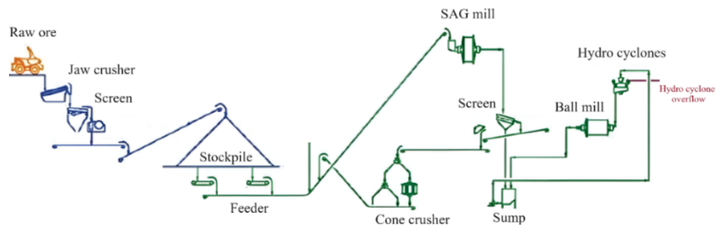

Fig. 3 Process flow diagram of Cortez gold mine

2.2. Simulations

Over the past four decades, computer-based process plant modelling started with the comminution models created by the JKMRC in the early 1970s [17]. In parallel, models were regularly developed and improved for other processes in a mining value chain, such as flotation and blast fragmentation [18]. Process modelling methodologies have also been developed in a computer environment by other research and commercial entities. These have taken the form of equations or specialised commercial software such as METSIM [19], MODSIM [20], SysCAD [21], CEET [22], FLEET [23], JKSimMet [24], and JKSimFloat [25]. Based on the objectives of this study, and with the goal of increasing plant productivity, optimising economic value, and minimising the environmental effects of mineral recovery, the Integrated Extraction Simulator (IES) [26] was chosen as a cutting-edge model that facilitates the quick assessment of processing scenarios in the mineral extraction value chain. Figure 4 shows the process flow diagram of the Wenban mine replicated in the IES platform.

