



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

Masoud Monjezi^{1*}, Morteza Baghestani¹, Peyman Afzal², and Ali Reza Yarahmadi Bafghi³

1. Faculty of Engineering, Tarbiat Modares University, Tehran, Iran

2. Department of Mining Engineering, South Tehran Branch, Islamic Azad University, Tehran, Iran

3. Department of Mining and Metallurgical Engineering, Yazd University, Yazd, Iran

Article Info

Received 23 October 2024

Received in Revised form 14 November 2024

Accepted 24 November 2024

Published online 24 November 2024

DOI: [10.22044/jme.2024.15240.2917](https://doi.org/10.22044/jme.2024.15240.2917)

Keywords

Blasting operation

Fragmentation feature

Fractal analysis

Logratio matrix

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

Corresponding author: monjezi@modares.ac.ir (M. Monjezi)

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

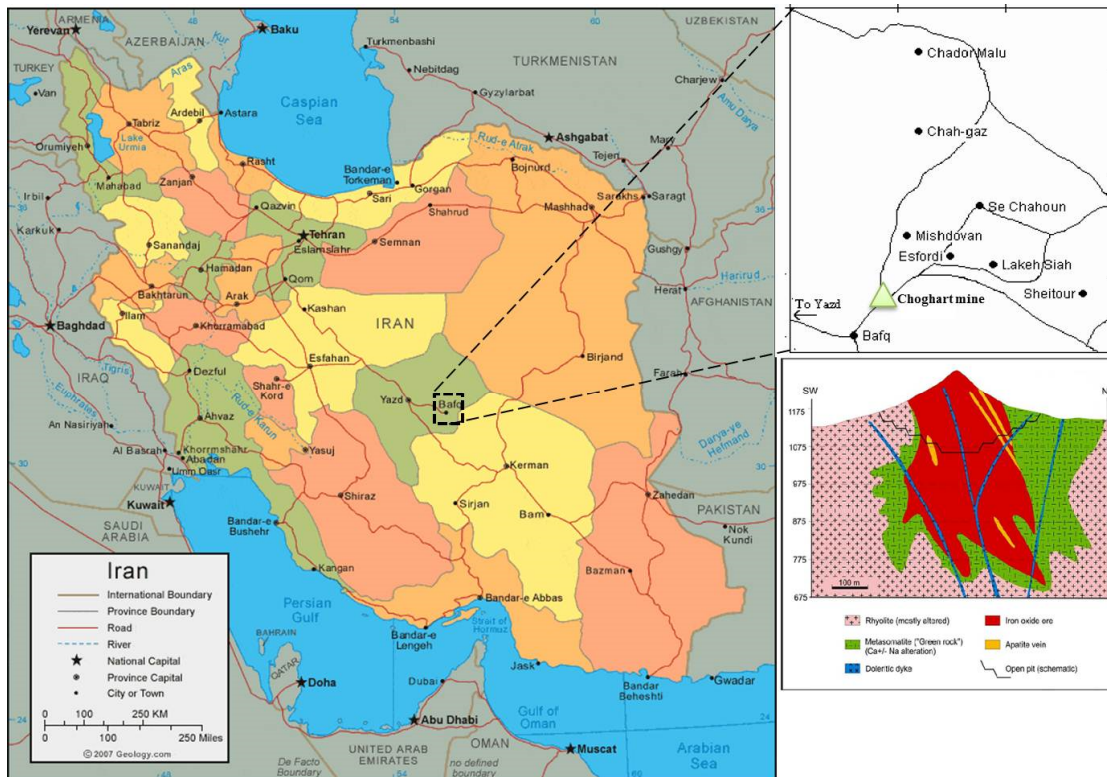


Figure 2. Geographical location and Geology section of the Choghart iron ore mine

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:

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

where β is variable value, $N(\beta)$ 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.

