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Investigation on Relationship between Rock Characteristics and Blasting Fragmentation using Fractal Analysis

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Abstract

Blasting is an essential operation in mining projects, significantly affecting the particle-size distribution, which is critical for subsequent processes such as loading, hauling, and milling. Effectiveness of the blasting operations rely on accurate rock characterization, especially when dealing with different rock types. Proper rock and fragmentation characterization allows for tailored blast designs and also can lead to precise predictions of fragmentation quality. Various characterization techniques exist. This paper examines the application of fractal analysis to classify fragmentation quality and rock types, utilizing the Choghart iron mine in Iran as a case study. Extensive fieldwork collected data on rock properties (uniaxial compressive strength and density) and fragmentation outcomes during blasting. The fractal modeling revealed distinct breakpoints for classification, followed by Logratio analysis to assess relationships among the identified classes. Finally, mathematical models were established to predict fragmentation features based on the relevant rock attributes. The models demonstrated improved predictive accuracy as compared to the prior classifications.

1. Introduction

In open pit mining, blasting remains the primary method for rock fragmentation [1-4]. The particle-size distribution (PSD) is crucial for subsequent mining operations, with parameters such as 50% (D50) and 80% (D80) passing size serving as indicators of fragmentation quality. For example, higher values of these indicators can cause reducing the efficiency of loading, hauling, and primary crushing systems [5-8]. Rock fragmentation quality is influenced by numerous factors including controllable parameters (burden, spacing, hole diameter, stemming, sub drilling, delay time and explosive type) and uncontrollable parameters (uniaxial compressive strength, tensile strength, Young's modulus, density and jointing) [4, 9-11]. Several methods have been proposed to assess fragment size distribution, ranging from time-consuming and costly screening methods to quicker and more cost-effective image processing techniques [13-19].

Recently, techniques such as regression analysis and artificial intelligence have been adapted for evaluating rock fragmentation [1-2, 20-26].

Fractal geometry, a non-Euclidean geometry, has proven effective in modeling natural phenomena [27]. Its significance lies in its ability to address geo-related issues where Euclidean geometry falls short [27-37]. This type of geometry is applicable for rock characterization [38-45]. Fractal analysis is particularly suitable for characterizing rock fragments in blasting operations [10, 46-47].

This study applies fractal analysis for the rock and fragmentation classification at the Choghart iron mine in Iran. It further utilizes Logratio matrices to investigate the interrelationships

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between identified classes of rock fragmentation quality and rock properties (uniaxial compressive strength and density) and develops non-linear regression models for predicting D50 and D80.

2. Case Study

The Choghart mine, a vital iron ore source in Iran, is situated 125 km southeast of Yazd. Various rock types, including phyllite, schist, gneiss, and marble, are present in the area. Activities related to the Panafrican, Cimmerian, and Alpine geological events have been noted in the tectonic reports of Choghart. Dominant minerals include magnetite and hematite-martite, with lesser amounts of minerals like sphen and calcite [48-50]. Exploration commenced in the 1960s, and the mine currently has an estimated reserve of approximately 216 Mt.

In this mine, rotary-percussion method is used to drill blastholes of diameter 165 mm. In the blasting operation, ANFO is the main explosive with detonating cord and Nonel as initiation system (Table 2). Shovel–truck fleet is used for loading and hauling of the extracted materials.

Table 1. Reserve estimation in the Choghart mine for different rock types

Rock Type	Composition		Amount (Mt)
	Fe (%)	P^*(%)	
Low P, High Grade Fe, Non Oxide	59.08	0.05	137
Low P, High Grade Fe, Oxide	61.60	0.07	5
High P, High Grade Fe, Non Oxide	56.41	0.98	46
High P, High Grade Fe, Oxide	54.34	1.48	17
Low P, Low Grade Fe	34.7	0.86	11
* Phosphorus			