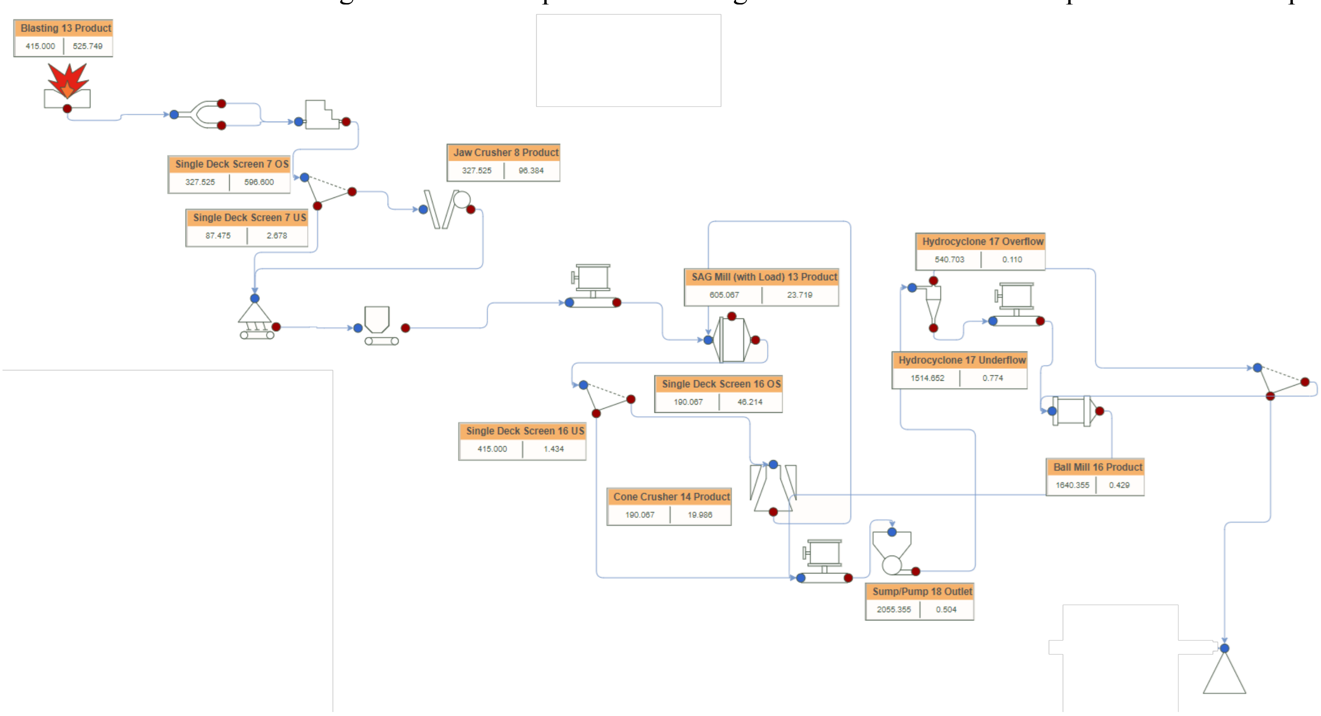

Fig. 4 Wenban mine process flow diagram

2.2.1 Blasting

With the comprehensive data collected from blasting patterns and detailed photographs and their analysis of stockpile post-blasting (see Figures 5-6), we were able to conduct an in-depth analysis. The particle size distribution was meticulously measured using advanced techniques, and the results are presented in Figure 7.

Fig. 5 Real post blasting stockpile

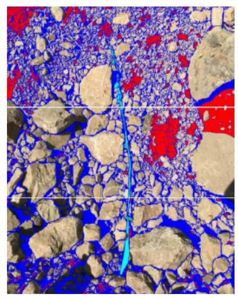

Fig. 6 Scanned post blasting stockpile

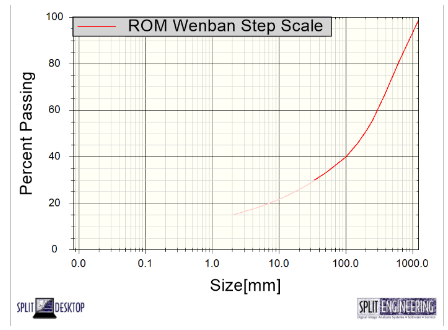

Fig. 7 Particle size distribution

These data were then used to simulate the blasting operation using the IES platform which provided a precise and realistic model of the process. The simulation results are illustrated in Figure 8.

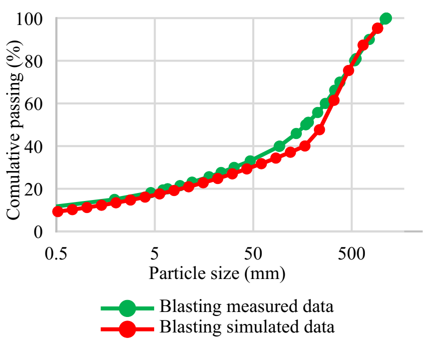

Fig. 8 Blasting surveyed data vs IES prediction

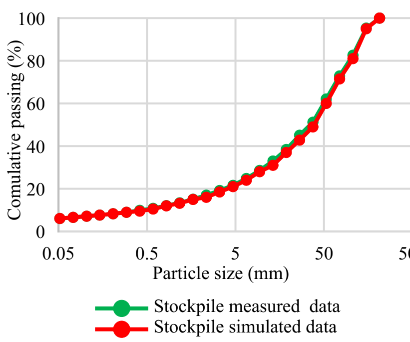

Fig. 9 Stockpile surveyed data vs IES prediction

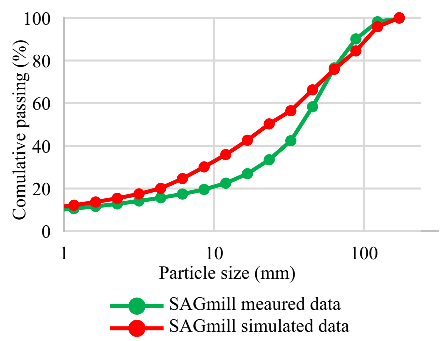

Fig. 10 SAGmill surveyed data vs IES prediction

2.2.2 Stockpile

Extracted materials are transported to a jaw crusher, which operates in a cyclic process alongside a single-deck screen. Figure 9 illustrates a comparison between the actual and predicted data of the particle size distribution within the stockpile, highlighting the effectiveness of the screening and crushing process in achieving the desired material size.