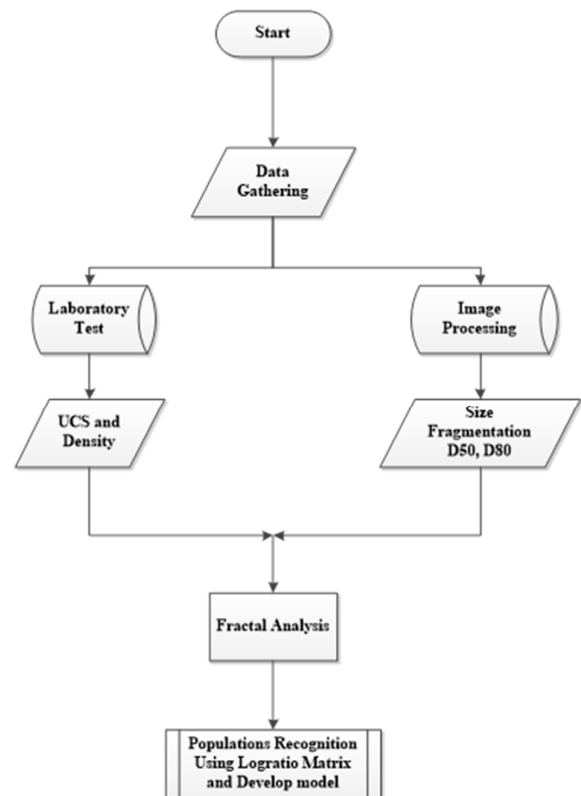


Figure 2. Model development

Table3. Comparing various populations using Logratio analysis

Characteristics I	Characteristics II	
	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.

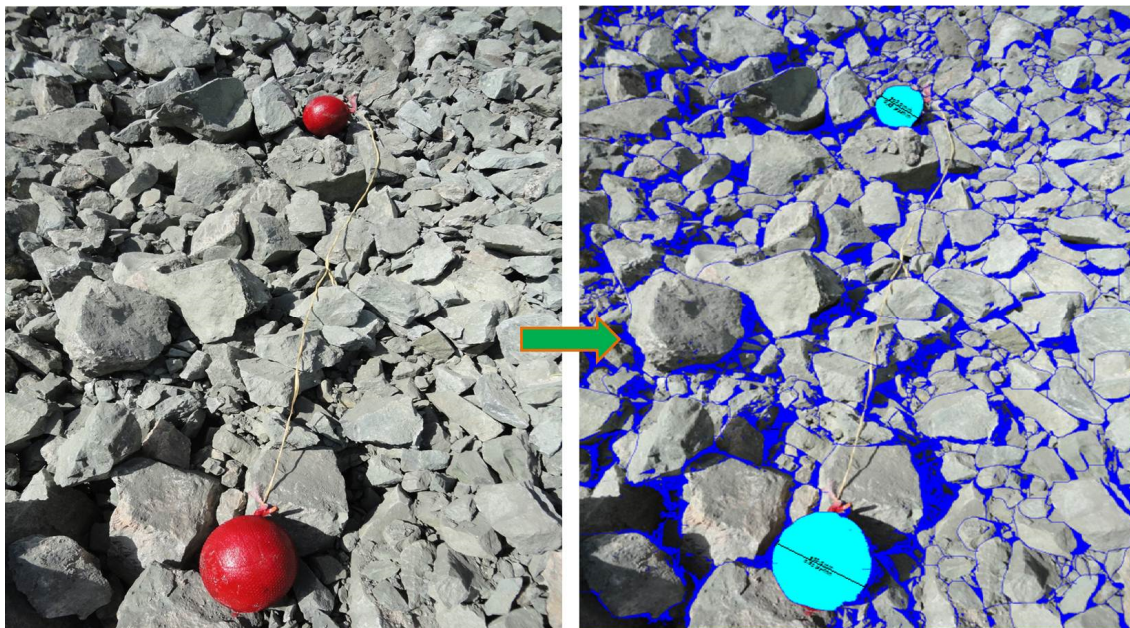


Figure 3. Example of a prepared image and outlined fragments boundaries

Table 4. Brief information about the prepared database

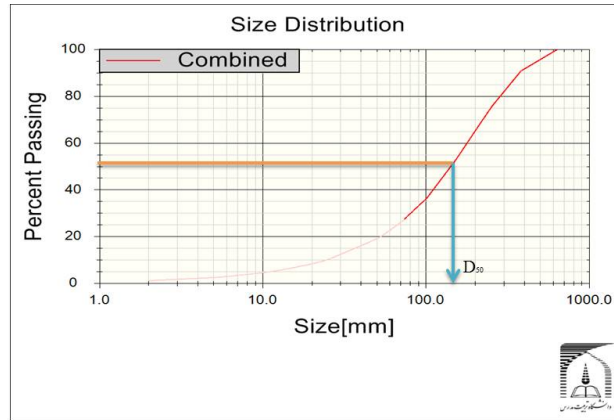
Parameter	Min	Mean	Max	Std.
D ₅₀ (mm)	100	153	349	61
D ₈₀ (mm)	218	308	608	98
Top size (mm)	512	739	1491	217
UCS (MPa)	15.2	58.8	100.8	25.8
ρ (gr/cm ³)	2.5	2.7	3.4	0.3

According to the N-S log-log plots it was revealed that there are two populations for the D₅₀ and D₈₀ 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/cm³, 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 ($UCS \leq 52.48$ 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/cm³); 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).



