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ASSESSMENT OF THE INFLUENCE OF MECHANICAL PROPERTIES AND MINERALOGICAL COMPOSITION ON FRAGMENTATION OF SELECTED GRANITIC ROCKS

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Abstract

In this study, a Proportional-Integral-Derivative (PID) control system was designed and implemented on a DC This study analysed the effect of geo-mechanical properties, modal composition of minerals, and powder factor on fragment size distribution (X80) in granitic rocks to optimise blasting operations. Using a data set that included UCS, Young's modulus (E), Poisson's ratio (V), Quartz (Qz), K-Feldspar (K-F), Plagioclase (Pc), Mica (M), and powder factor (PF), a Random Forest model was applied to model non-linearities and predict X80. The sensitivity analysis and regression techniques were applied to evaluate the significance of each parameter. Results indicate that primary predictors were PF and Qz, with PF having a significantly negative association with X80. Mica and plagioclase were more dependent on fragmentation, with sensitivity scores of 0.2808 and 0.1797, respectively, for mineralogical characteristics. The Random Forest model had R^2 and RMSE values of 0.8753 and 3.46, respectively. However, E and V geo-mechanical properties exerted minimal effects on X_{80}. Despite the model being relatively strong, the small sample size and multicollinearity among features in the study posed challenges. This study highlights the importance of both operational and compositional factors while predicting and optimising the rock fragmentation process. Future studies should expand the dataset, explore advanced machine learning techniques, and validate findings across diverse geological settings to enhance reliability and applicability.

Keywords: *biotite, powder factor, quartz, rock fragmentation, uniaxial compressive strength, Young's modulus.*

Introduction

The usage of explosive for rock fragmentation is still among the most used methods for extraction of consolidated minerals from their host rocks. Although, this method comes with much unwanted phenomenon like ground vibration, air blast, air and noise pollution and back break, its ease of operation and cost effectiveness make it the most sought-after (Prasad *et al.,* 2017). During blasting operation, detonated explosives send shock waves which create cracks on the wall of the drilled-holes and the produce high volume of gas. In attempt to escape, the gas open-up the cracks and move the minerals apart and into smaller pieces. The unwanted phenomenon encountered during fragmentation has been associated with the imbalance between mineral's geological and mechanical properties and the powder factor (Adesida, 2023). This often results in dissipation of explosive energy which is the root cause of almost all unwanted phenomena during blasting (Anas *et al.,* 2021). This is an interesting research area in mining engineering field.

Mitigation against the environmental impact of blasting is an important aspect of mine management. This is essential to the continuity of mining operations as human residence are moving closer to mining areas due to increasing population worldwide (Lawal and Idris, 2019). A very important aspect of mining that enhance continuity of operation is bench management. Unsuccessful blasting often leads to bench concerns such as hanging walls, back break and slope instability, which increases mine hazard, make drilling difficult and increases risk of accident, respectively. The aforementioned unwanted results of blasting may lead to increase in production cost and loss of valuable resources, including time and energy (Mishra *et al.,* 2023). A rock blasting operation is termed successful only when desirable fragment sizes are produced with little or no damage to the environment, and ease of future operation guaranteed (Chouhan *et al.,* 2021). These can be achieved when a balance is maintained between the powder factor which is a factor of blast design, and minerals geo-mechanical properties. Therefore, this is an important mining challenge that require constant and continuous studying.

Since blasting is the first major production operation in mining, its effectiveness influences other subsequent operations such as mucking, loading and crushing. The efficiency of other unit operations is a function of fragments size resulting from blasting (Kozan and Liu 2017). Alipour *et al*. (2018) stated that the total aggregate production cost hinge on geometric parameters and selection of explosives that conform to minerals' formation. Understanding of minerals formation will further enhance blast design, reduce dissipated energy during blasting and subsequent mitigate against its environmental impact. For these reasons, it is important to assess the influence of individual factors such as the blast design which is largely governed by powder factor, rock geo-mechanical properties and the combination of materials making the rock.

Blast design in concern with the organization of the controllable parameters such as the geometric measurement and explosive properties, to achieve desirable muck-pile size distribution. This is an important activity in mining because the operation is accountable for a substantial proportion (10 to 35%) of the overall production cost. Also, because the efficiency of subsequent operation depends on the size distribution of muck pile achieved after blasting (Kozan and Liu 2017). To achieve a good blast design, the knowledge of the uncontrollable parameters of rock fragmentation is essential. A blast design that conforms to the mechanical and geological properties of a rock mass will produce a desirable fragmentation. According to Mohamed *et al*. (2015*), some researcher had referred to blasting as* an art rather than science because desire muck pile size distribution was usually achieved through trial by error blasting. This is because prediction of fragment sizes is difficult due to heterogenous nature rock.

However, the understanding of the geo-mechanical properties of rocks and how they influence fragmentation may result in a blast design that will yield desire muck-pile sizes. Research on influence of geo-mechanical properties of rocks on fragmentation will improve blasting operations and make it more scientific. Since it was suggested that the environmental disturbances generated during blasting results from excess explosive charge (Kuzu and Guclu, 2008), a blast design that conform to the geo-mechanical properties of rocks and their mineralogical composition may reduce the environmental impact of blasting and cost of production drastically.

Rock fragmentation efficiency is often determined by size distribution of the fragmented rock and how best all resources are utilized to achieve optimization of overall economics of the operations (Shehu *et al.,* 2020). Fragmentation estimation is an important topic in mining field because it determines the efficiency of every other unit operation such as loading, haulage and crushing (Zhang et al., 2023). Prediction of rock fragmentation has been the concern of many researchers in the field of mining because it is considered as the most important aspect of production blasting. Since size distribution influence every other unit operation, estimation of fragments size is essential for forecasting the economic flow of returns and sustainability of mining operations. Salmi and Sellers (2021) stated that factors that influence fragmentation are rock mass properties and geometric parameters. The unpredictable nature of rock mass properties has made estimation and prediction of fragments size difficult.