2.2.3 SAG mill

The comminution circuit at Cortez Gold Mine features a Semi-Autogenous Grinding (SAG) mill, which is an integral component of the ore processing operation. The SAG mill receives material from a sump, which acts as a buffer and ensures a steady feed rate into the mill. Once the ore is ground in the SAG mill, the resulting slurry is directed towards a screen. The effectiveness of the circuit's performance can be assessed by analysing the validation results of the SAG mill feed. This validation process is depicted in Figure 10.

3. Sensitivity Analysis

Once the simulation models are constructed based on the real data sets, a sensitivity analysis is conducted by systematically varying the parameters of each stage to assess their individual and collective impact on the overall system performance. Numerous scenarios explore changes in mineral characteristics, blasting design, and grinding circuit parameters, ensuring modifications without equipment replacement. Initially, all process flow parameters are considered effective. Identifying key mining components requires analysing the data flowchart, as shown in Figure 11, which illustrates input and output parameters for each stage.

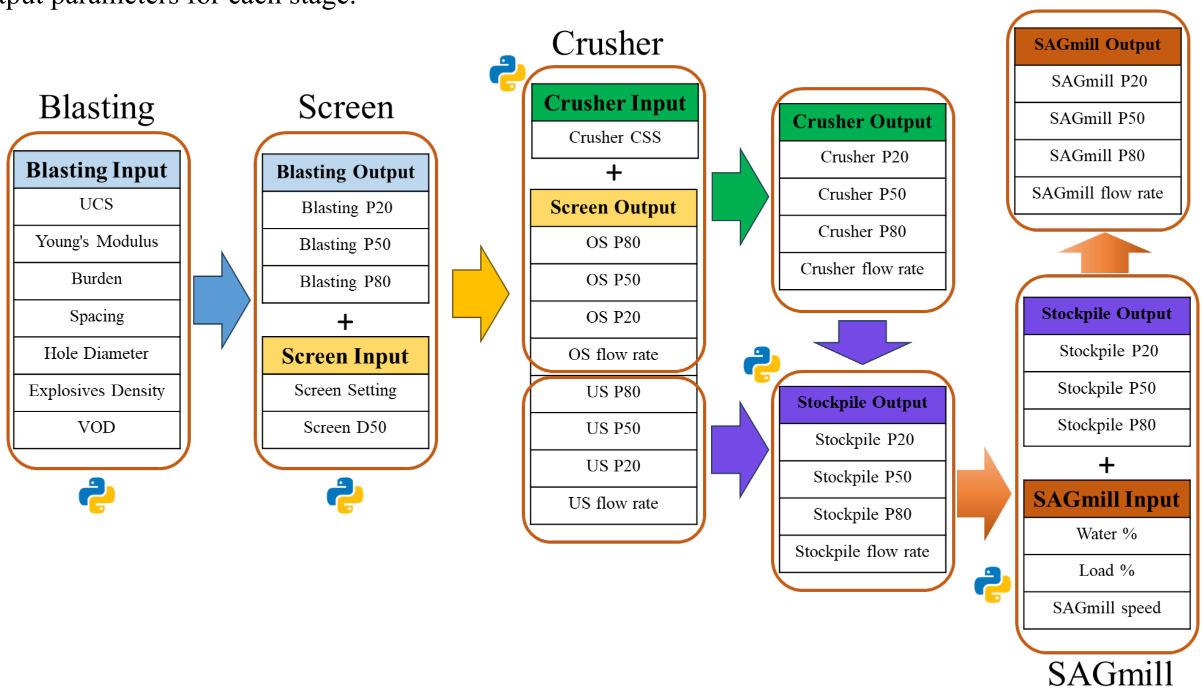

Fig. 11 Flow chart of required data

Based on the parameters and computational feasibility, 3 million different scenarios were simulated using the IES, and the output data were fed to machine learning algorithms to find the most reliable algorithms and create SHAP plots of different stages to show the importance of the parameters on the models' outcome.