Size [mm]	% Passing								
	Combined	S1	S2	S3	S4	S5	S6	S7	S8
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, Chohgart mine

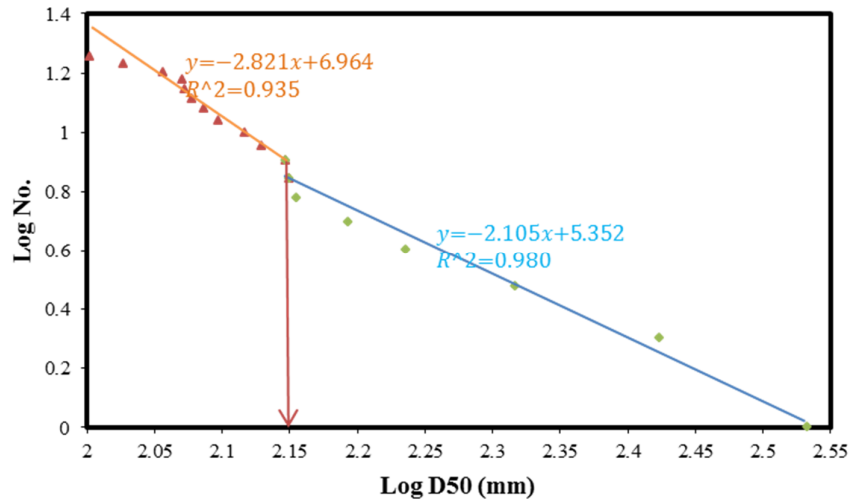


Figure 5. N-S fractal log-log plots of D_{50} for 18 blasts in the Chohgart mine

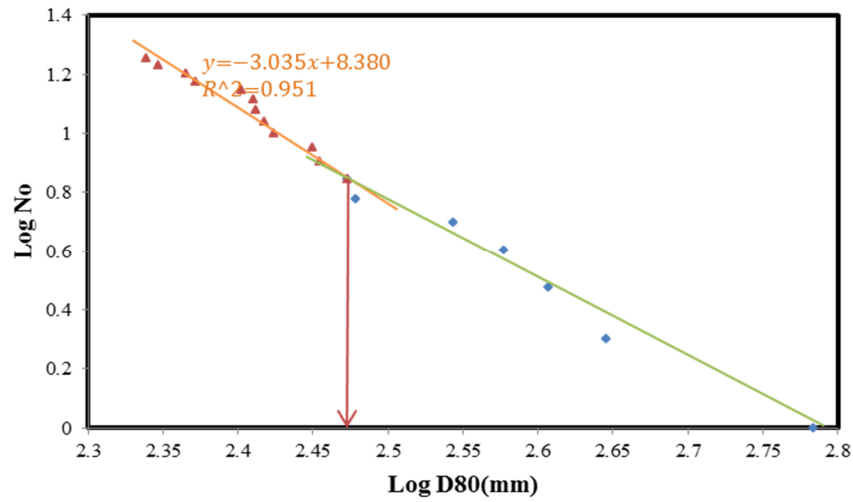


Figure 6. N-S fractal log-log plots of D₈₀ for the eighteen blasts in the Choghart mine