Many studies have shown that certain properties of rock mass such as strength, orientation of discontinuity, porosity, density and elasticity have substantial degree of influence on rock fragmentation. Blast design properties was also considered factors that can be used by blast engineers to optimise production (Singh *et al.,* 2016). Working on an appropriate synergy between rock mass properties, blast geometric parameters and explosive properties is the concern of many researchers. The understanding of how each parameters influence fragmentation may enhance optimization of rock fragmentation and prediction of fragment size distributions. The knowledge of how mineralogical composition of rock influence fragment size distribution will assist to optimise blast design.

Method

This research employed a Random Forest model to investigate the influence of geo-mechanical properties, modal mineral composition, and powder factor on fragment size distribution (X_{80}) in granitic rocks. Key parameters, including UCS, Young's modulus, Poisson's ratio, Quartz, K-Feldspar, Plagioclase, Mica, and powder factor, were analysed. The model was tuned from training data that included these variables to account for non-linear interactions and predicted X_{80}. Sensitivity analysis was performed using permutation importance to determine the relative importance of each parameter. Regression analysis was also performed on the model to approximate the Random Forest predictions using a smaller linear equation and to avoid multicollinearity. Lastly, 3D surface plots were created that visually evaluated the interaction between pairs of parameters and their impact on X_{80}. While limitations such as small sample size or collinearity exist, the approach led to a strong understanding of which types of underlying factors are most relevant to the influence of rock fragmentation, and also allowed for predictive tools to be developed for optimisation.

The Study Areas

Samples were collected from five selected locations in Ondo and Ogun States, Southwestern Nigeria. Ondo State lies between 4˚ 00’ 00’’ to 6˚ 00’ 00’’ E and 5˚ 27’ 00’’ to 8˚ 09’ 00’’ N. Its area covers 18,239.49 square kilometres, lying at the boundary of Kwara, Kogi, and Ekiti States in the north, Edo and Delta States in the east, Ogun, Oyo, and Osun States in the west, and bordered in the south by the Atlantic Ocean. Ogun State lies between 6˚ 59′ 44″ to 6˚ 62′ 15″ N as well as 3˚ 03′ 26″ to 3˚ 05′ 45″ E (Aladejana and Talabi, 2013). The geology of southwestern Nigeria is as follows: The Precambrian Basement Complex, which includes mainly metasedimentary, metavolcanic, and granitoid intrusions (Eludoyin *et al*., 2023). It includes schist belts, migmatites, and banded gneisses (Okunlola *et al.,* 2022). The Ilesha Schist Belt and Egbe-Isanlu Schist Belt are two prominent geological formations. Different kinds of granitic intrusions, including Older Granites resulting from the Pan-African orogeny, render an intricate geology. The tectonic history and metamorphic processes in the region can be interpreted from these formations (ISRM, 1989).

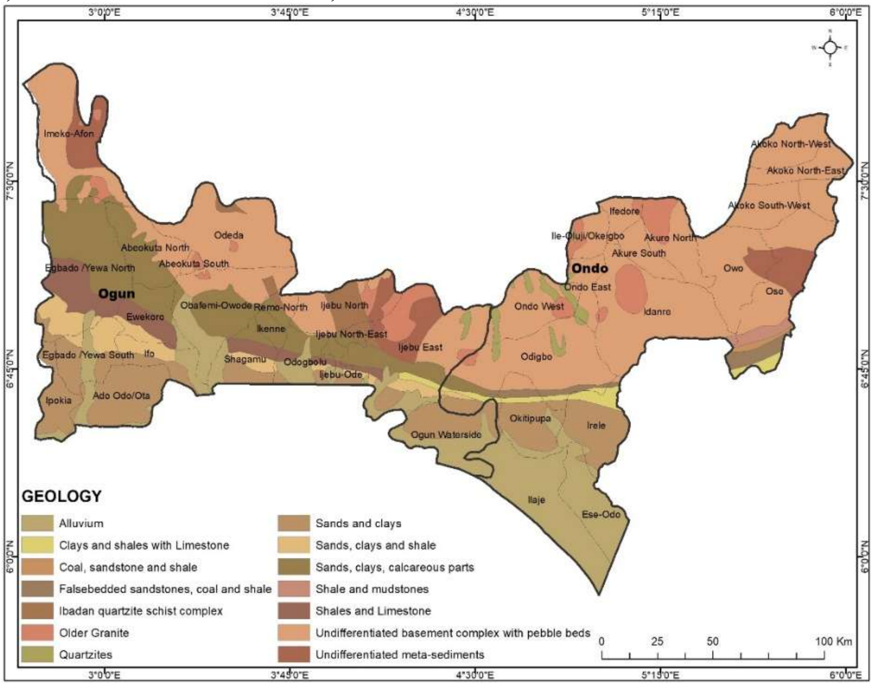


Figure 1: The Geological Map of the Study Areas (Eludoyin *et al.,* 2023)

Estimation of Rock Geo-mechanical Properties

Determination of Uniaxial Compressive Strength

The Uniaxial Compressive Strength (UCS) test was carried out on a cylindrical core specimen (approximately 50 mm diameter) subjected to axial loading with a length to diameter ratio of approximately 2.5 until failure. UCS was derived using the International Society of Rock Mechanics protocol (ISRM, 1989). The UCS of the core samples tested was calculated with Equation 1 as depicted.

$$C_o = \frac{P}{A} = \frac{4P}{\pi D^2} \tag{1}$$

where C_o stands for the UCS (MPa), P is the maximum load applied (kN), D is the core sample’s diameter (m), and A is the cross area of the sample (m^2).

