Journal of Mining and Environment (JME) Vol. 17, No. 3, 2026, 1051-1064

Shahrood University of Technology

Journal of Mining and Environment (JME)

Journal homepage: www.jme.shahroodut.ac.ir

Iranian Society of Mining Engineering (IRSME)

The Optimization of Statistical Models for Predicting Blast-induced Back-break in Mining using the Firefly Algorithm: A Case Study

Abbas Khajouei Sirjani[1*], Ruqyah Heydari[1], Ramin Rafiee[1], and Mohammad Amiri Hosseini[2]

1. Faculty of Mining, Petroleum & Geophysics Eng., Shahrood University of Technology, Shahrood, Iran
2. Department of Mining and Geology of Research and Technology Management of Gol-e-Gohar, Sirjan, Iran

Article Info

Received 1 February 2025

Received in Revised form 15 April 2025

Accepted 4 May 2025

Published online 4 May 2025

DOI: 10.22044/jme.2025.15683.3014

Keywords

Blasting

Back-break

Gol-e-Gohar mine

Multiple regression

Firefly algorithm

Abstract

In open-pit mining blasting operations, one of the most critical parameters that must be continuously and precisely monitored and evaluated is the extent of back-break caused by the blasts. This phenomenon can lead to mine wall instability, collapse of mining equipment, increased dilution rates, and disruption in drilling and charging operations in subsequent stages. The objective of this research is to predict and optimize back-break by combining statistical models with the Firefly Algorithm (FA). For this purpose, a database comprising data from 28 blasts in the waste rock section of Gol-e-Gohar Iron Ore Mine No. 1 was compiled. After data collection, the input parameters, including blast hole length, burden, spacing, Stemming, charge per delay, and Number of holes in the last row, were identified and utilized in the modeling process. To predict back-break, modeling was performed using multiple regression analysis. Among the developed models, the Polynomial statistical model with non-integer coefficients model with an adjusted coefficient of determination 0.885 was identified as the best-performing model and was subsequently used as the objective function in the Firefly Algorithm. The optimization process was then carried out using this algorithm. According to the findings of this research, the implementation of the current operational patterns in the mine along with the optimized proposed patterns resulted in a reduction of 4 meters in the average back-break, decreasing it from 7.5 meters in the waste rock section. The results demonstrate that the Firefly Algorithm is a highly effective and reliable tool for model optimization and a more accurate reduction of back-breaks. This approach has the potential to significantly enhance the efficiency of mining operations and reduce operational costs.

1. Introduction

Blasting operations are considered as one of the primary processes in surface mining, and are widely used in the extraction of mineral resources. However, mines that rely on blasting for extraction often face challenges such as back-break. gol-e-gohar iron ore mine No. 1 in Sirjan is no exception, where one of the major issues during blasting operations is the occurrence of back-break. Back-break refers to the zone located behind the final row of blast holes, which undergoes unintended fracturing and displacement due to the excessive propagation of cracks and fractures induced by shock waves and explosive gases. This affected area typically extends beyond the designed excavation limit. As a consequence, back-break leads to several operational challenges including the instability of mine walls, potential collapse of machinery, inadequate rock fragmentation, and a reduction in the overall efficiency of drilling and blasting operations [1, 2]. Back-break samples that occurred at gol-e-gohar iron ore mine No. 1 are shown in Figure 1. To control any phenomenon, the first step is to thoroughly understand its underlying mechanisms and the factors influencing its occurrence. Accordingly, numerous studies have been conducted by researchers to identify the