Multiple machine learning algorithms were evaluated to analyse and predict the key process parameters. Decision Tree Regressor was chosen as a baseline model due to its interpretability and ability to handle non-linearity. Random Forest was selected as an extension of decision trees, leveraging ensemble learning to reduce variance and improve generalisation. XGBoost was incorporated due to its superior performance in structured data, leveraging gradient boosting and regularisation techniques to enhance predictive accuracy. These models were chosen based on their ability to capture complex interactions between mining parameters, their robustness against overfitting, and their proven success in prior studies related to industrial process optimisation. To interpret predictions and quantify feature influence, SHapley Additive exPlanations (SHAP) analysis was applied. SHAP assigns importance scores by estimating each feature's marginal contribution across input combinations. By computing SHAP values, we identified the most impactful parameters on fragmentation (P20, P50, P80), throughput, and mass flow. Features with consistently high SHAP values were deemed most influential, offering actionable insights for process optimisation while ensuring transparency and reliability in feature selection. The accuracy of various algorithms for different stage outputs, including P20, P50, P80, and mass flow, exceeds 90%, demonstrating that the simulations, based on scenario combinations, are well-structured and reliable.

By considering seven input parameters for blasting, including hole diameter, explosive density, velocity of detonation, spacing, burden, UCS, and Young's modulus, the most significant parameters for P20, P50, and P80 are defined as shown in Figures 12a to 12c, respectively.

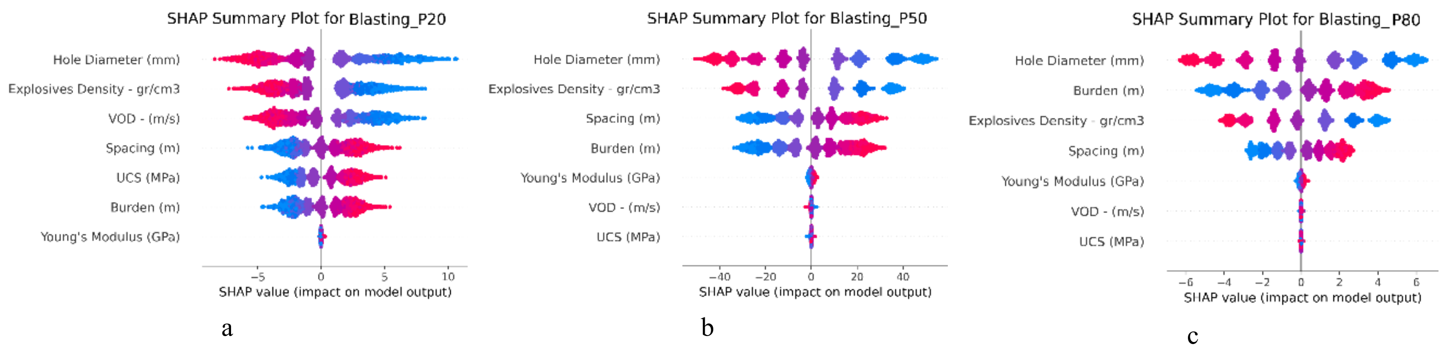

Fig. 12 SHAP summary plots for P20 (a), P50 (b), and P80 (c)

In the case study, the most important parameters that influence the crusher on-screen and under-screen, individual crusher settings, and loaded material data from the blasting step are considered, and the results are illustrated in Figures 13a to 13d for on-screen and Figures 14a to 14d for under-screen.