Determination of Young’s modulus and Poisson’s Ratio

The core samples were prepared such that the height-to-diameter ratios fell within 2.5 to 3.0, in accordance with ISRM guidelines (Ulusay and Hudson, 2007). Load was acquired from the machine’s internal load cell, and axial and diametric strains were recorded on strain monitoring equipment. These strains were obtained from displacement measurements and calculated using

Equations 2-5 for axial strain, diametric strain, Young's modulus (E), and Poisson's ratio (v), respectively. The slopes needed were calculated from the stress-strain curves. Axial strain was calculated from the actual change of axial length (lΔ), in which l0 represents the original specimen length preceding loading. Diametric strain is typically calculated using change in diameter (Δd), and the initial specimen diameter (d_0). The Young's modulus mean (E_a) was calculated in Pascal (Pa).

$$\varepsilon = \frac{\Delta l}{l_0} \tag{2}$$

$$\varepsilon_d = \frac{\Delta d}{d_0} \tag{3}$$

$$E = \frac{Change\ in\ axial\ stress}{Change\ in\ axial\ strain} \tag{4}$$

$$\nu = \frac{lateral\ strain}{axial\ strain} = -\frac{\varepsilon_r}{\varepsilon_a} \tag{5}$$

Estimation of Powder Factor

Burden, spacing, hole diameter, hole depth, and stemming length were directly measured in the field to verify the most important blast geometry parameters. The drill-bit size was matched by hole diameter, while the hole depth was calculated from the length of the drilling rod. Charged length and stemming were determined using calibrated rods. Tapes were used to measure the burden and spacing. The mass of explosives used (primer charge, column charge, and total charge per hole) was logged in kilograms. The Powder Factor (PF) was also determined based on Equation (6).

$$PF = \frac{Tonnage\ of\ Blasted\ Rock}{Quantity\ of\ Explosive\ used} \tag{6}$$

Measurement of Fragments Size Distribution

The photographic method was applied among the chosen quarries to assess sample size distribution. Images of blasting rock piles were taken at each blast site using a high-speed digital camera. The photographic granulometry outputs were presented as particle size distribution diagrams. WipFrag software was used to quantify the size distribution indices, especially X_{80}. The image analysis was carried out in three stages: image acquisition, pre-processing to rectify illumination issues, and removal of unsuitable images. A total of five images per blast were chosen to minimize uncertainties. Scaling, image fragment-based delineation, and manual editing were done to segment to achieve better accuracy and reliability of results.

Analysis of the Results

Random Forest model (Equation 7) was used to determine the influence of geo-mechanical properties, modal mineral composition, and powder factor on X_{80} (fragment size distribution). The result of a sensitivity analysis, done to quantify the contribution of each parameter by permutation importance, shows that Powder Factor (PF) and Mica (m) are the primary factors. Multicollinearity analysis was done to identify over-bearing dataset, while interpretability was accomplished through a simple linear equation from Random Forest predictions. Performance metrics such as R^2, MSE, and RMSE were calculated to assess the accuracy of the prediction and confirm the stability of the model when working with small datasets.

$$X_{80} = \frac{1}{N}\sum_{i=1}^{N} T_i(X) \tag{7}$$

Where N is the number of trees in the forest, T_i is the prediction from the ith decision tree, and X is the input vector with the features, and X_{80} is the 80% passing size of the rocks.

Results and Discussion

Geo-mechanical Properties

It is reported that Young's modulus (the stiffness of a material) ranges from 2.0 to 2.85 GPa, and UCS (the resistance of one rock to compressive forces) ranges from 95.4 to 130.5 MPa (Table 1). There is an overall positive correlation between the two parameters, as rock samples with a higher Young's modulus have higher UCS. Similarly, the relationship with the proposed structure correlates with the work of previous researchers such as Liu et al. (2023), who stated that larger granitic rocks tend to have a more compact, interlocked structure, which enables better resistance to compressive failure. Poisson's ratio indicates the extent of compressive strain when a material is expanding laterally, and the results for the various rock samples are in Table 1. Low Poisson's ratios are characteristic of granitic rocks, indicating an inherent brittleness combined with ductility loss. The range observed in this study (0.24-0.29) is consistent with values reported previously for granitic rocks (0.20-0.30) (Zhao et al., 2020).

Mineralogical Composition

The mineralogical composition of granitic rocks is reflected in the results in Table 2, indicating that the mechanical characteristics of granitic rocks are governed by the mineralogical composition. Granitic rocks mainly consist of quartz, K-Feldspar, plagioclase, and mica, with only occasional contributions from other minerals. Taken together, these minerals determine the stiffness (Young's modulus), strength (uniaxial compressive strength) and ductility (Poisson's ratio) of a rock. Quartz increases rocks' mechanical strength and rigidity, resulting in increased Young's modulus and UCS. The phenomenon is also in agreement with previous experiments, which indicates that quartz-rich granites are lower in both suboptimal compliance and compressibility to compression forces as a result of high hardness (Mohs scale: 7) and low degree of deformability of quartz. K-Feldspar and plagioclase are also vital parameters, influencing the structural strength (Akinbinu *et al.,* 2018; Guo and Wong, 2021). Feldspars, moderate to hard (Mohs: ~6), have the potential to improve the bearing capacity of granites, but do not provide nearly as much mechanical stiffness as quartz. Mica, in comparison, exhibits an anisotropic behavior and inferior mechanical performance. Being the shear (deformation) promoting platy structure of its structure. The findings from the influence of rock modal composition on mechanical property data obtained in our study are similar to those of Wu *et al* (2023). The high mica content of some of these materials makes it difficult to tune the Young's modulus and UCS values, which is indicative of mechanical features that are susceptible to mineralisation.