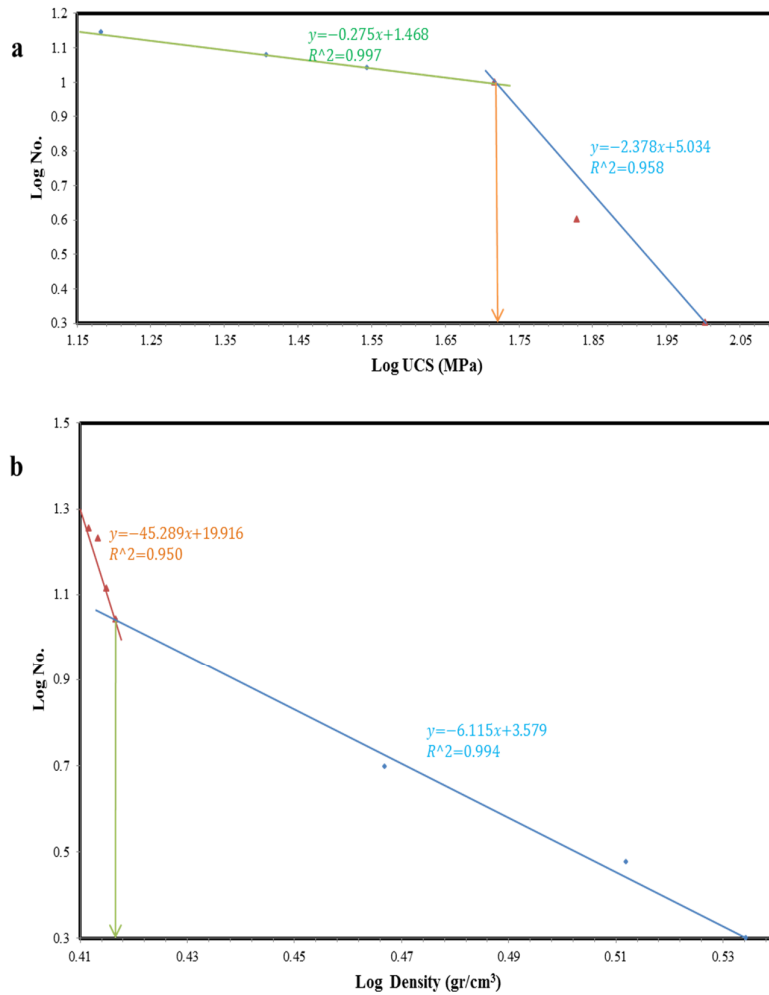


Figure 7. N-S log-log plots for a) UCS and b) Density

Table 5. Logratio matrix between D₈₀ 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 D₅₀ 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 D₈₀ and ρ

ρ ≤ 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 D₅₀ and ρ

ρ ≤ 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 D₅₀ and D₈₀ 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].

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

where D_α is passing size (mm), UCS is uniaxial compression strength (MPa), PF is powder factor (kg/t), ρ is rock density (gr/cm³), 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 (R²),

root mean square error (RMSE) and variance account for (VAF) were considered for evaluating the models' performance (Eqs. 3-5).

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

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

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

where y is measured values, \hat{y} is predicted values, \bar{y} is average measured values, $\bar{\hat{y}}$ 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 D₅₀ and D₈₀) is better than that of the original database.

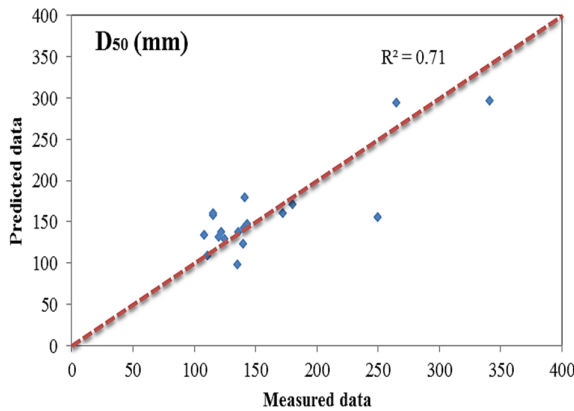


Figure 8. Determination coefficient of the measured and predicted D_{50} for the original database

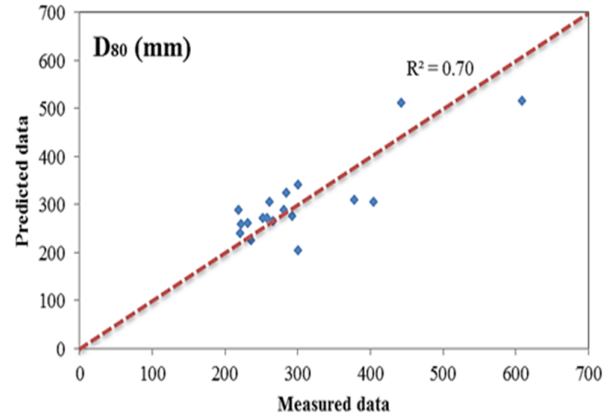


Figure 9. Determination coefficient of the measured and predicted D_{80} for the original database

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

Data type	All database		First population database	
	D_{50}	D_{80}	D_{50}	D_{80}
Constant				
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	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