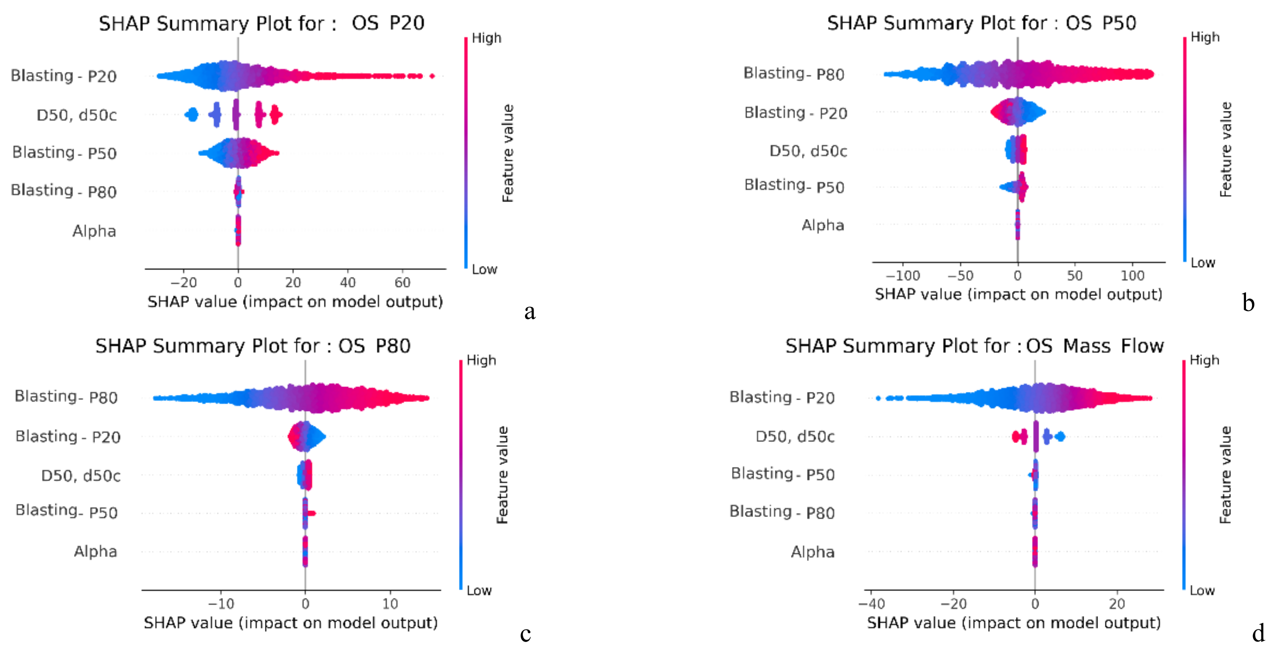

Fig. 13 SHAP summary plot for on-screen P20 (a), P50 (b), P80 (c), and mass flow (d)