Table 1: Results of the Geo-mechanical Properties of the Rock Samples

Site	UCS (MPa)	E (GPa)	*v*
1	95.4	2.50	0.28
2	107.3	2.55	0.25
3	100.6	2.40	0.26
4	97.3	2.30	0.26
5	87.5	2.00	0.29
6	105.2	2.50	0.25
7	95.1	2.25	0.27
8	115.0	2.85	0.24
9	114.5	2.60	0.24
10	130.5	2.85	0.24

Table 2: Modal Composition of the selected Granitic Rocks

Site	Quartz (%)	K-Feldspar (%)	Plagioclase (%)	Mica (%)	Others (%)	Total
1	35.30	48.20	8.90	6.80	0.80	100
2	35.80	47.80	8.50	6.00	1.90	100
3	34.90	48.50	9.30	6.00	1.30	100
4	35.10	48.30	8.70	5.70	2.20	100
5	34.70	49.00	9.20	6.00	1.10	100
6	35.40	48.10	8.70	5.20	2.60	100
7	34.50	49.10	9.10	5.60	1.70	100
8	35.50	48.00	8.80	6.00	1.70	100
9	36.00	47.60	8.00	4.50	3.90	100
10	36.20	47.50	8.10	4.60	3.60	100

Blast Design for the Selected Locations

These blast design parameters are then optimised for granitic rocks to minimise fragmentation risks from vibrations and fly rock and provide the required design to maximise a cost-effective blast model. The burden is the distance from the blast hole to the open face, and spacing is the distance between nearby holes. The hole depth (14.5-17.5 m) and diameter (100-125 mm) are optimised for the charge needed to break the granite properly. The deeper the hole, the larger the quantities of charge that will be dispersed through the rock stratum (larger rocks). However, smaller holes may have better fragmentation because the diameter allows the explosive to fit in the hole without too many gaps, which may reduce the energy transfer efficiency. In hard granitic formations, the range chosen is typical for quarrying and construction blasting. The charge quantity (48.0-62.0 kg per hole) is determined by the drilled-hole volume and explosive density. Granitic rocks require higher charge quantities than softer ones to subdue their high UCS. Excessive charging can result in over-break or damage to surrounding structures. These values are adequate to separate the granite well and release energy in a controlled manner. Stemming (3.2-4.5 m) is the inert material that is crammed into the top of the blast hole to entrap explosive gases. On granitic rocks, proper stemming prevents gases from escaping too early, allowing maximum energy exploitation in rock fragmentation with reduced air overpressure. The powder factor (0.78-0.92 kg/m³) is the parameter for the explosive rate per m³ of rock. The range indicates that high powder factors can lead to energy loss and poor fragmentation. Therefore, the powder factor makes for efficient explosive use of granitic rocks. These design parameters are congruent with blasting literature. The works performed by Adesida (2022) demonstrated that optimal spacing, stemming and moderate powder factors for granites are required for energy-efficient utilisation. Additionally, the chosen criteria are low in environmental impacts, therefore favourable to the sustainable blasting operation. Such a setting is considered to be a sensible compromise between the technical requirements and economic needs in blasting high-strength granitic rocks.

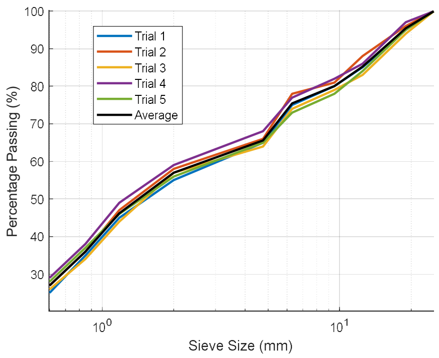
Stemming (3.2-4.5 m) is the length of inert material, which gets packed to fill the top of the blast hole to contain the explosive gases. It is well known that in granitic rocks, sufficient stemming prevents the gas from escaping prematurely and can maximise energy usage of rock breakage and reduce air overpressure. The powder factor (0.78–0.92 kg/m³) determines the number of explosives per cubic meter of rock. This range demonstrates the proper explosive use for granitic rocks, where wastage may be achieved by high powder factors, while inadequate fragmentation will likely occur if the powder number falls below this limit. Such design parameters are consistent with results in blasting literature. A study by Adesida et al. (2025) recommended fine dust from the drilled-holes for stemming and moderate powder factors to maximise energy usage. Moreover, the chosen parameters will reduce environmental effects significantly and ensure the sustainability of blasting operations. This design is a compromise between the engineering and economic concerns in blasting high-strength granitic formations.

Table 3: Blast Design Parameters

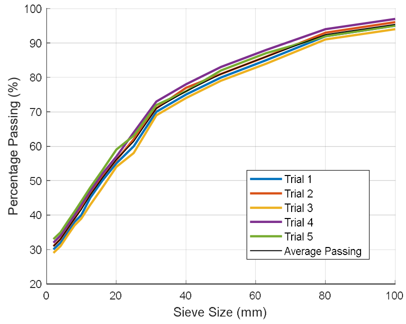
Site	S (m)	B (m)	H (m)	D (mm)	Q (kg)	St (m)	PF (kg/m³)
1	3.2	2.6	16.0	110	55.0	4.0	0.85
2	3.3	2.7	16.5	115	58.0	4.2	0.87
3	3.0	2.5	15.0	100	50.0	3.5	0.8
4	3.1	2.5	15.5	105	52.0	3.6	0.82
5	3.0	2.5	15.0	100	50.0	3.5	0.8
6	3.2	2.6	16.0	110	55.0	4.0	0.85
7	3.1	2.4	14.5	105	48.0	3.2	0.78
8	3.3	2.7	16.5	115	58.0	4.2	0.87
9	3.4	2.8	17.0	120	60.0	4.3	0.9
10	3.5	2.9	17.5	125	62.0	4.5	0.92

