Cave mine pillar stability analysis using machine learning

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Synopsis

The large scale of cave mines leads to many challenges, including operational logistics and geomechanics design. In current practice, pillar stability assessment relies almost exclusively on stress analysis. However, stability is also affected by other factors including those related to operational aspects of the mining method, the effects of which are difficult to account for during the design stages. In this paper we present a case study of the application of a machine learning approach to evaluate the influence of these operational factors on pillar stability at the Chuquicamata underground cave mine in northern Chile.

Due to the likely multi-factorial damage process leading to collapses and considering the different pillar conditions, a tree-based machine learning method was used and analysed to improve the understanding of the relative importance of the various contributing factors. Unlike stress analysis methods, it does not require any *a priori* knowledge of failure mechanisms, nor the calibration of associated controlling parameters. The proposed random forest model predicted pillar collapses with 80% accuracy despite limited samples to model from. The main contributing factors to collapses were found to be related to available pillar volume, cave front geometry, and time under abutment stress conditions. The effects and interactions of such factors were also studied, showing that careful and improved control over operational conditions can significantly reduce the likelihood of pillar collapses. These conclusions could not have been obtained from stress analysis alone, illustrating the complementary nature of conventional stress analysis and machine learning approaches.

Keywords

cave mining, pillar stability, machine learning, random forest.

Introduction

Cave mines represent the largest type of underground mines, and their scale leads to many challenges, including large capital investment requirements, operational logistics, and geomechanics design. This paper focuses on the latter, and on stability assessment of pillars. Their design, as with virtually all types of pillars, relies almost exclusively on stress analysis. However, there are other factors, including those related to operational aspects of the mining method, that affect stability and these can be difficult to quantify during the design stage. This paper outlines these challenges and presents a case in which machine learning was used to develop a better understanding of the various factors affecting stability so that they can be appropriately accounted for in both the design process and in mining operations.

The case under consideration is pillar stability at the Chuquicamata underground cave mine in northern Chile (Flores and Catalan, 2018). During mining of the first macroblock, severe damage to production level tunnels occurred, leading to pillar collapses. Since all collapses occurred behind the cave front, the collapse process was clearly not only stress-related. Due to the likely multi-factorial damage process, machine learning was selected as the analysis methodology as it had the potential to lead to an improved understanding of the relative importance of the various contributing factors, and does not require any *a priori* knowledge of failure mechanisms as does numerical modelling, nor the calibration of the associated controlling parameters.

This paper explores the impact that operational, geological, and geotechnical parameters have in pillar collapse development in a real caving scenario as part of an attempt to improve the understanding of this mode of rock mass failure. The traditional methods of pillar stability analysis, alongside machine learning (ML) methods and their characteristics, are discussed. The collapse phenomenon is described, and a tree-based ML modelling approach is applied using a set of features based on conjectured contributing factors inferred from detailed observations of the damage process in the mine. The results of the study and the insights gained from the model provide guidelines that can be used to aid operational practice in caving environments.

Background

Mining context

The Chuquicamata underground mine is located in a massive copper porphyry deposit, and is designed to continue exploiting the orebody that has been historically mined by open pit. The underground operation is projected to recover 1760 Mt of copper ore at a grade of 0.7% and rate of 140 000 t/d after achieving full productive capacity, extending the mine life for another 40 years (Flores and Catalan, 2018). The mining method is block caving using a post-undercutting macroblock (MB) variant with multiple levels, located directly underneath the open pit as shown in Figure 1.

Production to date has been principally from the central MB (shown in Figure 1), with MBs to the immediate north and south sequenced to commence production prior to completion of the central MB. Simultaneous extraction from multiple MBs enables the planned production rate to be achieved. Each MB is 280 m long and 128 m wide, and the production and undercut levels use the well-known El Teniente layout (Araneda and Sougarret, 2008), which consists of parallel main haulage tunnels with drawpoints and drawbells offset by 60°. Pillar dimensions are defined by the 32 x 16 m extraction mesh (measured along the sides of pillars), with a height of 18 m between undercut and production levels as shown in Figure 2. The resulting pillar geometry, once the drawbells and production excavations are extracted, is complex.

Although establishment of the production levels and undercut excavations entails a high capital cost, caving methods have low operating costs per ton as high-draw columns cave and fragment

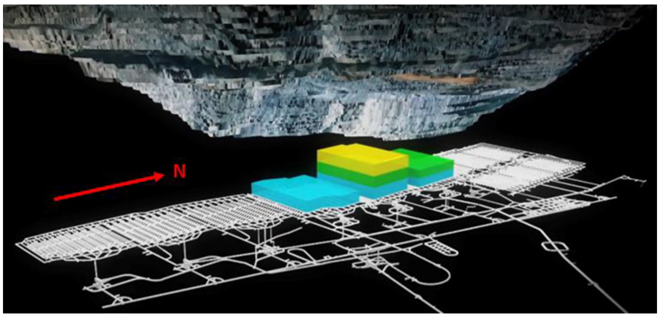

Figure 1—View of Chuquicamata underground mine beneath the open pit, showing the initial central macroblock with the extraction sequence progressing simultaneously to the north and south (image courtesy Codelco)