Corresponding author: abbas3457@gmail.com (A. Khajouei Sirjani)

parameters that can impact back-break. The findings of these studies indicate that various factors contribute to the occurrence of back-break. These factors can be broadly classified into three main categories: 1) Geometric parameters related to the design of the blasting pattern, 2) Properties of the explosive materials, and 3) Characteristics of the rock mass and its discontinuities. The mentioned studies emphasize the importance of analyzing and optimizing these factors to mitigate back-break phenomena, providing a foundation for improving blasting performance. In the first and second groups, Konya and Walter demonstrated that a high stiffness ratio reduces back-break. Furthermore, increasing the stemming thickness and the length of the stemming column leads to an increase in back-break [3]. Gate et al. stated that insufficient delay time between rows is the primary cause of back-break. They also found that increasing the number of blast rows results in a higher degree of back-break [1]. Subsequently, Aghajani and his colleagues employed a controlled pre-split blasting technique with large-diameter blast holes to reduce back-break in the Sarcheshmeh copper mine. Similarly, Singh and his team used controlled blasting methods in an open-pit mine in India to mitigate back-break [4, 5]. Bhandari, in his investigations, showed that reducing the borehole pressure lowers the extent of back-break-induced damage. Wilson and Moxon conducted experiments revealing that a mixture of salt and sawdust reduces the strength of ANFO explosives [6, 7]. Similarly, Iverson et al. evaluated the blast damage range caused by fully coupled explosive charges, and demonstrated that reducing charge coupling can decrease the extent of back-break [8]. In the third group, Bhandari stated that homogeneous rocks with high compressive and tensile strength are less likely to break around blast holes compared to rocks with lower strength. Additionally, closed or filled discontinuities result in less back-break compared to open discontinuities. Jia and his team utilized numerical modeling, and concluded that fractures with a dip angle greater than the friction angle can be considered one of the most significant factors contributing to back-break [9]. In the recent years, numerous researchers have developed models to predict back-break including multiple regression analysis [10, 11], artificial neural networks [12, 13], genetic programming [14], neuro-genetic methods [15, 16], and combinations of artificial neural networks with the bee colony algorithm and the ant colony algorithm [17, 18]. Table 1 presents the results of several recent studies along with an evaluation of their performance in predicting blast-induced fractures. In the present study, a logarithmic model and the firefly algorithm have been employed to predict back-break and optimize the effective parameters to minimize this phenomenon in blasting operations at Gol-e-Gohar Mine No. 1 in Sirjan.

Table 1. Some studies have predicted back break based on various models

Reference	Authors	Year	Inputs	Results
[19]	Kannavena et al	2024	B, S, ST, BH, NH, PF	This study investigates the prediction of back-break (BB) using feedforward neural networks (BPNN) and various machine learning (ML) methods including Decision Tree Regression (DTR) and Linear Regression (LR). The BPNN model was implemented in MATLAB, and its results were compared with those of DTR and LR models developed in Python. The BPNN demonstrated superior performance, achieving an R^2 value of 0.96, while the R^2 values for the DTR and LR models were 0.93 and 0.72, respectively. Additionally, the BPNN model outperformed the others with a prediction accuracy of 94%. This research highlights the high capability of neural networks in accurately predicting back-break and emphasizes that this approach offers more reliable and effective results compared to traditional machine learning techniques.
[20]	Sorabi et al.	2024	H, D, L, B, S, St, PF, De N, GSI,UCS, JC	In this study, various data-driven models were employed to predict the occurrence of back-break resulting from blasting activities at the gol-e-gohar iron ore mine. These models include Multivariate Linear Regression (MLR) and Computational Intelligence algorithms such as Whale Optimization Algorithm (WOA), MultiVerse Optimizer (MVO), Sine Cosine Algorithm (SCA), and Ant Lion Optimizer (ALO). The accuracy of these models was compared using statistical indices such as R^2, RMSE, MSE, VAF, and MAPE. The results indicated that the MVO algorithm performed the best in predicting back-break, with suitable values for both training and testing datasets, demonstrating its high accuracy. This algorithm showed R^2 = 0.9901, RMSE = 0.2161, MSE = 0.1127, VAF = 98.8472, and MAPE = 0.0180 for the training data, and R^2 = 0.6357, RMSE =