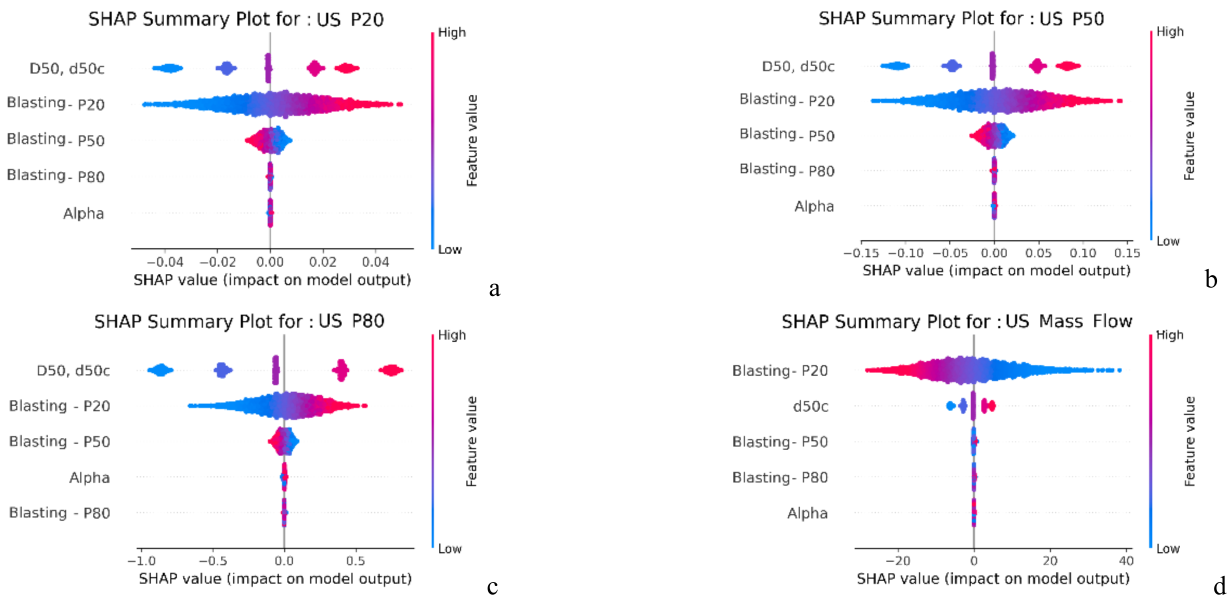

Fig. 14 SHAP summary plot for under-screen P20 (a), P50 (b), P80 (c), and mass flow (d)

By analysing four input parameters related to crusher settings and on-screen outputs, the key factors that influence the SAG mill were identified as P20, P50, P80, and mass flow. As illustrated in Figures 15a to 15d, these parameters play a significant role in determining the size distribution and throughput efficiency in the crusher process. The output of the crusher and under-screen product data are gathered as stockpile data used for input to the SAG mill in addition to the SAG mill's individual settings. The important parameters affecting the process of milling are depicted in Figures 16a to 16d.

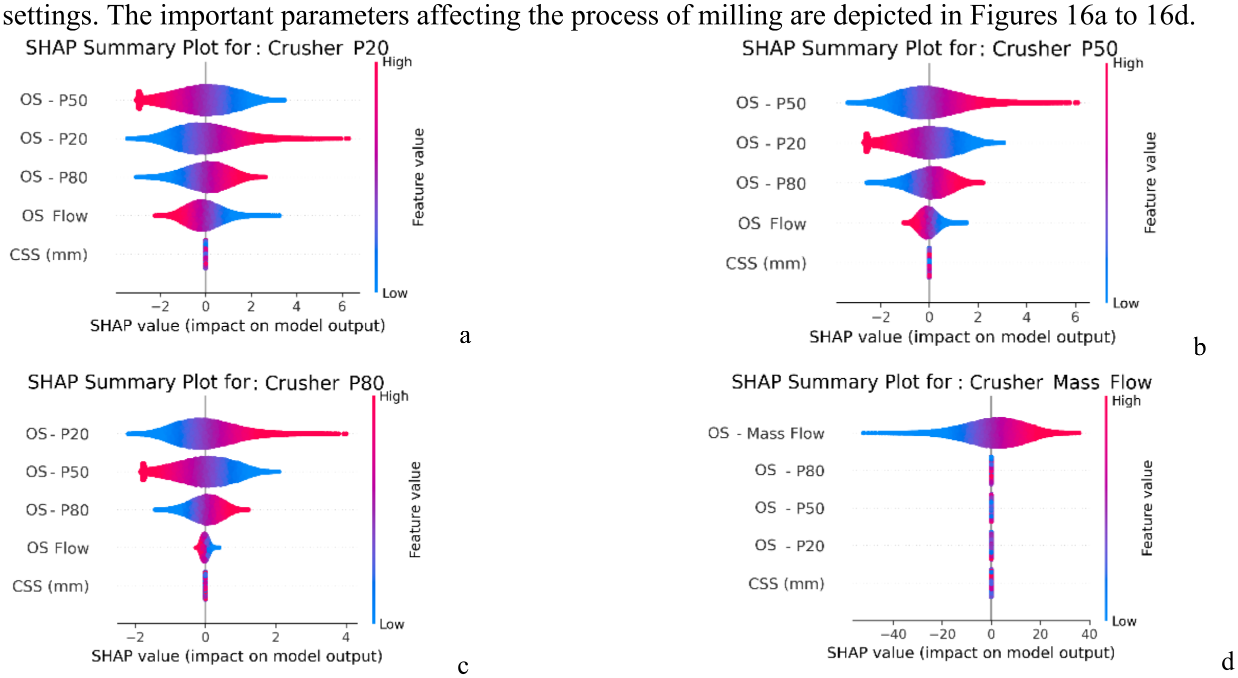

Fig. 15 SHAP summary plot for crusher P20 (a), P50 (b), P80 (c), and mass flow (d)