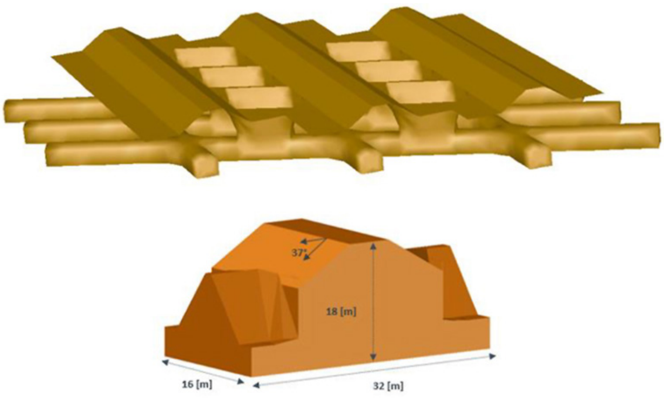

Figure 2—Details of pillar geometry showing perspective view of production level tunnels and drawbells (top) and pillar geometry (bottom) (image courtesy Codelco)

under the combined actions of gravity and induced stresses around the cavity boundary. However, the same stress conditions that favour sustained cavity growth also result in high abutment stresses. Since drawbells are opened ahead of the advancing cave front in the post-undercut method, pillars are subjected to these high abutment stress conditions.

To mitigate stress-related effects, operational guidelines have been established, known as 'caving rules', that derive from technical, operational, and empirical knowledge about cave mining (Cavieres and Rojas, 1993; Butcher, 1999). Through the application of these rules, the cave-back and cave-front geometries are monitored and controlled, along with numerous other aspects of the operation, to ensure the safety and stability of the mine by regulating the establishment, initiation, propagation, and breakthrough of the caving process (Cuello and Newcombe, 2018). The implementation of and compliance with these rules has a wide array of impacts on caving performance, ore production rates, and stability as well as construction costs and schedules. Aspects of mine development such as sequencing, undercutting rate, allowable lead-lags, drawbell opening rates, and extraction rates are addressed through these rules (Beard and Brannon, 2018), ultimately controlling the cave-back geometry and growth (Cornejo, *et al.*, 2016), on which the development of pillar collapse is considered to be highly dependent (Landeros 2012; Cornejo, 2014).

An important consideration for the Chuquicamata underground mine is that the central MB was the first to be caved. Despite over 100 years of open pit operating experience, the caving process was new; the resulting stress environment and rock mass and excavation stability conditions being completely different from those of an open pit. Similarly, while general aspects of caving rules may apply to any orebody, many aspects of rock mass behaviour depend on specific characteristics of the local geological conditions and stress environment. Uncertainties in behaviour are therefore expected to be most pronounced during the early stages of mining, and this was found to be the case at Chuquicamata.

Pillar damage and collapse process

As undercutting progressed over the footprint of the central MB, damage was observed in the sidewalls of the production level tunnels, initiating ahead of the advancing undercut, with deterioration continuing behind the cave front. The damage appeared to be associated with drawbell opening and the lead-lag of the cave front along adjacent undercut tunnels. Figure 3 shows two examples of this damage, consisting of moderate sidewall fracturing and bulking through to intense fracturing and deformation defined as the collapse state. These levels of deformation occurred over periods of days to weeks, *i.e.*, they were not sudden events. The locations of pillars that had collapsed as of November 2020 are shown in Figure 4.

Figure 3—Damage on the production level, showing moderate damage (left) and collapse conditions (right) (images courtesy Codelco)

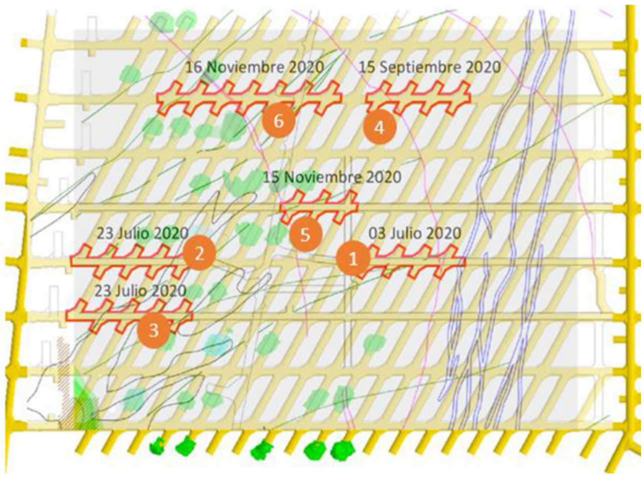

Figure 4—Plan view of the central macroblock production level, showing locations of collapsed pillars with their respective order of occurrence and date of registry (image courtesy Codelco)

Collapse is a matter of definition. Previous studies (Pardo *et al.*, 2012) have defined collapses as a gradual failure of the rock mass where deformation slowly develops across drifts, leading to the full closure of the cross-sections in worst-case scenarios. While this definition addresses collapse development and manifestation, it is also relevant to consider other definitions from the perspective of load-carrying capacity, operational function, and safety.

Owing to their complex geometry (Figure 2), pillars in cave mines have a relatively squat shape (high width to height ratio), such that 'collapse' may not involve a sudden catastrophic loss of load-bearing capacity. It has been well-known for some time that larger volume pillars may exhibit plastic or even strain hardening post-peak behaviour (Jager and Ryder, 1999), so loss of load-bearing capacity is not an adequate definition of failure in this case.