Muck Pile Size Distribution

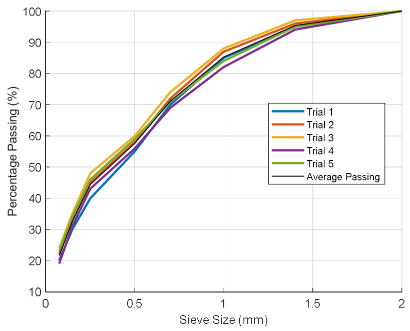
The muck pile size distribution depicted in Table 4 presents five blast images taken for each blast, showing the parameters used for processing fragment size in the selected blast sites. Across the study, the sizes of the sieves are the same, and each sieve processed with about 80% of fragmentation, implying a balanced result. This elucidates the translation of blast design to the resultant particle-size distribution and is utilised for mining/construction performance. The sieve sizes are arranged from the largest (>1000 mm) to the smallest (<5 mm), with a noticeable stepwise drop of particle diameter. As with all blasting applications, a variety of sieve sizes are employed to assess successive fragmentation and to assess the response to handling and processing of the following sieves. This is evident in the diminishing passing % of the sample, even with a smaller sieve size. An 80% passing rate in all trials suggests that fragmentation produces well-distributed sizes in the muck pile. Sieve analysis of the X_{80} measurement (40.5 to 76 mm) is provided in Figure 2 (a-j).


Percentage Passing (%)
Sieve Size (mm)
Trial 1
Trial 2
Trial 3
Trial 4
Trial 5
Average

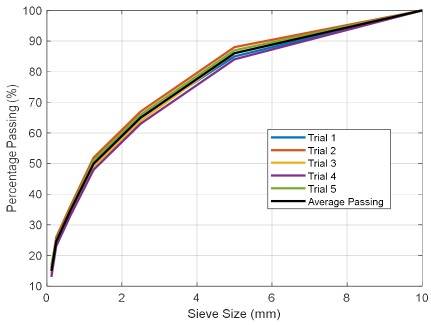
(a)


Percentage Passing (%)
Sieve Size (mm)
Trial 1
Trial 2
Trial 3
Trial 4
Trial 5
Average Passing

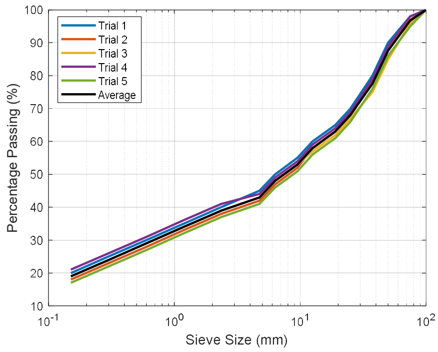
(b)


Percentage Passing (%)
Sieve Size (mm)
Trial 1
Trial 2
Trial 3
Trial 4
Trial 5
Average Passing

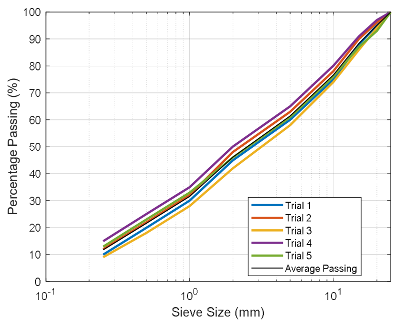
(c)


Percentage Passing (%)
Sieve Size (mm)
Trial 1
Trial 2
Trial 3
Trial 4
Trial 5
Average Passing

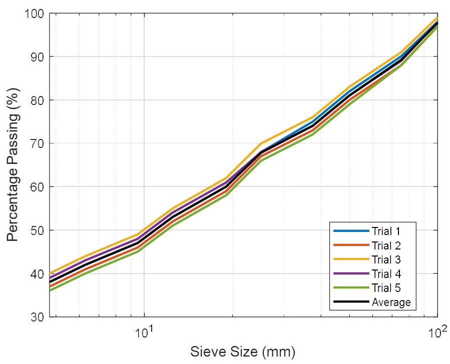
(d)


Percentage Passing (%)
Sieve Size (mm)
Trial 1
Trial 2
Trial 3
Trial 4
Trial 5
Average

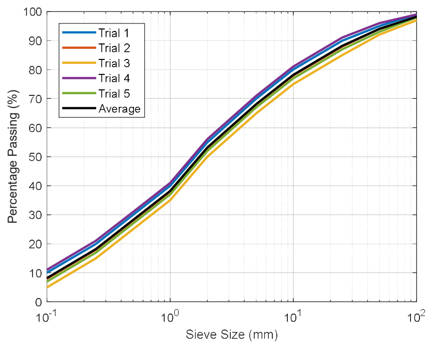
(e)


Percentage Passing (%)
Sieve Size (mm)
Trial 1
Trial 2
Trial 3
Trial 4
Trial 5
Average Passing

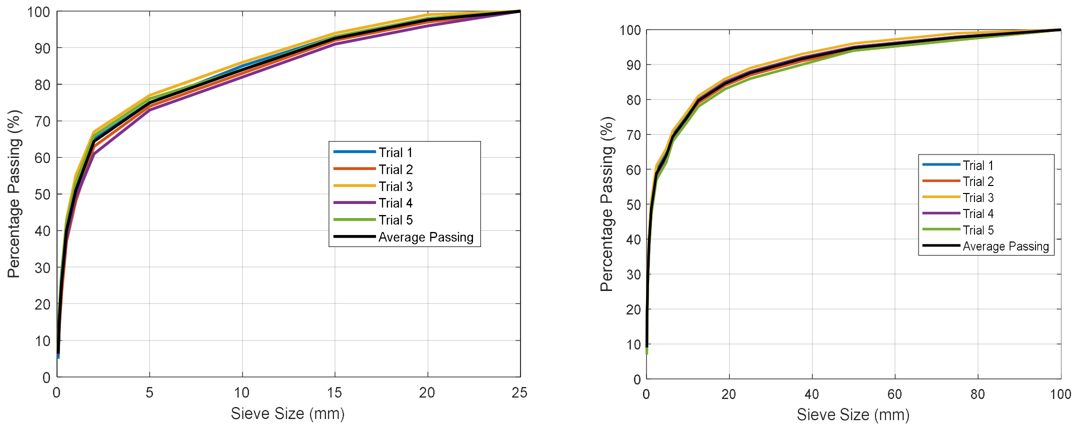
(f)