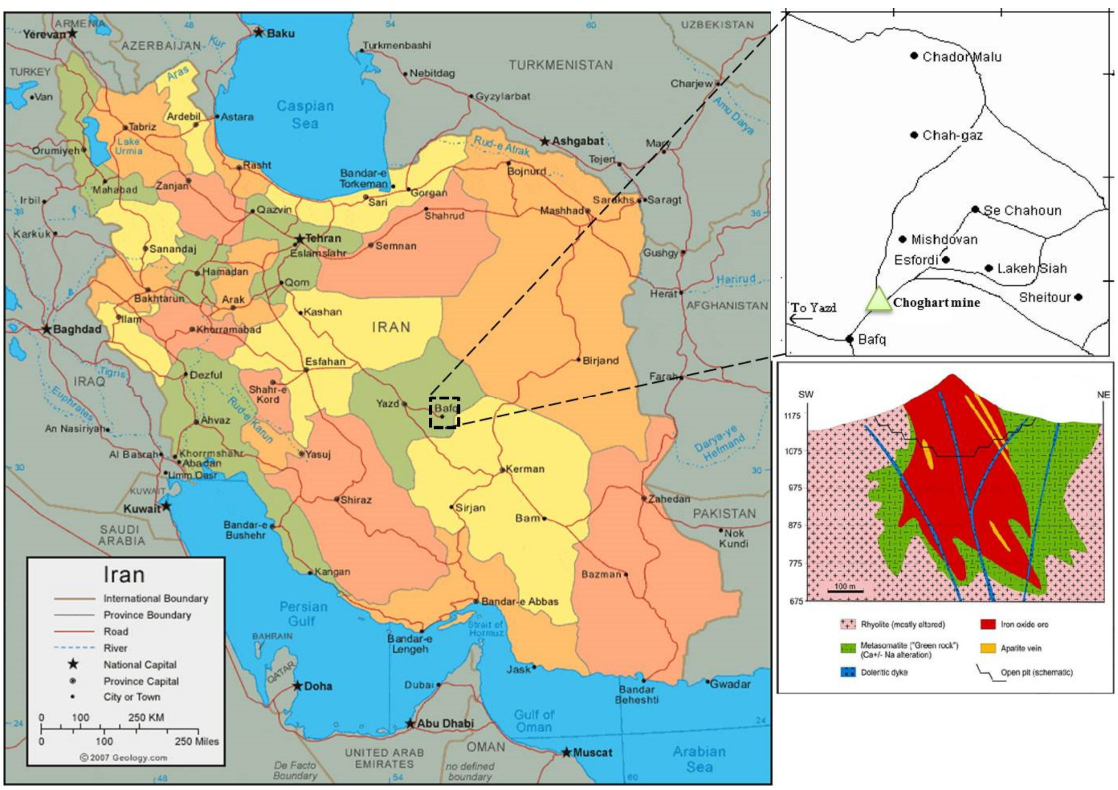


Figure 2. Geographical location and Geology section of the Choghart iron ore mine

Table 2 Blasting operation parameters

Parameter	Min	Max	Mean	Std
Burden (m)	3.00	4.00	3.80	0.38
Spacing (m)	3.00	5.00	4.3	0.53
Powder Factor (kg/t)	0.21	0.48	0.32	0.06
Bench Height	10.00	12.50	12.00	0.80
Subdrilling (m)	0.90	1.30	1.20	0.14

3. Methodology

3.1. Model development

The following steps were implemented for developing the regression models:

- Data collection
- Laboratory tests for determining uniaxial compressive strength and density
- Employing splitdesktop 4.0 for determining rock fragmentation quality
- Conducting fractal analysis for classification
- Developing regression models

3.2. Number-Size (N-S) fractal model

The N-S fractal model serves as a foundational tool in fractal analysis, applicable in various geoscience fields to describe variable distributions without requiring data pre-processing [27, 29, 51]. This method is especially useful for geomechanical parameters.

This model was used to determine the spatial distributions of giant and super-giant mineral deposits, known as size-grade model [29]. In addition, Saein et al. (2013) applied N-S fractal model to classify geochemical properties in Nowchun porphyry deposit [52]. Moreover, Yasrebi et al. was used this type of modeling for some of the rock geomechanical characteristics [43].

This model is as follows:

$$N(\geq \beta) = C\beta^{-D} \quad (1)$$

where β is variable value, N(β) is cumulative number of samples with values greater than or equal to β, C is a constant, and D is scaling exponent or fractal dimension of the variable distribution.