Considering the level of deformation shown in Figure 3, a more general definition of failure, stated as 'the inability of a system or component to perform its required functions within specific performance requirements' (IEEE, 1990) is appropriate. For the design of pillars, the performance requirement limits are best expressed in terms of allowable deformation on the production level, which may be further linked to allowable support deformation limits for safety and infrastructure operational requirements.

In the light of the perspectives from previous studies of the subject, the specific terminology used by the mining company to address these events and the more general definition of failure in terms of functionality of a component in a system, for this case study a 'collapsed pillar' refers to a pillar unit that has undergone deformation that resulted in the loss of functionality (*i.e.* no longer being able to fulfill its original purpose) due to the level of progression reached by the deformations and the complex sidewall fracturing.

In the collapsed pillars, in addition to sidewall fracturing and deformation, other characteristics of the failure process included the complete absence of floor heave, and almost total absence of roof damage. Most importantly, although damage initiated ahead of the cave front, generally within the abutment zone of influence, in every case the collapses occurred behind the cave front. This is particularly notable since loading of pillars by the draw column is believed to be significantly less than the peak (computed) stress magnitude experienced at the cavity abutment (Pierce, 2019). This observation implies that pillar damage was not purely related to the effects of stress. In this regard, previous studies have linked collapses to factors such as

- ➤ Cave-front geometry
- ➤ Relative cave-front position with respect to production level pillars
- ➤ Presence of remnant pillars in the undercut level associated with deficient blasting during undercutting
- ➤ Damage in the undercut level caused by increased abutment stress
- ➤ Reduction of the pillar dimensions in the undercut level by overbreak during construction
- ➤ Unfavourable global cave-front geometry and extraction angle that conditions the overall cave-back geometry
- ➤ Geological conditions (*e.g.* presence of major faults perpendicular to the direction of advancement of the caving).

(Gomes, Rojas, and Ulloa, 2016; Cornejo 2014; Landeros, 2012). However, for this case study the factors involved, and their relative importance was not clear.

Methods of pillar stability analysis

Pillar stability can be assessed using a variety of methods, among which empirical formulae and numerical modelling are the most frequently employed (Zhou, *et al.*, 2015). The simplest approaches are empirical strength formulae (Salamon and Munro, 1967; Obert and Duvall, 1967; Lunder and Pakalnis, 1997; Martin and Maybee, 2000; Esterhuizen, *et al*, 2011) that use simple parameters such as width, height, strength, plus calibration constants, and which are still widely used in early stages of design (Sinha and Walton, 2019; Kersten, 2019). While these approaches could oversimplify the stability assessment problem, they can be reliable provided they are calibrated using sufficiently large case databases, accounting for site variability by applying appropriate Factors of Safety. An advantage is that they do not require an understanding of failure mechanisms (Stacey and Wesseloo, 2022; Elmo, *et al.*, 2021), although the factors incorporated in the formulae should be directly related to (or be proxies for) the most important elements controlling the failure process, which in this framework are based on experience and insight.

Despite their widespread use, these formulae only apply to the pillar geometry, rock mass, and stress conditions for which they are calibrated. This precludes their application for cave mine pillar stability assessment for three principal reasons. Firstly, as shown in Figure 2, pillar geometry in cave mines is relatively complex. Subtle variations in this geometry may lead to different failure modes, which are not conducive to the development of case databases that are relevant for application at other mines (Stacey and Wesseloo, 2022). Secondly, the stress conditions applied to pillars in cave mines are complex, depending on many factors including the geometry of the cavity at the time of pillar formation, lead-lag of the cave-front, timing of drawbell opening, and advance rate, to name just a few. These complexities in stress path are difficult to account for empirically. Thirdly, pillar failure has often taken place behind the cave front, suggesting that factors unrelated to stress are at play. These may include progressive deterioration of the rock mass of the pillars that is initially triggered during abutment loading, variability of loading conditions during the ore draw process, and also wear-induced changes in the (pillar) geometry – leading to further changes in the internal stress conditions. Many of these factors are operationally induced, hard to anticipate and quantify, and difficult to account for in stability analysis.

In cave mines, the most extreme pillar loading condition exists in the immediate abutment zone of an advancing cave front (Pierce, 2019), which in conventional undercutting corresponds to the location where drawbells are blasted and the final pillar geometry is formed. Pillar stability is therefore strongly linked to the next (larger) scale of design (*i.e*. macrosequence) and requires the inclusion of sufficient detail at the panel, block, or mine scale such that stress conditions induced by the large-scale geometry are adequately considered. Empirical methods such as those used for the design of simpler pillars shapes in conventional room-and-pillar mining cannot account for all these factors (Maritz, 2014), hence the prevalence of numerical modelling in cave mine design (Hormazabal *et al*., 2018).

Numerical modelling has many advantages in being able to represent the complex geometrical conditions in cave mining, but still has limitations. Due to the extensive range in scale that must be included in the models, resolution limits arise at the pillar scale, requiring the rock mass to be represented as an equivalent continuum material. This constrains the failure modes that can be represented even when using complex stress-strain constitutive relationships (*e.g*., strain softening). Therefore, while mapping at the tunnel scale may reveal a rock mass with various discontinuities and lithological inhomogeneities, these typically cannot be incorporated into numerical models, which must be sufficiently spatially extensive to capture the block- or panel- scale geometry and rock mass characteristics. Similarly, experienced miners know that operationally controllable factors such as cave-front advance rate, blasting practice, lead-lags of cave-front geometry, among others, can also affect stability (Ferguson *et al*., 2017). Having no known constitutive laws, these factors do not fit into this framework, which means that rock mass behaviour is not adequately represented at the pillar scale in numerical modelling, due to not only its implicit constrains, but also to it not accounting for other factors influencing the failure processes.