Reference	Authors	Year	Inputs	Results
				1.4955, MSE = 1.2003, VAF = 63.5472, and MAPE = 0.1951 for the testing data, making it the superior model.The results also revealed that the blast hole spacing, burden, and Geomechanical Strength Index (GSI) have the most significant impact on the back-break phenomenon, while the powder factor, delay time, and joint condition have a lesser effect on this phenomenon.
[21]	Nabavi et al	2023	B, S, ST, D H, PF, N-R	In this study, a hybrid model based on Xtreme Gradient Boosting (XGB) is introduced for predicting back-break using Gray Wolf Optimization (GWO) and Particle Swarm Optimization (PSO). Additionally, the hybrid model's validation is performed by comparing it with various methods such as XGBoost, Gene Expression Programming (GEP), Random Forest (RF), Linear Multiple Regression (LMR), and Non-Linear Multiple Regression (NLMR). The results demonstrate that the hybrid models GWO-XGB (with R^2 = 99, RMSE = 0.01, MAE = 0.001, VAF = 0.99, α-20 = 0.98) and PSO-XGB (with values of 99, 0.01, 0.001, 0.99, and 0.98) significantly outperform other models, including XGBoost (with values of 97, 0.185, 0.132, 0.98, and 95), GEP (with values of 96, 0.233, 0.186, 0.967, and 0.935), RF (with values of 97, 0.210, 0.156, 0.97, and 0.94), LMR (with values of 96, 0.235, 0.181, 0.964, and 0.92), and NLMR (with values of 96, 0.229, 0.177, 0.968, and 0.93). Notably, the GWO-XGB hybrid model exhibits a significant overall performance advantage over the PSO-XGB model.
[22]	Sirjani et al	2022	H, B, S, PF N-H, UCS	In this study, a multi-layer perceptron artificial neural network (MLP-ANN) with a 6-12-1 architecture, along with six multi-variate statistical models (both linear and nonlinear), was employed to predict the phenomenon of back-break in blasting operations. The findings revealed that the artificial neural network model, with a coefficient of determination (R^2 = 0.798,$R^{\wedge 2}$ = 0.798) and error metrics including MAD (0.79), MSE (0.93), RMSE (0.97), and MAPE (11.63), demonstrated superior predictive accuracy and lower error rates compared to the statistical models.
[23]	Li et al	2022	SD, S, B, H ST, PF	In this study, six Swarm Intelligence Optimization (SIO) algorithms (ELM-PSO, ELM-FOA, ELM-WOA, ELM-LOA, ELM-SOA, ELM-SSA) were employed for Back-Break (BB) prediction, integrated with a deep learning model. The results indicated that the ELM-LSO model exhibited the best performance in predicting back-break compared to the other ELM-SIO hybrid models (ELM-PSO, ELM-FOA, ELM-WOA, ELM-SOA, and ELM-SSA). For the ELM-LSO model, during the training phase, the RMSE was 0.1129 (R: 0.9991, R^2: 0.9981, VAF: 99.8135%, MAE: 0.0706, and SSE: 2.0917), while in the testing phase, the RMSE was 0.2441 (R: 0.9949, R^2: 0.9891, VAF: 98.9806%, MAE: 0.1669, and SSE: 4.1710). Therefore, the application of swarm intelligence optimization (SIO) algorithms proves to be a highly effective solution in enhancing the performance of the ELM model.
[24]	Zhou et al	2021	H, B, S, ST SD, PF	This study developed two Hybrid RF models (HHO-RF and SCA-RF) alongside three classical models for predicting back-break. The performance of these models was evaluated using the metrics MAE, RMSE, VAF, and R^2. The hybrid RF models, particularly the SCA-RF model, demonstrated exceptional performance in back-break prediction. For the training dataset, the model achieved an MAE of 0.0444, RMSE of 0.0816, VAF of 96.82, and R^2 of 0.9876. For the testing dataset, the corresponding values were MAE = 0.0470, RMSE = 0.0996, VAF = 95.88, and R^2 = 0.9829. The results indicate that the hybrid RF models outperformed the non-optimized classical models.
[25]	Saghatforoush et al	2016	B, S, H, ST PF	This study used an Artificial Neural Network (ANN) to predict rock throw and back-break based on 97 blasts at the Delkan Iron Ore Mine. The ANN achieved high accuracy with Ea = 0.0137 and RMSE = 0.063. A novel Ant Colony Optimization (ACO) reduced rock throw by 61% and back-break by 58%.
[26]	Hassanpanah et al	2017	B, S, ST, PF	The study compared the MLR regression model and other methods. Using correlation coefficients, the PSO-ANFIS hybrid model showed stronger predictive potential with R = 0.922, outperforming regression (R = 0.857).
[27]	Shirani et al.	2016	B, S, ST, PF SR	Used GP (genetic programming) for back-break prediction in Sungun Copper Mine. GP outperformed Non-Linear Multiple