3.3. Image processing

Determining fragment size distribution is key in evaluating blasting efficiency. Direct measurement techniques, like sieving, are time-consuming. Consequently, indirect approaches such as image processing have evolved [53-56]. The accuracy of image processing is influenced by some parameters including quality of light, frequency and extent of the shadows, number of photos, operator proficiency [57-58]. There are several commercial image processing softwares such Wip-Frag and Splitdesktop are available. The study employed Splitdesktop 4.0 for this purpose.

3.4. Logratio matrix

Introduced by Carranza, the Logratio matrix facilitates the examination of relationships between different data sets through the calculation of various metrics such as true positives, false positives, and overall accuracy [59]. This method contains four parameters A, D, B and C (Table3). A is the number of elements which belong to both of the models and is called true positive. D indicates the number of elements, which do not satisfy settings of both of the models and is considered true negative. B is the number of elements, which are in accordance to the first model but not to the second and is defined false positive and C is the number of elements, which are in accordance to the second model but not to the first.

To examine the relationship between fragmentation features and rock characteristics, type I error (T1E), type II error (T2E), and overall accuracy (OA) is calculated according to the corresponding breakpoints of each parameter.

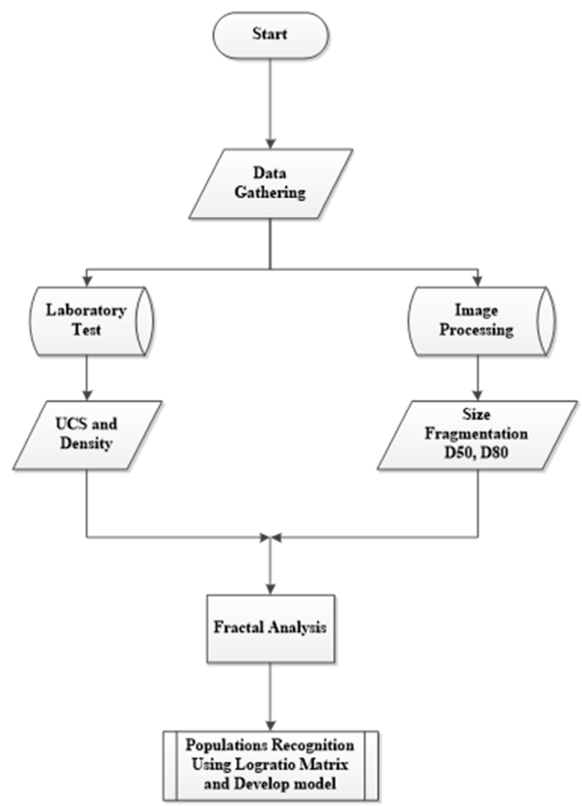


Figure 2. Model development

Table3. Comparing various populations using Logratio analysis

	Characteristics II	
Characteristics I	True positive (A)	False positive (B)
	False negative (C)	True negative (D)
	Type I error = C/(A+C)	Type II error= B/(B+D)
	OA=(A+D)/(A+B+C+D)	

4. Results and discussion

In the image processing, systematic image preparation, ensuring consistency in angles and lighting conditions, is essential. Also, in the prepared photos, there should not be anything other than the main subject, i.e., fragmented rocks. Moreover, to account for the hidden fine particles, image preparation should be accomplished at different stages of the loading process (i.e., after loading of one-third of the materials, after loading half of the fragmented rocks and before completion of loading). For each blast, twenty images were prepared. A sample image is shown in the Figs. 3 & 4. Data from image processing led to the creation of a database linking rock characteristics and fragmentation features (D50 and D80). Utilizing the N-S fractal model, distinct populations were identified for D50 and D80.