In this context ML provides a powerful and complementary analysis tool since it incorporates techniques that can be applied, provided sufficient 'training' cases exist. These methods are well-suited to finding relationships and patterns (correlations) between various factors and ranking their importance, which is fundamentally different from numerical modelling, which requires *a priori* inclusion of the constitutive behaviour controlling the failure process. Thus, the ML approach offers the possibility to identify which factors should be investigated and understood so that they may later be incorporated into deterministic methods of analysis based on failure mechanisms.

Methodology

Machine learning (ML) is a subfield of Artificial Intelligence (AI) composed of analysis methods that can automatically detect patterns in data and use them in behaviour prediction or decision-making under uncertainty (Murphy, 2012). These tools make it possible to model functions that map a set of inputs to a given output value by using recorded observations (data-points), which in turn can be used to forecast outcomes and even their respective probabilities.

In general, ML does not require prior knowledge, statistical assumptions, or rule definitions to work with the data, unlike many statistical methods and expert systems (Lawal and Kwon, 2021). ML can handle input complexity and can work with data-sets composed of different variables while still being able to determine interactions between them, which is crucial for interpretation. Furthermore, certain model types can quantify the relative importance of the inputs based on how they affect their internal parameters

Owing to these advantages, ML methods have gained traction in many scientific fields leading to significant breakthroughs, due to their ability to handle and model complex problems, such as those encountered in rock mechanics (Jordan and Mitchell, 2015; Lawal and Kwon, 2021). Regarding pillar stability analysis, ML algorithms offer ways to capture complex nonlinear relationships between different parameters, numerical model representations, and observed rock mass phenomena, and subsequently conduct more precise sensitivity analyses of the model's inputs to ensure the mechanics are being captured (Morgenroth, Khan, and Perras, 2019). These methods are being used in geomechanics-related problems such as rockbursts, tunnel deformation, rock mass classification, determination of strength properties, and stress-strain behaviour modelling, but there are few documented examples of applications to pillar collapse phenomena (Quevedo *et al.,* 2019). However, these applications do not focus on the contribution of design and operational factors to the development of this type of rock mass failure, which is further explored in this paper.

Supervised learning

Supervised learning (SL) is a branch of ML that aims to model and predict the value of an outcome measure based on a set of given input measures (Zhou, Li, and Mitri, 2015) either as regression of a continuous value or classification in discrete categories. In a classification problem, the output y is defined as y $\{1,\ldots,C\}$ where C is the number of classes. Then, the problem can be expressed in terms of function approximation, where some unknown function f represents the relationship between the inputs and the outputs:

$$y = f(x)$$

Using the labelled training set, SL algorithmically models the function f such that predictions can be made using $\hat{y} = \hat{f}(x)$, where $\hat{y}$ is the estimate of the output and $\hat{f}$ is the estimate of the function f. It is crucial that $\hat{f}$ estimates the outputs well, not just for the training observations but also for unseen instances, which means that when $\hat{f}$ is obtained after training, $\hat{f}$ should be able to generalize to unseen instances that were not included during the training process. This is a key concept in ML; it ensures that an underlying process is being captured, and it is different from just 'memorizing' the input-output pairs in the training set, which would be a case of overfitting. For this reason, the available data-set is typically divided into different portions, one for training and another for testing purposes. Then, the performance of $\hat{f}$ as an estimation of f would be evaluated over the instances that compose the latter by having been trained on the former.

Tree ensemble methods

Tree-based methods are a subset of ML models that rely on decision- ree algorithms, meaning they essentially split observations based on rules learned from their structure in a data-set. They offer flexibility, high predictive power, and have the capacity to detect interactions and nonlinearities contained in the data. They constitute a great baseline approach since they are nonparametric, giving them the advantage of not relying on prior statistical assumptions and not being hypersensitive to outliers or unbalanced data. These characteristics make them popular in many different research fields since they can handle multifaceted data (Carvalho *et al*., 2018). Tree ensemble methods are built as conglomerates of decision tree algorithms inheriting their properties, that is, they separate data into subsets by minimizing an impurity function, creating splits on the data-set that aim to isolate the most homogeneous instances contained in the most different sets (Breiman *et al*., 2017; Hastie, *et al*., 2009). The conglomerate is composed of simple decision trees that purposely behave as weak function approximators individually, and poorly capture the behaviour of the data by themselves but collectively compensate and help each other, ultimately acting as a robust and powerful function approximator, significantly improving the final performance, in contrast to a model composed of a single base learner (Rincy and Gupta, 2020). This is the basic concept of Ensemble Learning (EL), which can be intuitively understood as averaging different hypotheses and therefore reducing the risk of choosing an incorrect one (Sagi and Rokach, 2018).