Reference	Authors	Year	Inputs	Results
				Regression (NLMR): GP: RMSE = 0.327, VAF = 97.65% vs. NLMR: RMSE = 0.865, VAF = 81.816%.
[28]	Sari et al.	2014	B, S, ST, PF SR	Developed a site-specific empirical Equation for back-break prediction using multiple regression. Monte Carlo simulation demonstrated effectiveness in modeling the impact of blast parameter variability on back-break.
[29]	Mohammadnejad et al	2013	B, S, H, SD ST, PF	This study used the SVM system to predict back-break, and compared its performance with multiple variable regression analysis (MVRA). To evaluate the models, the coefficient of determination (R^2) and Mean Absolute Error (MAE) were utilized. The results revealed that the SVM model (R^2 = 0.987, MAE = 0.29) outperformed the MVRA model (R^2 = 0.89, MAE = 1.07) for back-break prediction.
[30]	Faramarzi et al	2013	B, Q, PF, S ST, N-R, D-T, RMR, B-S, D, H-A B/D	A new model based on Rock Engineering Systems (RESs) to predict and evaluate back-break. RES performance: R = 0.8, RMSE = 1.07. Back-break risk index over 60 correlates to a back-break > 9.25 m, while an index < 40 shows a back-break < 4 m.

Burden (B), Spacing(S), Stemming(ST), Powder Factor (PF), bench height (BH), Hole length (H), Hole diameter(D) Number of holes(N-H), Number of rows (N-R), Specific drilling (SD), uniaxial compressive strength (UCS) Stiffness ratio(SR), charge per delay (Q), delay time (D-T), RMR, bench slope (B-S), D, hole angle (H-A), burden-to-hole diameter ratio (B/D), Geological Gndex (GSI), Joint Condition (JC)

2. Case Study

The Gol-Gohar mining region is located approximately 50 kilometers southwest of Sirjan city in Kerman Province. Structurally, this mining area is situated on the margin of the Sanandaj-Sirjan zone, according to the tectonic zoning of Iran. The primary faults in the region are predominantly reverse, while the Quaternary faults are all normal and active, exhibiting displacements ranging from a few centimeters to several meters. Figure 2 illustrates the faults identified within the boundaries of mine No. 1. A preliminary analysis of this figure reveals that most faults in this area trend from NW-SE to E-W, with a few exhibiting an N-S orientation. All faults display steep dip angles (greater than 60 degrees). The final pit of the mine is designed as an ellipse with approximate dimensions of 2,900 meters by 700 meters, incorporating 31 benches, each with a height of 15 meters. The overall slope angle of the pit walls ranges between 38 and 45 degrees, and the access ramps to the mine are designed with an 8% gradient and a width of 25 meters. The safety benches are designed to be 10 meters wide, with one safety bench remaining in the final pit wall for every two benches (equivalent to 30 meters in height). The elevation of the highest point of the mine is 1,755 meters, while the lowest point in the final design is at an elevation of 1,290 meters (Figure 3).