Percentage Passing (%)
Sieve Size (mm)
Trial 1
Trial 2
Trial 3
Trial 4
Trial 5
Average

(g)


Percentage Passing (%)
Sieve Size (mm)
Trial 1
Trial 2
Trial 3
Trial 4
Trial 5
Average

(h)



(i) (j)

Figure 2: Muck Pile Size Distributions for the Selected Quarries

Table 4: The Muck Pile Size Distribution for 80% Passing Size

Site	Sample 1 (mm)	Sample 2 (mm)	Sample 3 (mm)	Sample 4 (mm)	Sample 5 (mm)	Mean (mm)	Std
1	50.20	48.20	51.00	51.20	50.40	50.20	1.07
2	60.60	61.20	58.40	58.60	61.20	60.00	1.25
3	70.30	68.70	71.40	71.40	68.20	70.00	1.34
4	54.30	54.20	56.20	53.20	55.10	54.60	1.00
5	64.40	62.60	66.30	64.50	65.20	64.60	1.21
6	74.10	78.30	74.40	77.10	76.10	76.00	1.59
7	59.20	59.40	61.00	62.10	60.20	60.38	1.07
8	55.30	57.50	56.30	57.30	56.60	56.60	0.78
9	41.50	38.50	41.80	40.80	39.90	40.50	1.20
10	50.20	52.40	48.30	51.10	50.00	50.40	1.35

The Influence of Geo-Mechanical Properties and Mineralogy on Fragmentation

Correlation Matrix

Figure 3 heatmap depicts the relationships among UCS, Young's modulus (E), Poisson's ratio (v), Quartz (Qz), K-feldspar (KF), Plagioclase (Pc), Mica (M), Powder Factor (PF), and fragment size distribution (X80). Correlation coefficients range from -1 to 1. That is, values close to 1 reflect a strong positive correlation, values closer to -1 indicate a strong negative association and values close to zero mean minimal or no relationship. The patterns are visually shown with the aid of a colour gradient; darker shades denote stronger associations (positive or negative), and lighter colours represent weaker associations. Based on the heat map, there are clear relationships amongst the main X80, PF and Qz variables (indicating their contribution to the fragmentation processes). On the other hand, variables like Mica (M) and Poisson ratio (v) might have a lesser influence on the size of the fragment (X80), as may be observed for the parameters that are less correlated. The correlation and interaction of independent parameters, such as UCS and E or Qz and KF, were further explored. It is essential to understand these correlations because they provide information about the most influential parameters on rock fragmentation. The information provided will enable the optimisation of the conditions accordingly, with the primary goal being to attain the given results. The heat map is a good way to visualise these complex dynamics.

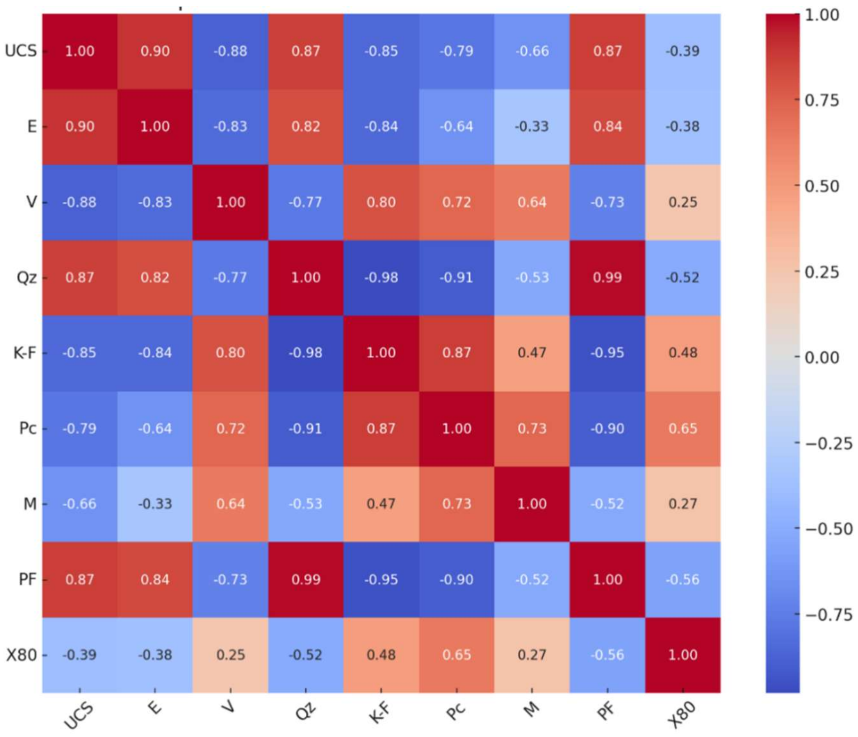


Figure 3: The Correlation of the Parameters

***X_{80}* Random Forest Prediction**

Random Forest is an ensemble-based learning approach that helps connect disparate decision trees to improve prediction accuracy. Random Forest was used to estimate the fragment size distribution according to UCS, Young's modulus (E), Poisson's ratio (v), Quartz (Qz), K-Feldspar (KF), Plagioclase (Pc), Mica (M), and Powder factor (PF) for determining the fragment size. The algorithm is based on a “forest” construction with decision trees, where all trees are fed a random subset of the data (input case). Such trees predict X80, and the average of all trees is used to arrive at the final output. This ensemble approach reduces the risk of overfitting when you add the bias and variance into individual decision trees. The model computes the importance of every input feature under investigation and shows PF and Qz to have the highest importance for X_{80}. This model was trained with learned features and made significant forecasts. Random Forest is also effective in handling nonlinear interactions, noise, and complex systems such as rock fragmentation. These key metrics are used to measure the predictive performance of the model. The coefficient of determination (R^2) of 0.8753 indicates that 87.53% of the variance in X_{80} can be explained by the model, indicating strong prediction accuracy. The MSE of 11.95 indicates the average squared difference between predicted and actual values, and the RMSE of 3.46 provides a more interpretable measure of prediction error, in the same units as X_{80}. The reliable model contributes to the discovery of several key contributors to rock fragmentation and to the optimisation of operational parameters required for successful completion. The model fit of refitting the equation to the random forest outputs is shown in Equation 8.