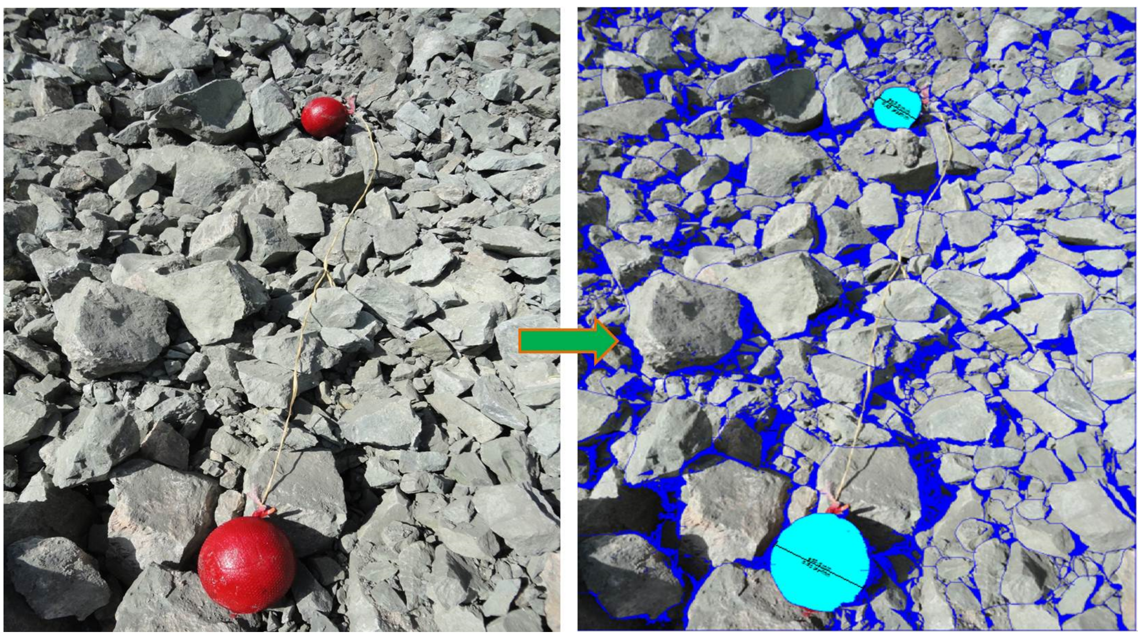


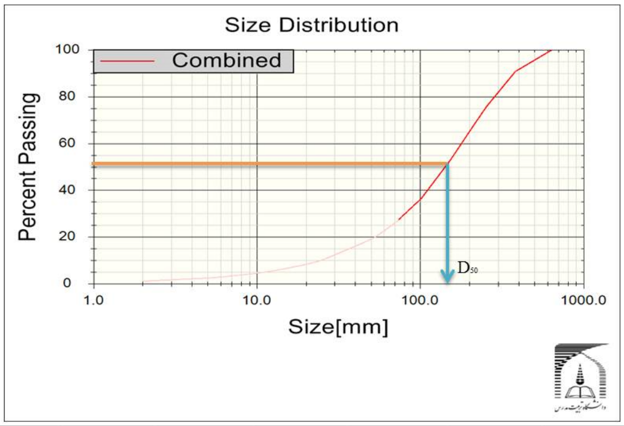
Figure 3. Example of a prepared image and outlined fragments boundaries

Table 4. Brief information about the prepared database

Parameter	Min	Mean	Max	Std.
D_{50} (mm)	100	153	349	61
D_{80} (mm)	218	308	608	98
Top size (mm)	512	739	1491	217
UCS (MPa)	15.2	58.8	100.8	25.8
ρ (gr/cm^3)	2.5	2.7	3.4	0.3

According to the N-S log-log plots it was revealed that there are two populations for the D_{50} and D_{80} with a threshold of 141 and 295 mm, respectively (Figs. 5 & 6). The values lower than the threshold is considered as the first population whereas the values greater than the threshold are classified as the second population. In the same way, the information related UCS and ρ was analyzed by the N-S model (Figure 7). As seen in Figure 7, threshold for UCS and ρ is 52.4 MPa and 2.61 gr/cm^3, respectively. The determined thresholds can be used for prediction of fragmentation features. For blasting operations in which the values are greater than the thresholds, it is supposed that higher mean fragment size is predictable and probability boulder creation is higher.

Once populations are recognized, Logratio matrix was applied (Tables 5 to 8) to find out the present relationships according to characteristics I and II (i.e., fragmentation features and rock characteristics). As it can be seen the first populations for D_{50} (OA=89%) and D_{80} (OA=72%) have a good correlation with the UCS threshold (UCS≤52.48 MPa). It is also seen that the second populations for D_{50} (OA=72%) and D_{80} (OA=72%) show a good correlation with ρ threshold ($\rho \leq 2.61$ gr/cm^3); the same trend can also be observed for the second populations of the fragmentation features. Multivariate regression analysis (MVRA) was implemented for developing mathematical models, predicting fragmentation features from rock characteristics [60]. (Yilmaz and Yuksek 2009).