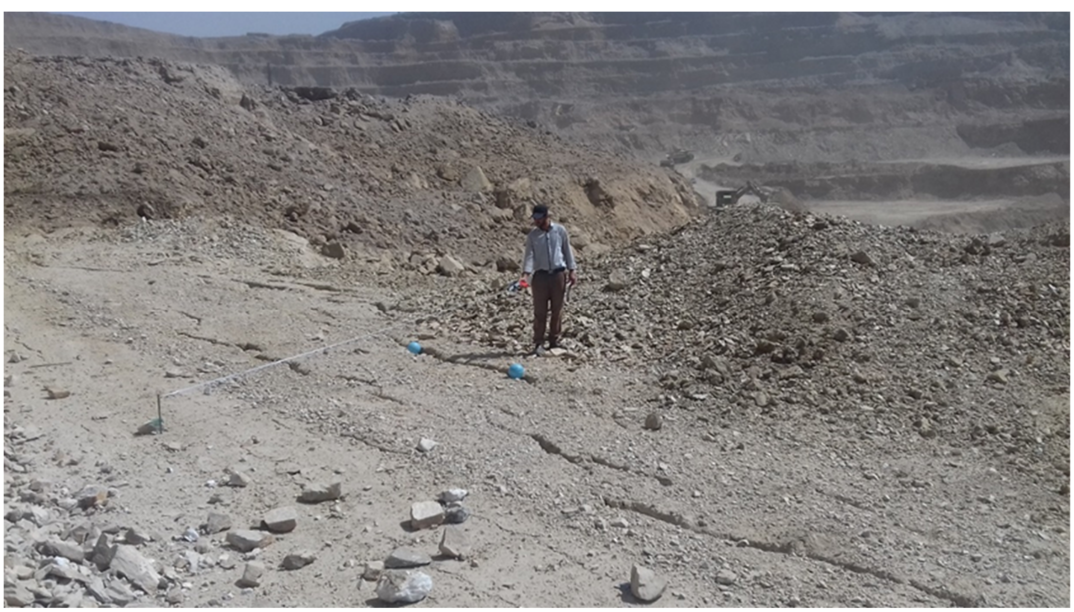


Figure 1. Back-break that resulted from blasting operations at Gol-e-Gohar Mine No. 1