For this case study the problem is tackled as a class prediction problem where the goal is to predict whether a pillar collapse will take place given a set of attributes ($\vec{X}$), indicated as a value of 1 in case of a collapses and 0 otherwise. The number of classes is two, thus constituting a binary classification problem where $f(\vec{X})$ is estimated by learning $\hat{f}(\vec{X})$ through the minimization of a cost function C. For decision trees, the minimization of C leads to splits which ultimately separate data-points, organizing portions of the data-set into similar groups, where C takes the shape of

$$C = \frac{m_1}{m_t} * I_1 + \frac{m_2}{m_t} * I_2$$

Here C represents the average cost of a tree having a set of observations m_t being split into groups m_1 and m_2 according to an impurity metric I (typically Gini or entropy). By using the values of the features contained in $\vec{X}$ as thresholds, splits are evaluated at every data-point. In this way a feature value is selected as a split if at that threshold the value of C is minimal.

Random forest (RF) is an EL tree-based approach that implements the above splitting strategy across collections of decision trees. It samples several instances from a data-set through a procedure known as *bootstrap aggregation*, building a tree on each separate set of randomized bootstrapped instances, making them completely independent from each other. This whole set of trees is called a forest. In addition to the random sampling of instances, random feature sampling can also be incorporated for the bootstrapping process, thus increasing randomness across the trees in the forest by having each tree randomly biased. Since the forest output is built by averaging outputs from every single tree that composes it (Figure 5), such biases are averaged out and potential overfitting issues are reduced (Breiman, 2001).

Through bootstrapping, some observations of the data-set will not be sampled when building the model even if they are incorporated in the training set. Therefore, this technique provides a set of unsampled instances referred to as out-of-bag (OOB) samples that can be used to estimate the final performance of the RF, similar to having an extra test set. Furthermore, RF models, like other tree-based methods, make it possible to obtain relative metrics of the importance of the input features based on their contribution to the impurity reduction process of the learning algorithm.

In this case study, pillar damage is predicted by using a RF model incorporating historical information through the following steps:

- Data preprocessing and feature selection to determine the input attributes
- Portioning the data-set into training and test sets
- Training a RF and measuring its generalization performance on the test set
- Analysing the feature effects and interactions.

Case study

Feature selection

For every pillar, a series of features related to its operational conditions, geological architecture, local rock mass strength properties, and stress environment was collected. These included operational- and design-related conditions listed in the caving rules, such as the number of drawbells that were opened in its vicinity, maximum lead-lag, time under abutment stress conditions, among others.

A preliminary feature selection process was carried out aiming to keep most conceptually representative and unbiased features and to remove non-informative, correlated, and redundant features. In general, feature selection helps ML algorithms by improving learning efficiency and model performance while also simplifying learning results (Cai *et al*., 2018). In this case, features were analysed with the Spearman correlation, which is a good proxy for feature redundancy in tree-based models since it detects monotonic relationships that would not be conducive when using this ML model architecture.

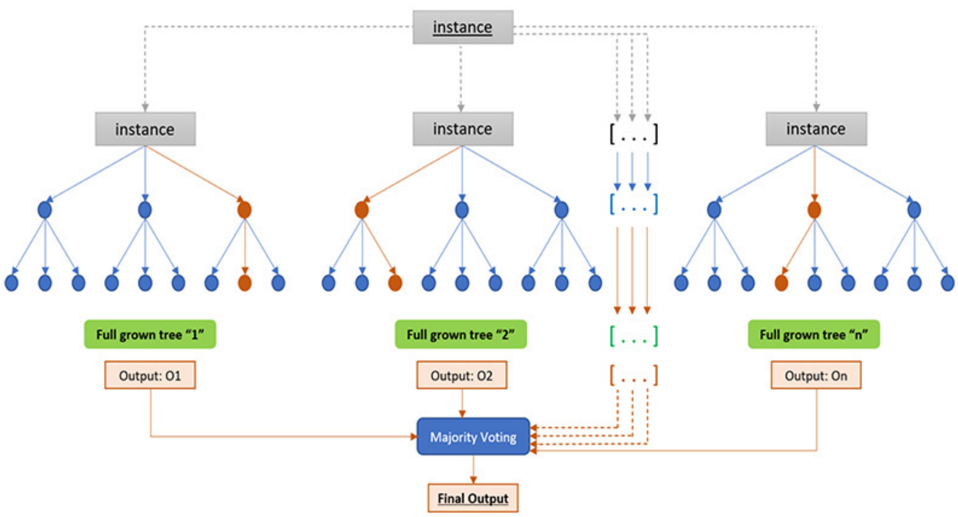

Figure 5—Ensemble of decision trees forming a random forest architecture

The final set of input features after the feature selection process is shown along with their description in Table I.

Modelling

Following the SL approach described earlier, the training and testing sets were obtained considering the sequence of events and information sufficiency of the labelled instances, giving rise to the split shown in Figure 6.

Using this instance separation, the collapse ratios in the sets were 39%, 69%, and 55% for the training set, test set, and the complete data-set respectively. Since these ratios differ significantly, the possibility of the model learning a naive approach that mainly reproduces the ratio of collapses was suppressed, thus success in modelling could be reasonably attributed to the information contained in the selected features and not simply to the replication of an average behaviour. The pillar coordinates (x,y,z) were not included alongside the rest of the features to avoid fitting the model directly to spatial information, instead forcing focus on generalizable parameters of rock mass conditions and operational parameter history.