$$X_{80} = 48.89(Qz) - 0.78(UCS) + 18.15(E) - 123.94(v) + 12.53(KF) + 34.11(P_c) - 9.28(M) - 278.07(PF) - 2215.49 \quad (8)$$

Sensitivity Analysis

Mica (M) and plagioclase (Pc) are reported to be the most influential factors on fragment size, according to this sensitivity analysis, with 0.2808 and 0.1797, respectively. This indicates mineralogical properties, especially Mica content, as well as other components, are closely matched with fragmentation. K-Feldspar (KF) and Powder Factor (PF) also show moderate importance, corresponding to both operational and compositional effects. Young’s modulus (E) and Poisson’s ratio (v) have shown lower sensitivity scores (0.0183 and 0.0455) as mechanical properties compared to mineral composition, which shows that they contribute to the characteristics of rock deformation but influence fragmentation in a less direct manner. These findings are consistent with previous work with emphasis on mineralogy and powder factor dominance in rock fragmentation. Mica content is a significant factor known to decrease rock strength and hence produce more granular rock fragmentation, whereas plagioclase has a significant influence on elasticity. The powder factor, one of the operational variables, has a moderate influence as it determines a direct effect from the energy used during blasting. The results validate the reduced sensitivity of mechanical properties; indeed, fragmentation of the rock is mostly governed by blasting energy and mineralogical heterogeneity rather than by its elastic nature alone. This reinforces the importance of integrating compositional and operational factors for forecasting. Sensitivity analysis was performed based on Equation 9.

$$I_j \frac{1}{n}\sum_{i-1}^{n}\left(L(f(X),y) - L\left(f\left(X_j^{perm}\right),y\right)\right) \quad (9)$$

Where Ij is the permutation importance of feature j, n is the number of permutations performed, L(f(X),y) is the loss function (e.g., Mean Squared Error or another metric) on the original dataset, L(f(X_j^{perm}),y) is the loss function after randomly permuting feature j's values, breaking its association with the target variable y, f is the trained predictive model, X is the input dataset and X_j^{perm} is the dataset where feature j has been permuted.

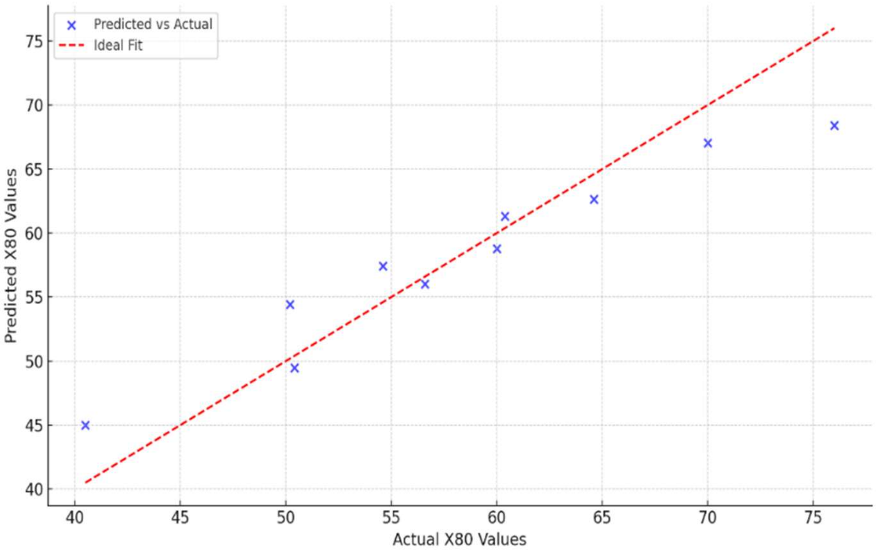


Figure 4: Predicted vs Measured X_{80}

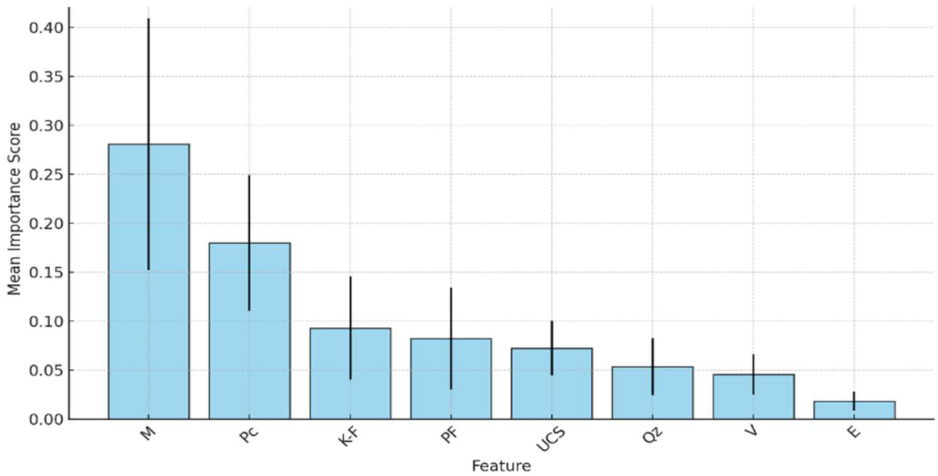


Figure 5: Feature Importance Analysis

Feature Interactions and the Critical Role of PF in Optimising Rock Fragmentation