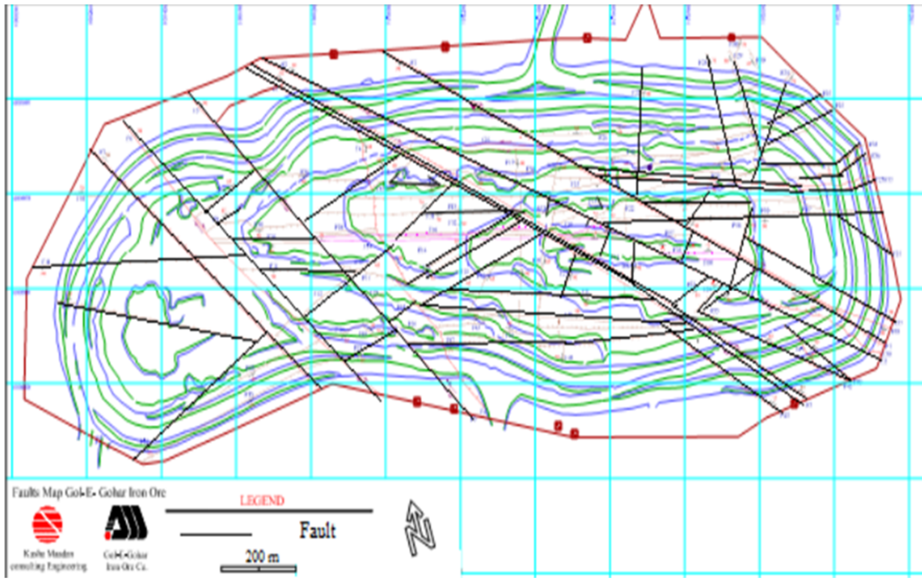


Figure 2. Faults in the Area of Gol-e-Gohar mine No. 1

Figure 3. A view of the overall pit of Gol-e-Gohar mine No. 1

3. Data Collection

For this work, a comprehensive database comprising key parameters from 28 blasting operations conducted in the Gol-Gohar mine was compiled. After collecting the raw data, descriptive statistics were initially employed to organize and prepare the data for analysis, as shown in Table 2.

To accurately predict back-break, the correlation between the main research variables was first examined using the Pearson correlation coefficient. This coefficient measures the strength and direction (positive or negative) of the linear relationship between variables, with values ranging from -1 to +1. The Pearson correlation coefficient can be calculated using Equation 1:

$$\boldsymbol{COrr(y,x)} = \frac{\sum(\boldsymbol{y_i}-\bar{\boldsymbol{y}})\,(\boldsymbol{x_i}-\bar{\boldsymbol{x}})}{\sqrt{\sum_{(y_i-\bar{y})}\mathbf{2}\ \sum_{(x_i-\bar{x})}\mathbf{2}}} \qquad (1)$$

where:

$y_i-\bar{y}$: Deviation of each y_i value from the mean of variable y.

$x_i-\bar{x}$: Deviation of each x_i value from the mean of variable x.

After conducting the Pearson correlation analysis on the collected variables, Table 3 presents the correlation matrix for key parameters such as borehole length, burden, spacing, stemming, charge per delay, and number of holes in the last row, which were selected as the main input variables for back-break prediction. Although several factors influence the occurrence of back-break, the selection of input variables in this study was purposefully focused. Only the aforementioned parameters were utilized for model development, while other factors, such as rock mass properties and explosive types, powder factor, and number of blasting rows, were excluded due to their lesser impact. additionally, blast hole diameter and delay time between blasting rows, which were fixed at 0.254 meters and 65 milliseconds, respectively, across all blasting stages, were not considered input variables. In Figure 4, the location of some blasting patterns where back-break occurred is illustrated.

Table 2. Descriptive Statistics of the collected data

T	Symbol	Minimum	Maximum	Mean	Standard Deviation
Bench height (m)	H	10	18	14.39	1.85
Burden (m)	B	2.5	7	4.85	1.17
Spacing (m)	S	3.5	9.5	6.38	1.64
STemming (ST)	ST	3	6	4.52	0.74
Charge per delay (kg)	Q	4000	27000	14369.23	6254.7
Number of holes in the last row	NOH	6	26	12.26	4.33
Back-break (m)	BB	3.8	11.2	7.17	1.80

Table 3. Matrix of Pearson correlation coefficients for geometric parameters of blast patterns

Variables	H	B	S	ST	ST	Q	NOH	BB
Bench height	1							
Burden	0.605	1						
Spacing	0.624	0.93	1					
Stemming	0.87	0.616	0.642	1	1			
Charge per delay	0.401	0.56	0.534	0.507	0.507	1		
Number of holes in the last row	0.56	0.514	0.595	0.554	0.554	0.466	1	
Back-break	0.752	0.658	0.718	0.796	0.796	0.6	0.654	1