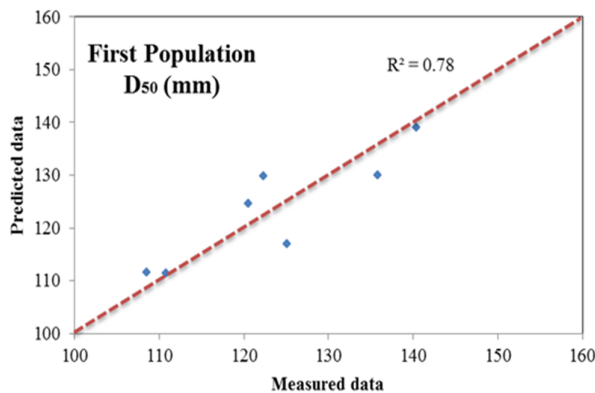


Figure 10 Determination coefficient of the measured and predicted D_{50} for the first population

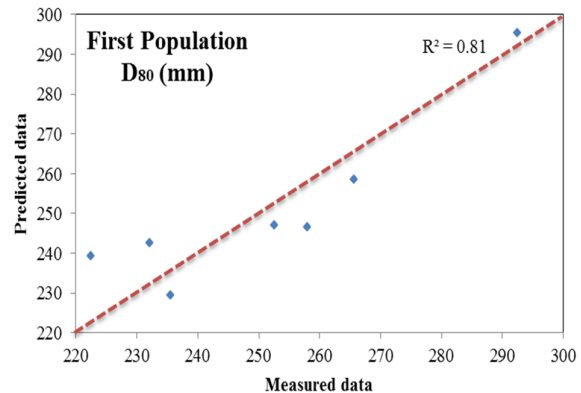


Figure 11 Determination coefficient of the measured and predicted D_{80} for the first population

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

(D_{50} and D_{80}), mathematical models were developed. It was observed that determination coefficient of the measured and predicted D_{50} 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.

Acknowledgements

The authors express gratitude to Mr. Moradian for assisting in data collection at Choghart iron mine.