Table I

Features used to characterize pillars in the analysis, with ranges of values

Feature	Acronym	Domain	Unit	Range	Description
Pillar area	PA	Operational factor	m^2	211–245	Pillar area projected in plan view as a proxy for the total pillar volume
Abutment time	AT	Operational factor	months	2–6	Time that a pillar is under abutment stress condition
Open drawpoints	OD	Operational factor	–	3–7	Average number of open drawpoints surrounding a pillar before the cave front reaches its position
Inactive drawbell time	IDT	Operational factor	days	6–126	Time between drawbell opening and its incorporation in extraction activities under the caving line
Column height	CH	Operational factor	m	75–325	Extraction column height
Stress component Y	SY	Local stress/strength	MPa	21.2–26.5	Compressive stress Y-axis component extracted from numerical model information
Uniaxial compressive strength	UCS	Local stress/strength	MPa	22.6–96.5	Uniaxial compressive strength of pillar
Fracture frequency	FF	Local stress/strength	–	5–20	Average mapped fracture frequency observed on rock mass
UCS/FF ratio	UCS/FF	Local stress/strength	–	1.1–13.5	Ratio between UCS and FF values
Maximum lead-lag	MLL	Cave-front geometry	m	12–34	Maximum lead-lag
Cave-front Curvature	CVC	Cave-front geometry	m	17.8–60.0	Local curvature of a smoothed projection of the CF in plan view as a measure of concavity or convexity

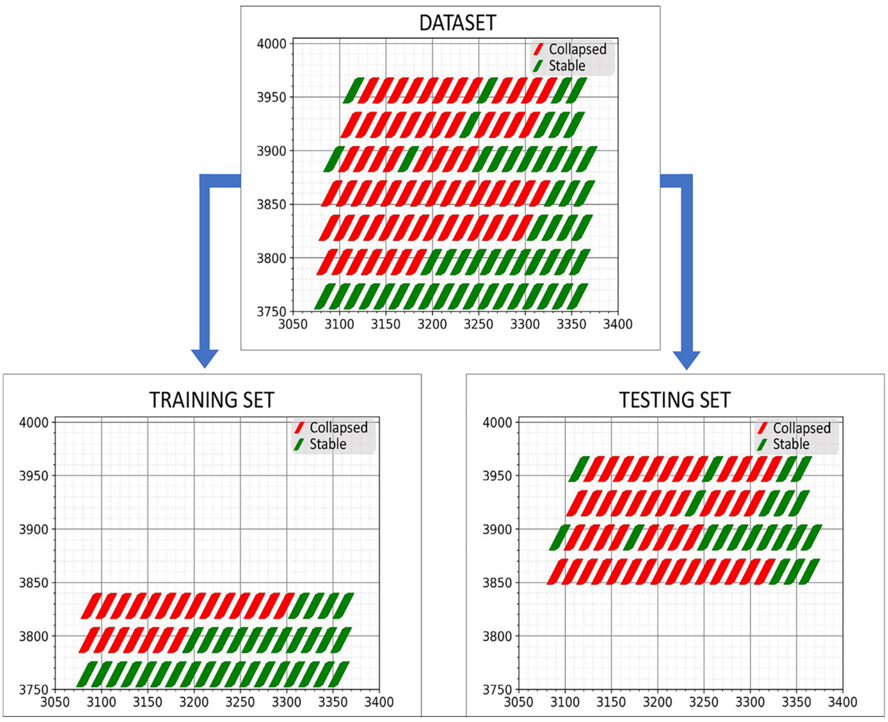

Figure 6—Visualization of the data-set conformed by the centroids of the production level pillars and their state (red: collapsed, green: stable) plus the subsequent training test set selection

Results

The expected accuracy of the model was estimated using the OOB score that the RF architecture provides, which reached a value of 81% accuracy, indicating a sufficiently good model. The real test set accuracy was measured at 78%, which is close to the expected accuracy obtained from the OOB score and shows consistency in the modelling process. Considering these results and the sampling approach, the model generalization was visualized across the footprint and an adequate representation of the phenomena in the test set was observed, as shown in Figure 7.

Evaluating the modelling results as acceptable and spatially representative of the collapse distribution in the footprint, model analysis was carried out to understand how the selected input features affect the modelled collapse response.

Model and feature effect analysis

Explainability of ML models becomes difficult when implementing flexible but complex architectures such as ensemble methods. This aspect is usually considered as a trade-off and is an active area of research that has resulted in different approaches to interpret the inner workings of ML models (Agarwal and Das. 2020; Goldstein *et al*., 2015). By using these approaches, feature importance, effects, and interactions were studied.

The feature impacts were first studied via the MDI metric, which represents each feature's contribution to the generation of splits during the learning algorithm's process when trees are built in the forest. It is calculated by computing the total loss reduction that a given feature contributes across all the splits generated through it (Li *et al*., 2019). The feature rankings according to the MDI metric are presented in Figure 8.

The highest ranked features correlate well with those initially hypothesized as being the main drivers of collapses according to expert assessment and previous studies of this type of failure (Landeros, 2012; Cornejo, 2014) where parameters such as pillar area, cave front geometry, and time under abutment stress are highlighted.

Nevertheless, although the MDI metric is commonly used in tree-based models, it is important to complement this feature-importance approach with other techniques since MDI can misrepresent the actual contribution of certain features, for example, by overemphasizing continuous and/or discrete categorical features with high cardinality (Strobl *et al*., 2007). Moreover, MDI does not provide an explanation of how the values of certain features can affect the output of the model.