The quality of interaction between feature pairs is a powerful predictor of X_{80} prediction (R^2-measured) as shown in Figure 6. Combinations including powder factor (PF) have a very high predictive power, especially for combinations such as PF and plagioclase (Pc), PF and mica (M), and PF and UCS. These interactions demonstrate PF's role in regulating fragmentation. PF combinations exhibited high R^2 values, indicating further reinforcement of PF influence in combinations with mineralogical and mechanical parameters, underscoring their role in optimising blasting operations. However, PF controls how energy is delivered, whilst blasting in real-world applications shapes the size of fragments directly. When combined with other features, such as mineral composition, it enables blast designs to be adapted to rock heterogeneity, permitting efficient energy transfer and desired fragmentation. For example, combining PF with relatively high Mica (and therefore rock brittleness) allows the adjustment to avoid over-fragmentation. PF and UCS also provide compatibility of blasting energy and rock strength to address energy waste or inadequate breakage. Figure 7 provides actionable recommendations for the development of data-driven, site-specific blasting methods that maximise efficiency and minimise costs and environmental impact. This highlights the pragmatic utility of PF and its combining, to ensure fragmentation to the best of our knowledge. This knowledge reveals the predictive capability of multiple feature pairs with Powder Factor (PF) for X_{80} as shown in Table 5. The best combinations are UCS + PF and UCS + Pc + PF with R^2 values of 0.883 and 0.880, respectively, while E + PF with R^2 value of 0.607 is weaker. This finding indicates that PF has a stronger interaction with strength and mineralogical composition.

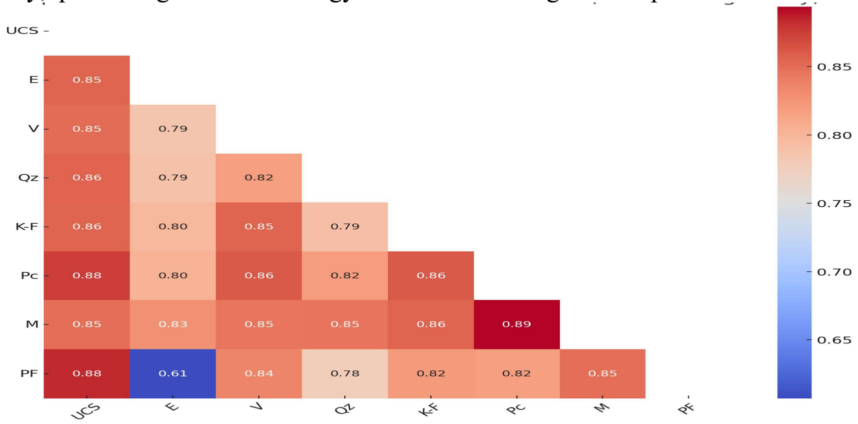


Figure 6: Correlation of Paired Parameters Estimating X_{80}

Table 5: Error Analysis for X_{80} Prediction using PF Pairing Features

S/N	Feature Pair	R^2	MAE	MSE	RMSE
1	UCS + PF	0.883	2.792	11.191	3.345
2	M + PF	0.850	3.202	14.366	3.790
3	*v* + PF	0.836	3.438	15.726	3.966
4	K-F + PF	0.821	3.516	17.182	4.145
5	Pc + PF	0.818	3.243	17.398	4.171
6	Qz + PF	0.777	3.891	21.397	4.626
7	E + PF	0.607	4.207	37.654	6.136
8	UCS + Pc + PF	0.880	2.711	11.470	3.387

Conclusions

In this study, the influence of geo-mechanical properties, mineral properties (modal composition), and powder factor on the size distribution of fragments (X_{80}) was investigated and used to predict rock fragmentation. UCS (95.4-130.5 MPa), Young's modulus (2.0-2.85 GPa), and Poisson's ratio (0.24-0.29) were used for the evaluation of the geo-mechanical properties that contributed to X_{80}. Nonetheless, although these properties are essential to explain the strength and deformation of rock, their effect on X_{80} was indirect, with a low feature importance score (v = 0.0455; E = 0.0183) for the Random Forest model. The different mineral modal composition had a significant impact on fragmentation as well. The most important parameter was Mica, which had a feature importance score of 0.2808 and influenced rock brittleness and elasticity. Quartz and Plagioclase similarly showed moderate influence on rock fragmentation results because of their influences on rock heterogeneity and mechanical properties. The powder factor (feature importance 0.0823) became strongly dependent on X_{80} as an operational parameter. This is significant in blast optimisation as increasing powder factor tends to lead to smaller particles during fragmentation.

The Random Forest model yielded an R^2 of 0.8753, indicating that 87.53% of the X_{80} variance could be explained using Random Forest, with a Root Mean Squared Error (RMSE) of 3.46. The model explained complex non-linear interactions well and also significantly outperformed regression methods, which are constrained by multicollinearity and dataset size. Nevertheless, the small sample size and collinearity are drawbacks to the study. Nevertheless, the Random Forest prediction reinforces the need to consider both the operational and compositional aspects in the preparation of predictive models, providing powerful methodologies for rock fragmentation optimisation. The recommendation in this respect is based on the results obtained from this study, serving as input for the optimization of blasting to achieve the desired muck pile size distributions in granitic rocks.

Additional studies should be carried out to increase the number of granitic rock samples and blasting situations. This will further increase analytical power and, in particular, decrease uncertainties of relationships among features. Further work should also be conducted on ridge regression or the principal component analysis strategy for multicollinearity analysis. Time-dependent data, like dynamic fragmentation during blasting, would also enhance the understanding of the influence of the geological and mechanical properties of rocks. Further exploration of additional operational parameters, such as explosive type and stemming, with powder factor, will enhance prediction accuracy for X_{80}. Models using gradient boosting or deep learning can combine Random Forest models to represent more complex interactions, as it may improve prediction accuracy. Finally, verifying these findings across diverse geological conditions would help to define their generalizability.

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