References

- [1]. Monjezi, M., Rezaei, M., & Yazdian Varjani, A. (2009). Prediction of rock fragmentation due to blasting in Gol-E-Gohar iron mine using fuzzy logic. *International Journal of Rock Mechanics and Mining Sciences* 46(8). 1273–1280.
- [2]. Akbari, M., Lashkaripour, G., Bafghi, A.Y., & Ghafoori, M. (2015). Blastability evaluation for rock mass fragmentation in Iran central iron ore mines. *International Journal of Mining Sciences and Technology* 25(1) 59–66.
- [3]. Sasaoka, T., Takahashi, Y., Sugeng, W., Hamanaka, A., Shimada, H., Matsui, K., & Kubota, S. (2015). Effects of Rock Mass Conditions and Blasting Standard on Fragmentation Size at Limestone Quarries. *Open journal of geology* 05(05) 331.
- [4]. Singh, P.K., Roy, M.P., Paswan, R.K., Sarim, M.D., Kumar, S., 7 Ranjan, R. (2016). Rock fragmentation control in opencast blasting. *Journal of Rock Mechanics and Geotechnical Engineering*, 8 (2), 225-237.
- [5]. MacKenzie, A.S. (1966). Cost of explosives—do you evaluate it properly? *Mining Congress Journal* 32–41.
- [6]. Michaud, P., Lizotte, Y., & Scoble, M. (1997). Rock fragmentation and mining productivity: characterization and case studies. In: *Proceedings of the 23rd annual conference on explosives and blasting technique*, Las Vegas, NV, 61–72.
- [7]. Sanchidrián, J., Segarra, P., & López, L. (2006). A practical procedure for the measurement of fragmentation by blasting by image analysis. *Rock Mechanics and Rock Engineering*, 39(4), 359–382.
- [8]. Kulatilake, P.H.S.W., Hudaverdi, T., & Wu, Q. (2012). New prediction models for mean particle size in rock blast fragmentation. *Geotechnical and Geological Engineering* 30(3) 665–684.
- [9]. Konya, C.J., & Walter, E.J. (1991). Rock blasting and overbreak control. *United States Department of Transportation, McClean*.
- [10]. Latham, J.P., & Lu, P. (1999). Development of an assessment system for the blastability of rock masses. *International Journal of Rock Mechanics and Mining Sciences* 36(1):41–55.
- [11]. Azimi, Y., Osanloo, M., Aakbarpour-Shirazi, M., & Aghajani Bazzazi, A. (2010). Prediction of the blastability designation of rock masses using fuzzy sets. *International Journal of Rock Mechanics and Mining Sciences*, 47(7), 1126–1140.
- [12]. Kuznetsov, V.M. (1973). The mean diameter of fragments formed by blasting rock. *Journal of Mining Sciences*, 9, 144–148.
- [13]. Hjelmsberg, H. (1983). Some ideas on how to improve calculations of the fragment size distribution in bench blasting. 1st International Symposium on Rock Fragmentation by Blasting, 469–494.
- [14]. Kou, S., & Rustan, A. (1993). Computerized design and result predictions of bench blasting. In: *Rossmannith HP (ed) Proceedings of 4th international symposium on rock fragmentation by blasting (Fragblast 4)*, Vienna, Austria, Balkema, Rotterdam, pp 263–271.
- [15]. Cunningham, C.V.B. (1983). The Kuz-Ram model for prediction of fragmentation from blasting. In: *Proceedings of the 1st international symposium on rock fragmentation by blasting*, Lulea, Sweden, 439–453.
- [16]. Cunningham, C.V.B. (1987). Fragmentation estimations and the Kuz-Ram Model—Four years on. In: *Proc. 2nd Int. Symposium on Rock Fragmentation by Blasting*, 475–487
- [17]. Cunningham, C.V.B., (2005) The Kuz–Ram fragmentation model—20 years on. In: *Proceedings of the 3rd EFEE World Conference on Explosives and Blasting, England*, 201–210.
- [18]. Dahlhielm, S. (1996). Industrial applications of image analysis—the IPACS system. *Measurement of Blast Fragmentation, first edition, Routledge*.
- [19]. Djordjevic, N. (1999). A two-component model of blast fragmentation. *Australian Institute of Mining and Metallurgy Proceedings* 304, 9–13.
- [20]. Bahrami, A., Monjezi, M., Goshtasbi, K., & Ghazvinian, A. (2011). Prediction of rock fragmentation due to blasting using artificial neural network. *Engineering with Computers* 27(2) 177–181.
- [21]. Hudaverdi, T., Kulatilake, P., & Kuzu, C. (2011). Prediction of blast fragmentation using multivariate analysis procedures. *International Journal of Numerical and Analytical Methods Geomechanics* 35(12) 1318–1333.
- [22]. Shi, X.Z., Jian, Z.H., Wu, B.B., Huang, D., & Wei, W.E. (2012). Support vector machines approach to mean particle size of rock fragmentation due to bench blasting prediction. *Transactions of Nonferrous Metals Society of China* 22(2) 432–441.
- [23]. Sayadi, A., Monjezi, M., Talebi, N., & Khandelwal, M. (2013). A comparative study on the application of various artificial neural networks to simultaneous prediction of rock fragmentation and backbreak. *Journal of Rock Mechanics and Geotechnical Engineering* 5(4) 318–324.