	Combined	S1	S2	S3	S4	S5	S6	S7	S8
Size [mm]	% Passing								
635	99.9	99.6	100	100	100	100	100	100	100
381	90.79	79.58	86.68	99.06	98.42	82.43	95.62	91.18	100
254	75.79	59.94	67.3	84.35	91.94	62.23	80.11	75.16	94.96
203.2	65.95	51.01	58.45	69.79	84.36	50.4	67.4	66.93	87.34
152.4	52.87	40.06	48.6	51.31	70.72	37.82	51.02	56.24	72.99
101.6	36.56	27.16	37.15	33.17	47.89	26.7	33.91	41.3	49.57
50.8	19.44	14.4	23.71	16.38	22.67	14.65	17.4	25.03	23.4
25.4	10.44	7.57	15.06	7.96	10.71	7.92	8.84	15.02	11.04
19.05	8.1	5.8	12.47	5.9	7.85	6.13	6.67	12.14	8.08
12.7	5.69	3.98	9.55	3.87	5.07	4.28	4.49	9	5.21
9.53	4.45	3.05	7.9	2.87	3.71	3.31	3.39	7.27	3.82
6.35	3.16	2.09	6.05	1.88	2.4	2.31	2.28	5.38	2.46
4.75	2.48	1.59	4.99	1.39	1.75	1.78	1.72	4.34	1.8
2	1.22	0.71	2.81	0.57	0.69	0.82	0.74	2.28	0.71

