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Prediction of blast boulders in open pit mines via multiple regression and artificial neural networks

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ABSTRACT

The most important objective of blasting in open pit mines is rock fragmentation. Prediction of produced boulders (oversized crushed rocks) is a key parameter in designing blast patterns. In this study, the amount of boulder produced in blasting operations of Golegohar iron ore open pit mine, Iran was predicted via multiple regression method and artificial neural networks. Results of 33 blasts in the mine were collected for modeling. Input variables were: joints spacing, density and uniaxial compressive strength of the intact rock, burden, spacing, stemming, bench height to burden ratio, and specific charge. The dependent variable was ratio of boulder volume to pattern volume. Both techniques were successful in predicting the ratio. In this study, the multiple regression method was superior with coefficient of determination and root mean squared error values of 0.89 and 0.19, respectively.

1. Introduction

The main objective of rock blasting in open pit mines is optimal rock fragmentation. One of the key metrics of an optimal blasting operation is the size distribution of crushed rocks. If the in situ rocks are over crushed, this implies over estimated design parameters which results in higher costs and consequent difficulties in the following operations i.e. loading, hauling, crushing, and mineral processing. However, if the in situ rocks are under-crushed, similar difficulties will arise in the subsequent operations. One of the main constraints, in an open pit mine, for the size of crushed rocks is the accepting size of the primary crusher. In Golegohar's mine No.1, the primary crusher can accept rock fragments up to 1.5 m. Hence, in case that the blast operation results in larger rock fragments, a secondary blasting operation on the produced boulders will be inevitable. This translates into higher costs and longer production cycles which decreases the mine productivity. Osanloo and Hekmat investigated the effect of rock fragments sizes on shovel productivity in mine No.1 of Golegogar [1]. Morin and Ficarazzo applied Monte Carlo simulation technique to predict rock fragmentation based on Kuz–Ram model [2]. Saavedra et al. and Monjezi et al. used artificial neural networks (ANN) for prediction of rock fragmentation [3,4]. Monjezi modeled rock fragmentation in mine No.1 of Golegohar using Fuzzy logic [5]. Gheibie et al. modeled rock fragmentation in Songun copper mine, Iran based on geomechanical characteristics [6]. Chakraborty et al. and Hudaverdi et al. used multiple regression method to model rock fragmentation [7,8]. Faramarzi et al. proposed an engineering systems technique to predict rock fragmentation [9]. Dindarloo used genetic programming and support vector machines to optimize blasting in Golegohar mine, Iran [10,11]. In this study, the amount of boulder, with respect to blast pattern volume, is predicted based on 8 different effective factors on the operation. Results of 33 blasts were collected and a database was constructed, covering all specified parameters.

2. Case study

Golegohar iron ore complex is located in southern Iran which is a large producer of iron ore in the region. The mining method is open pit. Mine No.1 has a production elliptical pit with dimensions 800 m × 3000 m (Fig. 1). There are 26 benches with 15 m heights. The overall pit slope is between 30 and 40 degrees in different azimuths. Frequently, large amount of boulders are produced as a consequence of under-optimal blast practices in this mine (Fig. 2).

3. Data collection

Results of 33 blasts in Golegohar mine No.1 were used to make a database for the study. Burden, spacing, bench height to burden ratio, stemming, specific charge, uniaxial compressive strength of

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Fig. 1. Golegohar's pit No. 1.

Fig. 2. Over-sized rocks (boulders) in a typical Golegohar's blast operation.

the intact rock, rock density, and joints spacing were the eight independent variables. The ratio of the resulting boulders (>1.5 m in size) to the volume of the blast pattern was set as the output (dependent variable). Descriptive statistics of the collected data are summarized in Table 1.

4. Regression analysis

The four main steps in a regression analysis are: (i) variables selection, (ii) data collection, (iii) model fitting, and (iv) validation.