- [24]. Karami, A., & Afiuni-Zadeh, S. (2013). Sizing of rock fragmentation modeling due to bench blasting using adaptive neuro fuzzy inference system (ANFIS). *International Journal Mining Science and Technology* 23(6) 809–813.
- [25]. Bakhtavar, E., Khoshrou, H., & Badroddin, M. (2015). Using dimensional-regression analysis to predict the mean particle size of fragmentation by blasting at the Sungun copper mine. *Arabian Journal for Geosciences* 8(4) 2111–2120.
- [26]. Ebrahimi, E., Monjezi, M., Khalesi, M.R., & Jahed Armaghani, D. (2015). Prediction and optimization of backbreak and rock fragmentation using an artificial neural network and a bee colony algorithm. *Bulletin of Engineering, Geology and the Environment* 75(1) 27–36.
- [27]. Mandelbrot, B.B. (1983). *The Fractal Geometry of Nature: Updated and Augmented*. WH Freeman, New York, NY.
- [28]. Cheng, Q., Agterberg, F.P., & Ballantyne, S.B. (1994). The separation of geochemical anomalies from background by fractal methods. *Journal of Geochemical Exploration* 51(2) 109–130.
- [29]. Agterberg, F.P. (1995). Multifractal modeling of the sizes and grades of giant and supergiant deposits. *International Geology Review* 37(1) 1–8.
- [30]. Cheng, Q., Xu, Y., & Grunsky, E. (2000) Integrated spatial and spectrum method for geochemical anomaly separation. *Natural Resources*, 9, 43–52.
- [31]. Davis, J.C. (2002). *Statistics and data analysis in geology, 3rd edition*. John Wiley & Sons Inc., New York.
- [32]. Li, C., Ma, T., & Shi, J. (2003). Application of a fractal method relating concentrations and distances for separation of geochemical anomalies from background. *Journal of Geochemical Exploration*, 77, 167–175.
- [33]. Zuo, R., Xia, Q., & Zhang, D. (2013). A comparison study of the C-A and SA models with singularity analysis to identify geochemical anomalies in covered areas. *Applied Geochemistry*, 33, 165–172.
- [34]. Afzal, P., Alghalandis, Y.F., Khakzad, A., Moarefvand, P., & Omran, N.R. (2011). Delineation of mineralization zones in porphyry Cu deposits by fractal concentration–volume modeling. *Journal of Geochemical Exploration* 108(3). 220–232.
- [35]. Hassanpour, S., & Afzal, P. (2013). Application of concentration–number (C–N) multifractal modeling for geochemical anomaly separation in Haftcheshmeh porphyry system, NW Iran. *Arabian Journal for Geosciences* 6(3) 957–970.
- [36]. Yasrebi, A.B., Wetherelt, A., Foster, P., Coggan, J., Afzal, P., Agterberg, F., & Kaveh Ahangaran, D. (2014). Application of a density–volume fractal model for rock characterization of the Kahang porphyry deposit. *International Journal of Rock Mechanics and Mining Sciences* 66 188–193
- [37]. Yasrebi, A.B., Hezarkhani, A., & Afzal, P. (2017). Application of Present Value-Volume (PV-V) and NPV-Cumulative Total Ore (NPV-CTO) fractal modelling for mining strategy selection. *Resources Policy* 53:384–393.
- [38]. Zhao, Y., Huang, J., & Wang, R. (1993). Fractal characteristics of mesofractures in compressed rock specimens. *International Journal of Rock Mechanics and Mining Sciences* 30(7), 877–882.
- [39]. Ehlen, J., (2000). Fractal analysis of joint patterns in granite. *International Journal of Rock Mechanics and Mining Sciences* 37(6), 909–922.
- [40]. Billi, A., & Storti, F. (2004). Fractal distribution of particle size in carbonate cataclastic rocks from the core of a regional strike-slip fault zone. *Tectonophysics* 384, 115–128.
- [41]. Hamdi, E. (2008). A fractal description of simulated 3D discontinuity networks. *Rock Mechanics and Rock Engineering* 41(4), 587–599.
- [42]. Kruhl, J.H. (2013). Fractal-geometry techniques in the quantification of complex rock structures: a special view on scaling regimes, inhomogeneity and anisotropy. *Journal of Structural Geology*, 46, 2–21.
- [43]. Yasrebi, A.B., Wetherelt, A., Foster, P.J., Afzal, P., Coggan, J., & Ahangaran, D.K. (2013). Application of RQD- Number and RQD-Volume to delineate rock mass characterization in Kahang Cu-Mo porphyry deposit, central Iran. *Archives of Mining Sciences* 58(4), 1023–1035.
- [44]. Ficker, T. (2017). Fractal properties of joint roughness coefficients. *International Journal of Rock Mechanics and Mining Sciences* 94, 27–31.
- [45]. Zhan, J., Xu, P., Chen, J., Wang, Q., Zhang, W., & Han, X. (2017). Comprehensive characterization and clustering of orientation data: A case study from the Songta dam site, China. *Engineering Geology* 225, 3–18.
- [46]. Crum, S.V. (1990). Fractal concepts applied to bench-blast fragmentation. In: *Proc. 3rd US Rock Mechachanics. Symposium Balkema, Rotterdam*, 913–919.
- [47]. Ghosh, A., Daemen, J.J., & Van Zyl, D. (1990). Fractal-based approach to determine the effect of discontinuities on blast fragmentation. In: *The 31th US Symposium on Rock Mechanics (USRMS), American Rock Mechanics Association*.
- [48]. Samani, B. A., (1988). Metallogeny of the Precambrian in Iran. *Precambrian research journal* 39, 85–106.
- [49]. Jami, M., (2005). Geology, Geochemistry and evolution of the Esfordi phosphate–iron deposit, Bafq

area, central Iran. Ph.D. thesis, *University of New South Wales, Sydney, Australia*.

[50]. Sadeghi, B., Moarefvand, P., Afzal, P., Yasrebi, A.B., & Saein, L.D. (2012). Application of fractal models to outline mineralized zones in the zaghia iron ore deposit, central Iran. *Journal of Geochemical Exploration* 122, 9–19.