Figure 4. Muckpile size distribution curve, blasting No 1037-223, Choghart mine

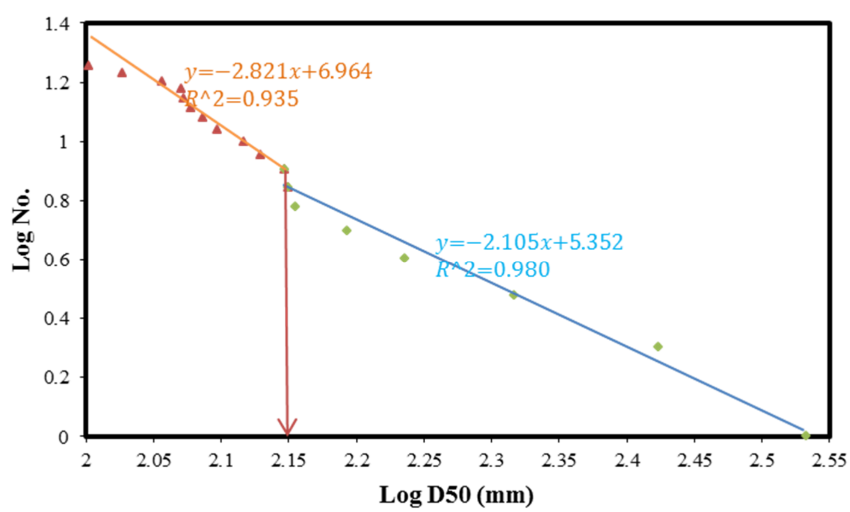


Figure 5. N-S fractal log-log plots of D_{50} for 18 blasts in the Choghart mine

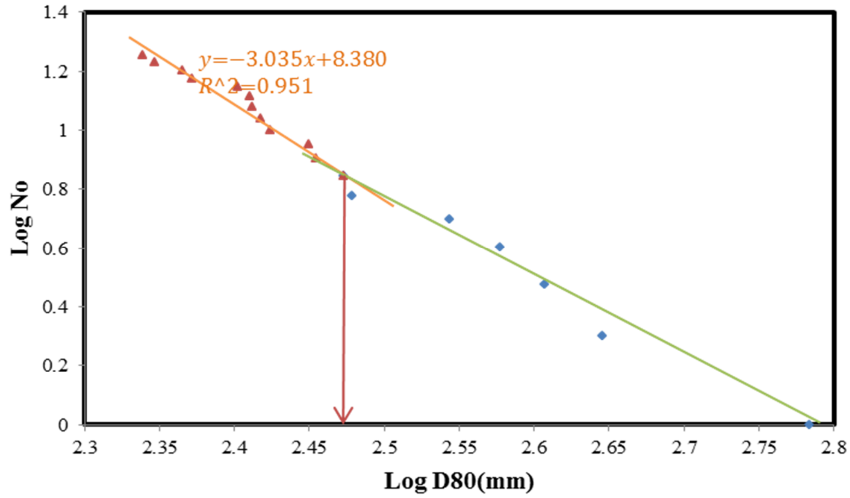
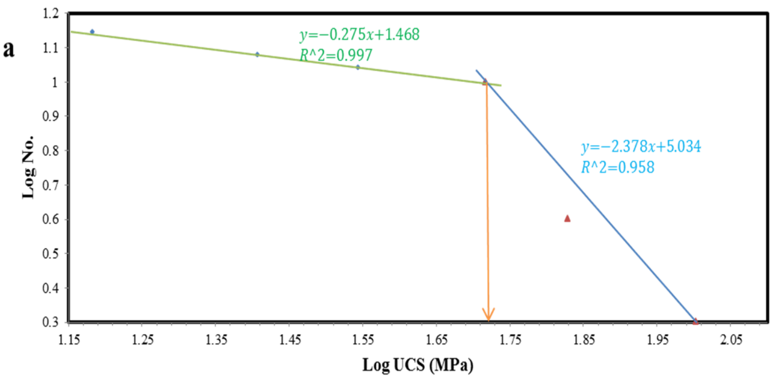


Figure 6. N-S fractal log-log plots of D_{80} for the eighteen blasts in the Choghart mine

a



b

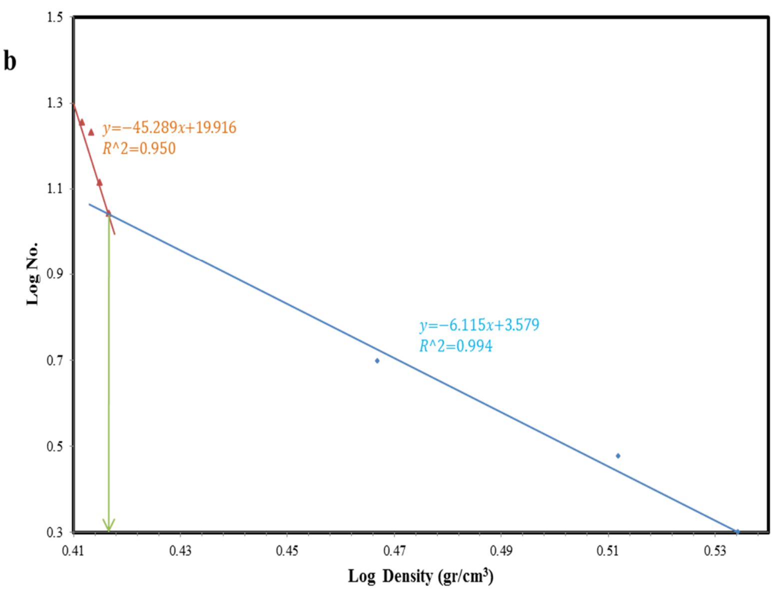


Figure 7. N-S log-log plots for a) UCS and b) Density

Table 5. Logratio matrix between D_{80} and UCS

	UCS≤ 52.4 (MPa)	
D_{80}≤295(mm)	8	3
	2	5
	Type I error = 0.20	Type II error= 0.37
	OA=0.72	

Table 6. Logratio matrix between D_{50} and UCS

	UCS≤ 52.4 (MPa)	
D_{50}≤141(mm)	10	2
	0	6
	Type I error = 0.17	Type II error= 0.0
	OA=0.89	

Table 7. Logratio matrix between D_{80} and ρ

	$\rho \leq 2.61$ (gr/cm^3)	
D_{80}≤295(mm)	9	2
	3	4
	Type I error = 0.25	Type II error= 0.33
	OA=0.72	

Table 8. Logratio matrix between D_{50} and ρ

	$\rho \leq 2.61$ (gr/cm^3)	
D_{50}≤295(mm)	9	3
	2	4
	Type I error = 0.18	Type II error= 0.43
	OA=0.72	

MVRA can easily be used for determining curve fitting and finding out existing relation between dependent and independent variables. Dependent variables are D_{50} and D_{80} whereas independent variables are controllable parameters (burden, spacing and powder factor); and uncontrollable parameters (UCS and ρ). Equation 2 is considered as the base model for regression analysis [8, 21, 61-62].

$$D_\alpha = \left(\frac{UCS}{PF}\right)^a (\rho)^b \left(\frac{S}{B}\right)^c + \mathrm{d} \quad (2)$$

where D_α is passing size (mm), UCS is uniaxial compression strength (MPa), PF is powder factor (kg/t), ρ is rock density (gr/cm^3), S is spacing (m), B is burden (m), and a, b, c and d are constants.