To gain a quantitative appreciation of how these features contribute to pillar collapse, their individual and combined effects were analysed through partial dependence (PD) with individual conditional expectation plots (ICE) (Friedman, 2001).

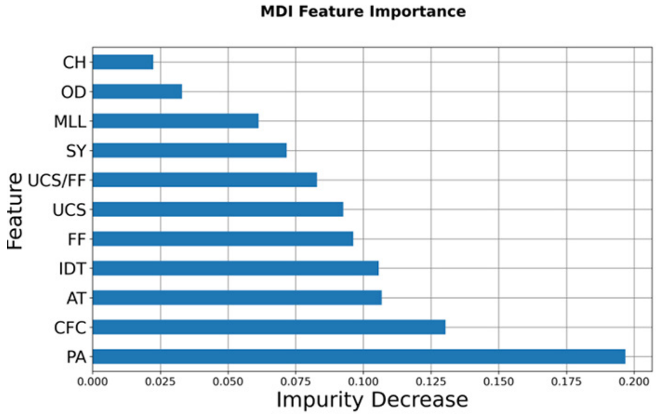

Figure 8—Relative importance of features in contributing to pillars identified as being in a collapsed state

The PD function of a model describes the *expected effect* of certain features after marginalizing out the effects of all others by taking their average value. Thus, a PD plot (PDP) shows the change in the average predicted value of a model as the selected features vary over their marginal distributions. A PDP helps visualize the average partial relationship between the predicted response and one or more features (Molnar *et al*., 2021; Elith, *et al*., 2008; Goldstein *et al*., 2015). It is important to note that these visualizations do not perfectly represent the effects of each feature in the model but are a useful basis for interpreting their impact when there are strong effects caused by a feature or a combination of them. Also, by disaggregating the PDPs by plotting individual conditional curves that form the average, a series of ICE plots can be obtained to visualize variabilities in the conditional relationships (Goldstein *et al*., 2015).

The visualizing tool for this exercise was PDPbox (Jianchung, 2018), which allows plotting of ICEs and PDPs simultaneously. The pillar area and time under abutment stress were selected for this analysis since intuitively the best condition for a pillar would be to have a well-preserved volume exposed to adverse conditions for short periods. The individual effects of these parameters are shown in Figure 9. Both features exhibit a behaviour in which they start to significantly affect the model output after they cross a certain threshold, and their combined effect can be appreciated through the PDP interaction visualization shown in Figure 10.

Based on the behaviour of the main features under analysis displayed in Figures 9 and 10, it is observed that low values of 'pillar area' significantly increase the probability of a pillar being classified as collapsed, as do high values of 'time in abutment'.

Figure 9 shows that 'pillar area' has a critical influence over the output and a distinct threshold at the 225 (m^2) mark can be seen. Values above that threshold significantly diminish the probability

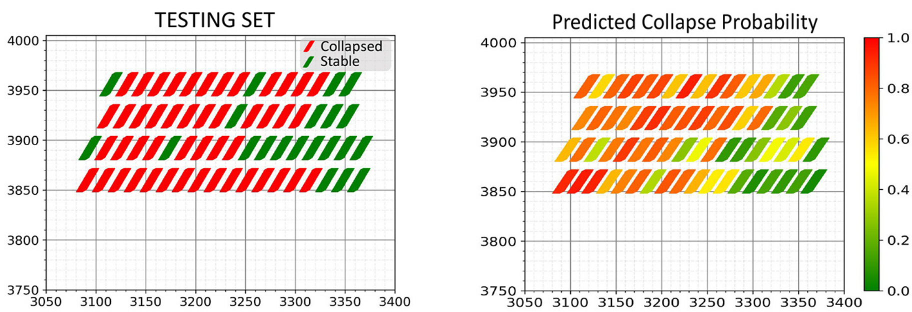

Figure 7—Visualization of predicted probabilities of collapse assigned by the output of the trained model over the pillars of the production level that compose the test set for this case study

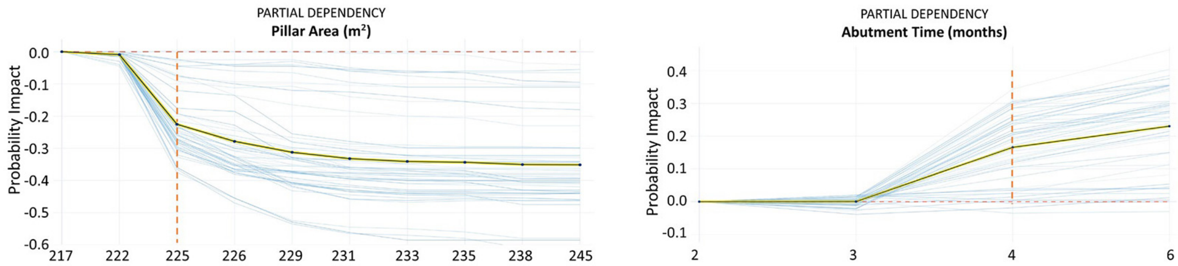

Figure 9—Partial dependency plots (PDPs) showing the contribution of pillar area and time in abutment stress conditions to pillar collapse. Negative numbers indicate that increases in pillar area suppress likelihood of pillar collapse, and positive numbers that increasing time in abutment loading increases likelihood of pillar collapse