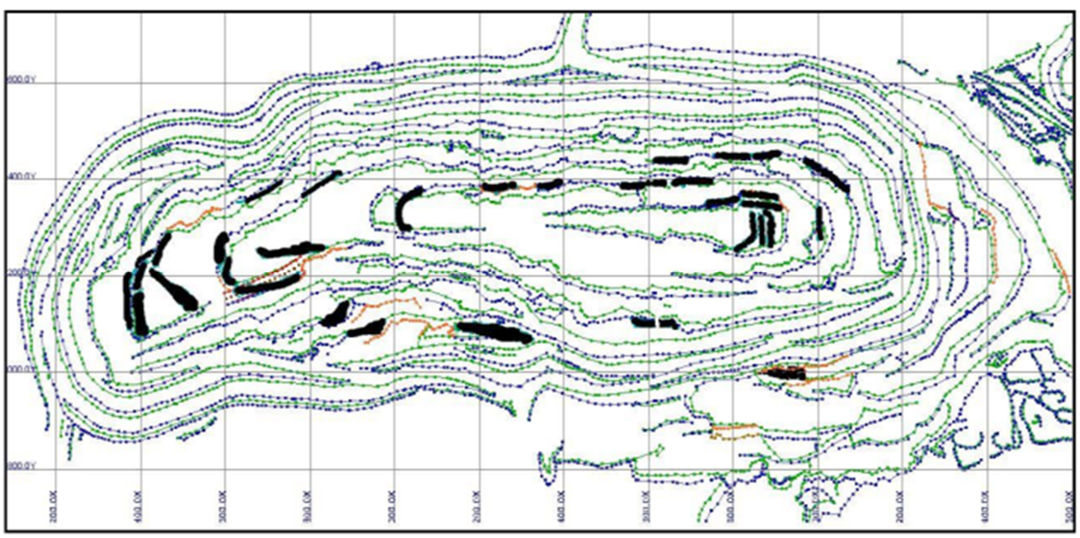


Figure 4. The locations of some blast patterns where the back-break phenomenon has occurred

4. Methodology
4.1. Statistical models

Various statistical models have become key tools in solving engineering problems across different fields due to their high interpretability and ability to generalize effectively. Linear and nonlinear multiple regression models effectively analyze the influence of various independent variables on a dependent variable [22, 31].

4.2. Modeling and predicting back-break using statistical models

The study aims to develop multi-variable linear and non-linear statistical models for predicting the back-break phenomenon and selecting the best model to optimize the blast pattern using SPSS27 software. To construct the models, 70% of the data was randomly selected for model training, and the remaining 30% was used for model evaluation. The statistical models, including linear regression, polynomial regression with integer coefficients, polynomial regression with non-integer coefficients, and exponential, and logarithmic models, were designed to the mentioned models are listed in Table 4 predict back-break based on Equations (2 to 6).

Table 4. The relationships between the developed models

Model	Equation	
L R	$BB = [-1.762 + 0.177(H) - 0.313\ (B) + 0.422\ (S) + 0.803\ (ST) + 5.628E - 5\ (Q) + 0.063\ (NOH)]$	(2)
P(Z)	$BB = [2.788 + 0.159(H)^1 - 0.013\ (B)^2 + 0.003\ (S)^3 + 0.003\ (ST)^4 + 5.859\ E - 23\ (Q)^5 - 8.879E - 10(NOH)^6]$	(3)
PSM-NIC	$BB = [-55.363 + 2.852E - 6(H)^{4.529} - 23.796(B)^{0.057} + 17.523(S)^{0.118} + 0.00015(ST)^{5.478} + 0.123(Q)^{0.288} + 60.66(NOH)^{0.019}]$	(4)
Log	$BB = [-14.117 + 1.855 \ln(H) - 1.692 ln(B) + 2.704 \ln(s) + 3.239 \ln(ST) + 0.634 ln(Q) + 1.313 ln(NOH)]$	(5)
Exp	$BB = EXP\ [-1.464 + 1.623\ (H)^{0.077} - 0.006\ (B)^{1.822} + 0.242\ (S)^{0.575} + 0.087\ (ST)^{1.279} + 1.37(Q)^{-0.633} + 0.053(NOH)^{0.591}]$	(6)

Linear Regression (LR), Polynomial with Integer Coefficients (P(Z)), Polynomial statistical model with Non-Integer coefficients (PSM-NIC), Logarithmic (Log), Exponential (EXP).