After regression analysis, the constants of Eq. 2 were computed (Table 9) for the original database as well as for the first populations, however for the second populations due to lack of sufficient databases, MVRA is not applicable. Statistical indices including determination coefficient (R^2), root mean square error (RMSE) and variance account for (VAF) were considered for evaluating the models' performance (Eqs. 3-5).

$$VAF = 100\left[1 - \frac{var(y - \acute{y})}{var(y)}\right] \quad (3)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{n}(y - \acute{y})^2} \quad (4)$$

$$R^2 = \left[\frac{\sum_{i=1}^{N}(y - \bar{y})(\acute{y} - \acute{\bar{y}})}{\sum_{i=1}^{N}(y - \bar{y})^2 \sum_{i=1}^{N}(y' - \acute{\bar{y}})^2}\right] \quad (5)$$

where y is measured values, $\acute{y}$ is predicted values, $\bar{y}$ is average measured values, $\acute{\bar{y}}$ is average predicted values, and $var(.)$ is a variance.

As can be seen from Table 10 and Figs. 8-11, it is obvious that accuracy of the clustered populations (first population of D_{50} and D_{80}) is better than that of the original database.

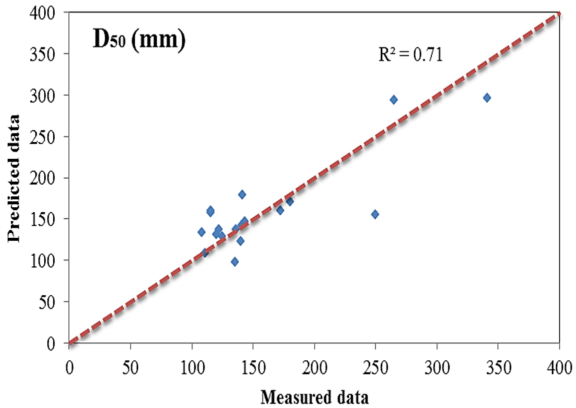


Figure 8. Determination coefficient of the measured and predictedD_{50} for the original database

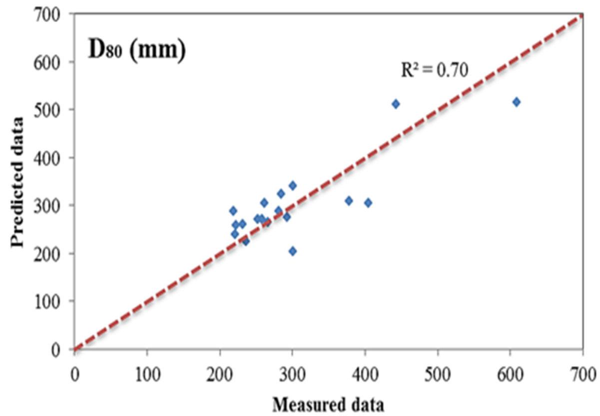


Figure 9. Determination coefficient of the measured and predicted D80 for the original database

Table 9. Models' constants obtained from original database and first population

Constant \ Data type	All database		First population database	
	D_{50}	D_{80}	D_{50}	D_{80}
A	0.48	0.55	0.08	0.22
B	2.55	2.57	5.08	3.66
C	0.20	0.11	0.26	1.88
D	-1.60	71.15	-76.43	111.82

Table 10. models' performance for original database and first populations

Indices \ Data type	All database		First population database	
	D_{50}	D_{80}	D_{50}	D_{80}
Determination coefficient (R^2)	0.71	0.70	0.78	0.81
VAF	70.91	69.90	77.91	80.89
RMSE	33.22	52.87	5.14	9.62