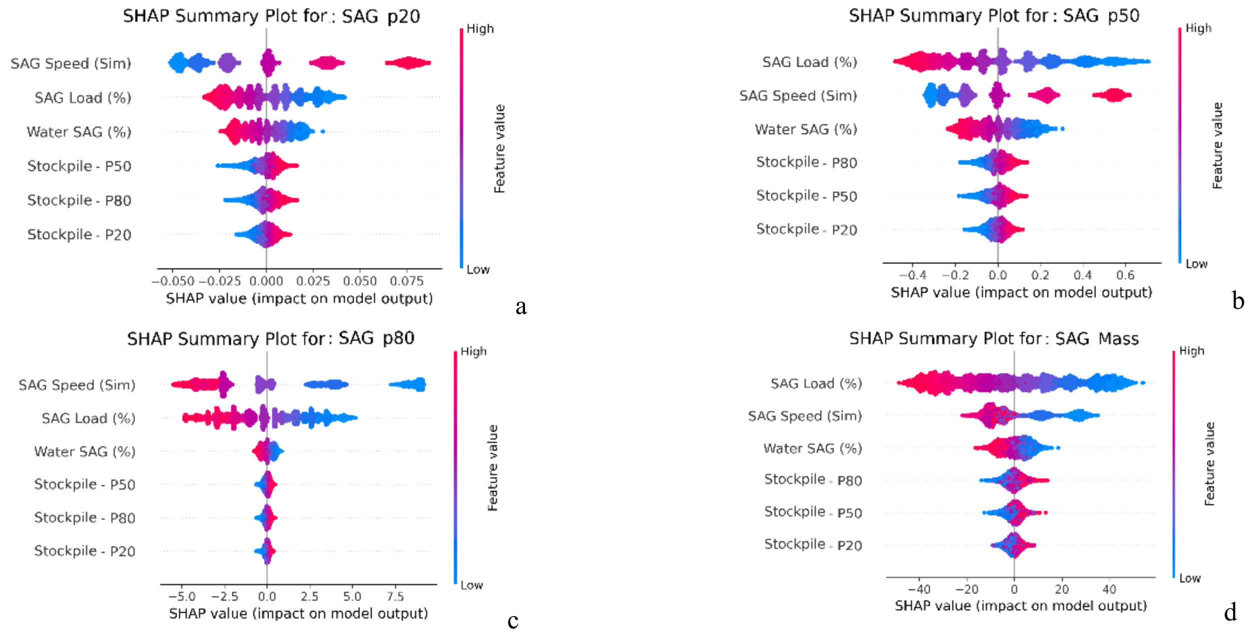

Fig. 16 SHAP summary plot for SAGmill P20 (a), P50 (b), P80 (c), and mass flow (d)

4. Conclusion

In this study the most influential parameters in each stage of the mining process, from blasting to SAG milling, were identified through extensive simulations and machine learning analyses. By evaluating 3 million scenarios, key parameters affecting fragmentation, material flow, and comminution efficiency were determined. SHAP analysis was employed to interpret the impact of individual features on model predictions, providing a transparent and data-driven approach to feature importance assessment. The results from machine learning models, including Random Forest, XGBoost, and Decision Tree Regressor, were used to generate SHAP plots, illustrating how variations in input parameters influence critical output metrics such as P20, P50, P80, and mass flow. These insights enhance our understanding of operational dependencies and offer practical guidance for optimising mining processes through targeted adjustments of influential parameters.

The generalizability of the model is also site-dependent, as geological and operational differences may affect transferability. Adaptive AI techniques, such as transfer learning, could help tailor the model to different mining conditions with minimal retraining. Additionally, while SHAP analysis provides insights into feature importance, 3D visualisations could further illustrate how key parameters interact and influence outputs. Future work should incorporate 3D surface plots to visualize parameter dependencies, aiding decision-making and operational adjustments. By addressing these challenges, future research can enhance the scalability and practical adoption of AI-driven meta-models in mining operations.

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