[51]. Afzal, P., Ghasempour, R., Mokhtari, A.R., & Haroni, H.A. (2015). Application of Concentration-Number and Concentration-Volume Fractal Models to Recognize Mineralized Zones in North Anomaly Iron Ore Deposit, Central Iran. *Archives of Mining Sciences* 60(3), 777–789.

[52]. Saein, L.D., Rasa, I., Omran, N.R., Moarefvand, P., Afzal, P., & Sadeghi, B. (2013). Application of number-size (N-S) fractal model to quantify of the vertical distributions of Cu and Mo in Nowchun porphyry deposit (Kerman, Se Iran). *Archives of Mining Sciences* 58, 89–105.

[53] Havermann, T., & Vogt, W. (1996). TUCIPS- A system for the estimation of solid particulate after production blasts. In: Franklin, J.A., Katsabanis, T. (eds.) *Measurement of Blast Solid particulateation, Balkema, Rotterdam* 67–71.

[54]. Maerz, N.H., Palangio, T.C., & Franklin, J.A. (1996). WipFrag image based granulometry system. In *Proceedings of the FRAGBLAST, 5 Workshop on Measurement of Blast Fragmentation, Montreal*, 91–99.

[55]. Sanchidrián, J., Segarra, P., & López, L. (2006). A practical procedure for the measurement of fragmentation by blasting by image analysis. *Rock Mechanics and Rock Engineering*, 39(4), 359–382.

[56]. Siddiqui, F.I., Shah, S.A., & Behan, M.Y. (2009). Measurement of size distribution of blasted rock using digital image processing. *Journal of King Abdulaziz University* 20(2), 81–93

[57]. Franklin, J.A., Kemeny, J.M., & Girdner, K.K. (1996). Evolution of measuring systems: A review. *Measurement of Blast Fragmentation, first edition, Routledge*.

[58] Bamford, T., Esmacili, K., & Schoellig, A.P. (2016). A real-time analysis of rock fragmentation using UAV technology. *6th International Conference on Computer Applications in the Minerals Industries*, arXiv:1607.04243 [cs.RO].

[59]. Carranza, E.J.M. (2011). Analysis and mapping of geochemical anomalies using logratio-transformed stream sediment data with censored values. *Journal of Geochemical Exploration* 110(2), 167–185.

[60]. Yilmaz, I., & Yuksek, G. (2009). Prediction of the strength and elasticity modulus of gypsum using multiple regression, ANN, and ANFIS models. *International Journal of Rock Mechanics and Mining Sciences*, 46(4), 803–810.

[61]. Faramarzi, F., Mansouri H, & Ebrahimi Farsangi M.A. (2013). A rock engineering systems based model to predict rock fragmentation by blasting. *International Journal of Rock Mechanics and Mining Sciences*, 60, 82–94.

[62]. Hasanipanah, M., Jahed Armaghani D, Monjezi, M., & Shams, S. (2016). Risk assessment and prediction of rock fragmentation produced by blasting operation: a rock engineering system. *Environmental Earth Sciences*, 75(9), 808.



دانشگاه صنعتی شاهرود

نشریه مهندسی معدن و محیط زیست

نشانی نشریه: www.jme.shahroodut.ac.ir

انجمن مهندسی معدن ایران

بررسی رابطه بین خصوصیات سنگ و خردایش ناشی از انفجار با استفاده از تحلیل فرکتال

مسعود منجری^{۱*}، مرتضی باغستانی^۱، پیمان افضل^۲، علیرضا یار احمدی بافقی^۳ و سید علی هاشمی^۱

۱. دانشکده فنی و مهندسی، دانشگاه تربیت مدرس، تهران، ایران

۲. دانشکده فنی و مهندسی، گروه مهندسی معدن، دانشگاه آزاد، واحد تهران جنوب، تهران، ایران

۳. دانشکده مهندسی معدن و متالورژی، دانشگاه یزد، ایران

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 شناسایی شده 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.

اطلاعات مقاله

تاریخ ارسال: ۲۰۲۴/۱۰/۱۳

تاریخ داوری: ۲۰۲۴/۱۱/۱۴

تاریخ پذیرش: ۲۰۲۴/۱۱/۲۴

DOI: 10.22044/jme.2024.15240.2917

کلمات کلیدی

عملیات انفجار
ویژگی خردایش
تحلیل فرکتال
ماتریس
Logratio