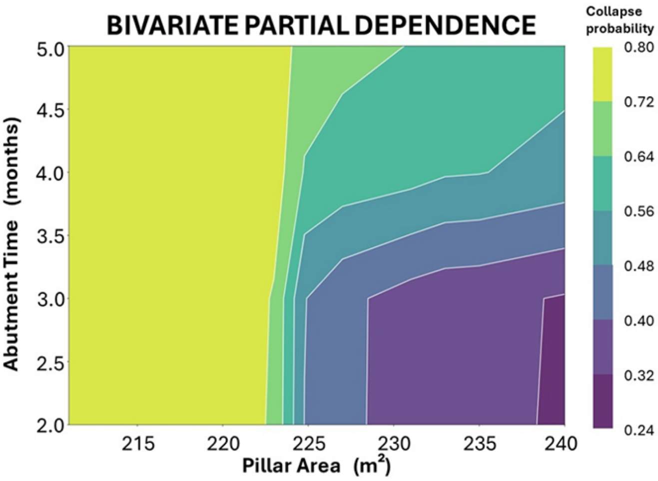

Figure 10—Combined PDP of time in abutment stress loading and pillar area

of a pillar being categorized as collapsed. Keeping areas above 230 [m2] can reduce that probability by more than 30%, which can be achieved with careful operational control over drilling and blasting activities during tunnel construction and drawbell opening. On the other hand, high values of 'time in abutment' contribute positively to drive the target response to a collapse. The effect accentuates starting from the 3rd month mark and can increase to 15% at the 5th month mark.

Figure 10 shows a region where high 'pillar area' values and low 'time in abutment' values coexist, and collapse probability is very well restrained. This implies that even when accounting for the other various effects that the mean values of the remaining features have on the model, it should still be possible to mitigate the development of collapses by exerting control over only these two features. Moreover, the individual feature threshold of 'pillar area' detected in Figure 9 is also present in Figure 10, showing that under the 225 (m2) threshold it is no longer possible to regulate the outcome by controlling the 'time in abutment', as the outcome becomes insensitive to it.

Discussion

Since ML and complex model architectures can be effective at modelling phenomena without a deep understanding of the inner workings of the data or their algorithms, it is not wise to deploy them without addressing aspect such as input feature selection, interpretation *versus* complexity trade-offs, and result analysis (Rudinm 2019; Lawal and Kwon, 2021; McGaughey, 2020). Considering the sampling approach, the model accuracy, and the information extracted from the interpretation approaches alongside their coherence with expert evaluation, it is possible to state that the selected features contain sufficient information to adequately model the phenomena. It also confirms the validity of concepts contained in the 'rules of caving' as being significant parameters that can control overall stability in this caving scenario, which further validates the feature selection. The results also show that even if the loads should not be enough to cause rock mass failure according to stress criteria alone, operational elements do have a significant influence on pillar stability.

In physical terms, the results indicate that a collapse is more likely to develop when pillars are subjected to high loads for long periods. The reduction in rock strength when loaded for long time periods (static fatigue) has been known for some time (Lajtai and Schmidtke, 1986). It has been studied in connection with the underground storage of nuclear waste (Damjanac and Fairhurst, 2010) and is the subject of ongoing investigation (Shirani Faradonbeh, *et al.*, 2022); however, it has not to date been incorporated into the 'rules of caving' Although it has been identified as a critical factor in pillar degradation and stability, it cannot yet be strictly generalized as it is dependent on the characteristics of the rock mass in which mining is taking place.

In practical terms, the presence of the threshold at 225 [m2] in 'pillar area' shows the dominance of this feature over the general outcome. Since it is an operational parameter, the vulnerability to time-dependent degradation effects can be mitigated through good practices that ensure proper pillar volume preservation. It should be noted that 'cave front curvature', which is a cave-back geometry proxy that also controls collapse potential (Pardo *et al.*, 2012; Landeros, 2012; Gomes, *et al.*, 2016), is implicitly related to 'time in abutment' as a concept of the overall advancement rate of the cave front in terms of production rate and therefore can also be controlled. In general, the analysis shows that operational-related features have the highest importance for modelling collapse events, in this case particularly the 'pillar area' feature.

Conclusion

The machine learning approach presented enables a diverse range of factors to be evaluated for their effect on pillar stability and their contribution to the collapse process to be ranked. It was possible to incorporate both geomechanical and non-conventional factors, such as those related to mining operations and time, that are not accounted for when employing conventional stability analysis methods such as numerical modelling or empirical formulae. It was shown how those factors contributed significantly to the pillar collapse process. This suggests that, at least for this case study, stress analysis alone does not present a feasible way to capture the full complexity of the rock mass damage and failure process, and ML approaches offer a useful and complementary methodology.

Regarding the results obtained from the case study, specific points are as follows.

- ➤ Operational and design factors exert significant control over the development of collapses in the production level, which can be regulated through careful engineering and operational control, thus reducing the probability of generating this type of instability.
- ➤ The elements that were accounted for and incorporated as features correlate highly with aspects about caving methods design and implementation that have been widely acknowledged through experience and condensed in the format of 'rules of caving'.
- ➤ This work constitutes a first approach to understanding how the elements present in the 'rules of caving' affect the outcome of collapses in relative and quantitative terms and can help guide and improve future mine design based on the measured effects the elements have on stability.
- ➤ The model interpretation methods constitute a framework to support decision-making when two operational or design aspects are locally incompatible by providing a relative measurement of the effect of each of the feature on the probability of collapse.

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