4.1. Linear regression model

In a linear regression model, the output(s) might be modeled as a function of one or more independent variables. In this study, linear multiple variable regressions were applied on results of 25 datasets (out of the total of 33 collected datasets). The remaining randomly selected 8 datasets were used in model validation. V_B/V_p was predicted based on the specified 8 independent variables (Table 1) with SPSS software (Eq. (1)).

Table 1
Descriptive statistics of collected data.

No.	Parameter	Symbol	Min	Max	Mean	Standard deviation
1	Burden (m)	B	3.83	5.88	4.81	0.68
2	Spacing (m)	S	4.37	7.11	6.14	0.91
3	Height-burden ratio	H/B	2.04	4.44	3.40	0.62
4	Stemming (m)	S_T	3.86	7.95	5.19	0.79
5	Specific powder (kg/t)	PF	0.21	0.47	0.32	0.07
6	Uniaxial compressive strength (MPa)	UCS	35.0	130	86.8	29.7
7	Rock density (t/m^3)	Den	2.70	4.50	3.74	0.67
8	Joints spacing (m)	SJ	5.00	75.0	33.0	18.3
9	Boulder to pattern ratio (%)	V_B/V_P	1.12	3.16	2.21	0.62

$$V_B/V_P = -0.829 + 0.226(B) + 0.066(S) - 0.149(H/B) + 0.002(ST) + 0.244(PF) + 0.011(SJ) + 0.103(Den) + 0.014(UCS) \quad (1)$$

For validation of the proposed linear regression function; errors independence, errors normality, and linearity of independent variables were analyzed. Errors independence was evaluated using Durbin–Watson test [12]. If the linearity between variables is high, model might not be valid even if it has a high coefficient of determination value. This issue can be addressed by controlling the variance inflation factor (VIF) and tolerance [13]. The Table 2 shows that there is no linearity between the variables. Furthermore, frequency distribution of errors and variances are illustrated in Figs. 3 and 4.

Error distributions are roughly normal (Fig. 4). Standard deviation is nearly equal to one. Residuals are scattered around a horizontal line (Fig. 3) which is acceptable. Table 3 shows regression statistics and analysis of variance.

From Table 3, F value is 17.302 which is acceptable for $p < 0.0001$. In addition to the above linear regression model, several nonlinear models were tested for the dataset. Coefficient of determination, root mean square error (RMSE), value account for (VAF), and mean absolute percentage error (MAPE) were calculated from Eqs. (2)–(5), respectively.

$$R^2 = 100\left[\frac{\left(\sum_{i=1}^{N}(y_{meas}-\bar{y}_{meas})(y_{pred}-\bar{y}_{pred})\right)^2}{\sqrt{\sum_{i=1}^{N}(y_{meas}-\bar{y}_{meas})^2\sum_{i=1}^{N}(y_{pred}-\bar{y}_{pred})^2}}\right] \quad (2)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_{meas}-y_{pred})^2} \quad (3)$$

$$VAF = 100\left[1-\frac{\mathrm{var}(y_{meas}-y_{pred})}{\mathrm{var}(y_{meas})}\right] \quad (4)$$

Table 2
Regression coefficients and variables co-linearity.

Independent variables	Unstandardized coefficients		Standardized coefficients	t values	Collinearity statistics	
	B	Standard error	Beta		Tolerance	VIF
Constant	−0.829	1.569		−0.529		
B	0.226	0.152	0.219	1.487	0.298	3.354
S	0.066	0.160	0.097	0.415	0.118	8.467
H/B	0.149	0.161	−0.149	−0.926	0.250	4.004
S_T	0.002	0.129	0.005	0.019	0.120	8.338
PF	0.244	0.972	0.026	0.251	0.603	1.658
S_J	0.011	0.004	0.327	2.661	0.429	2.331
Den	0.103	0.112	0.112	0.915	0.431	2.321
UCS	0.014	0.003	0.672	4.246	0.259	3.865