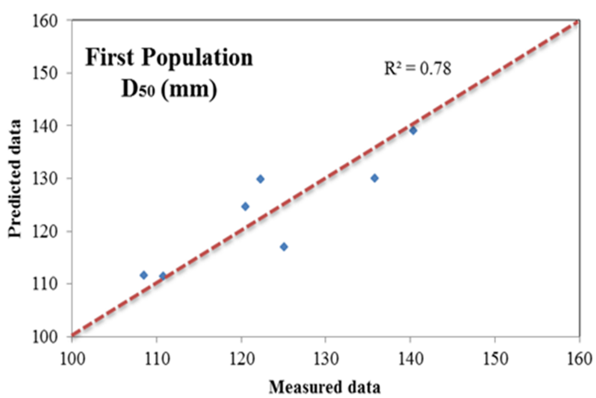


Figure 10 Determination coefficient of the measured and predicted D_{50} for the first population

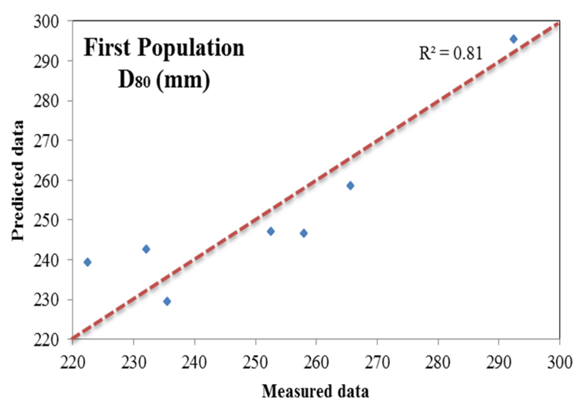


Figure 11 Determination coefficient of the measured and predicted D_{80} for the first population

5. Conclusions

This study demonstrated the implementation of fractal analysis in characterizing different rock types based on their geomechanical properties, enhancing the predictability of rock fragmentation outcomes. The findings highlight the importance of classification techniques in improving the accuracy of predictive models related to fragmentation features. Finally, using multivariate regression analysis for predicting rock fragmentation features (D50 and D80), mathematical models were developed. It was observed that determination coefficient of the measured and predicted D50 and D_{80} for the original database are .71 and .70, respectively. Whereas this statistical index was improved to .78 and .81 after implementing fractal analysis. Further research should aim to encompass a broader range of case studies and integrate artificial intelligence methods for enhanced outcomes.

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کلمات کلیدی

عملیات انفجار
ویژگی خردایش
تحلیل فرکتال
ماتریس Logratio

چکیده

انفجار یک عملیات ضروری در پروژه‌های معدنی است که به طور قابل توجهی بر توزیع اندازه ذرات تأثیر می‌گذارد، و برای فرآیندهای بعدی مانند بارگیری، حمل و نقل و سنگ‌شکنی بسیار مهم است. اثربخشی عملیات انفجار متکی بر شناخت دقیق سنگ است، به ویژه هنگام روبرو شدن با انواع مختلف سنگ. طبقه‌بندی و شناسایی مناسب سنگ و خردایش، امکان طرح‌های مناسب انفجار را فراهم می‌کند و همچنین می‌تواند منجر به پیش بینی دقیق کیفیت خردایش شود. تکنیک‌های مختلف طبقه‌بندی وجود دارد. در این مقاله، با استفاده از اطلاعات معدن آهن چغارت در ایران به عنوان مطالعه موردی، کاربرد آنالیز فرکتالی برای طبقه‌بندی کیفیت خردایش و انواع سنگ مورد بررسی قرار می‌گیرد. در این خصوص، یک عملیات میدانی گسترده برای جمع‌آوری داده‌های مربوط به خواص سنگ (مقاومت فشاری تک محوری و چگالی) و نتایج خردایش ناشی از انفجار صورت پذیرفت. مدل‌سازی فرکتال نقاط شکست متمایز را برای طبقه‌بندی نشان داد و به دنبال آن تحلیل Logratio برای ارزیابی روابط بین طبقات شناسایی‌شده انجام شد. در نهایت، مدل‌های ریاضی برای پیش‌بینی ویژگی‌های خردایش بر اساس ویژگی‌های سنگ‌ها توسعه داده شدند. در مقایسه با طبقه‌بندی‌های قبلی، مدل‌های توسعه داده شده از دقت پیش‌بینی بالاتری برخوردار بودند.

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