5. Evaluation of PPV Prediction Models

To evaluate and compare the models during the training and testing phases, various statistical metrics were utilized. These metrics include the Coefficient of Determination (R^2) based on Equation (7), the Root Mean Square Error (RMSE) as defined by Equation (8), and the Mean Absolute Percentage Error (MAPE) according to Equation (9). In these equations, Y_{meas} and Y_{pred} represent the observed and predicted values, respectively, while $\overline{Y}_{meas}$ and $\overline{Y}_{pred}$ denote the mean of the observed and predicted values. Furthermore, n refers to the total number of data points.

$$R^2 = 100\left[\frac{\sum_{i=1}^{N}(Y_{meas} - \overline{Y}_{meas})(Y_{pred} - \overline{Y}_{Pred})}{\sqrt{\sum_{i=1}^{N}(Y_{meas} - \overline{Y}_{meas})^2\ (\sum_{i=1}^{N} Y_{pred} - \overline{Y}_{pred})^2}}\right] \quad (7)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(Y_{meas} - Y_{pred}\right)^2}{n}} \quad (8)$$

$$MAPE = \frac{\sum_{i=1}^{n}\frac{\left|Y_{meas} - Y_{pred}\right|}{Y_{meas}}}{n} \times 100 \quad (9)$$

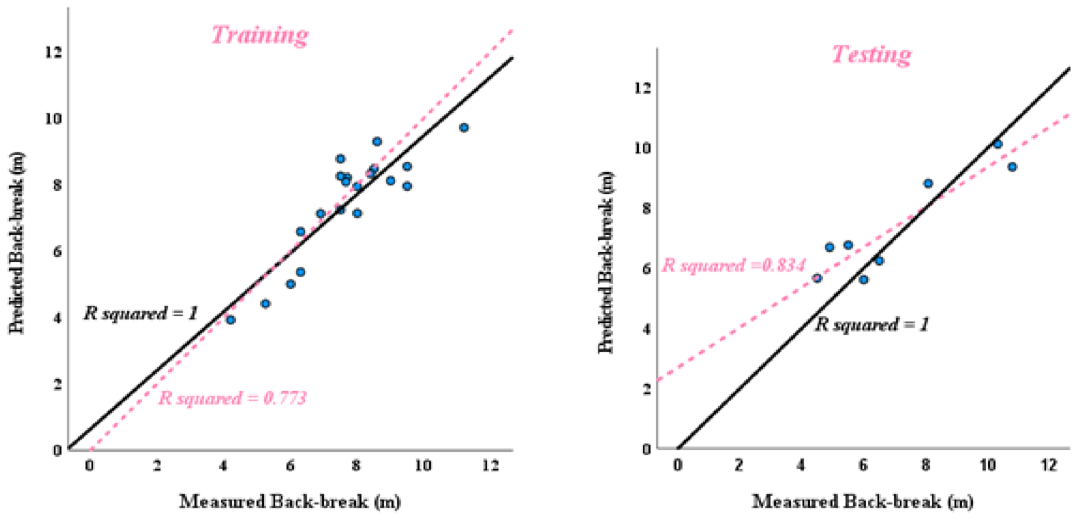
6. Evaluation of Statistical Models in Predicting Back-break

In this research, back-break prediction was conducted using multivariate linear and nonlinear statistical models. To assess the accuracy and effectiveness of the models and identify the most suitable model for optimizing blast designs to minimize back-break, equations (7 to 9) were utilized. Table 5 presents the evaluation metrics of the models during the training and testing phases. According to the results summarized in this table, the Polynomial statistical model with non-integer coefficients model achieved the highest accuracy. the analysis based on the coefficient of determination across both training and testing stages, as depicted in Figure 5, highlights the superior performance of the Polynomial statistical model with non-integer coefficients statistical model compared to the other statistical approaches.

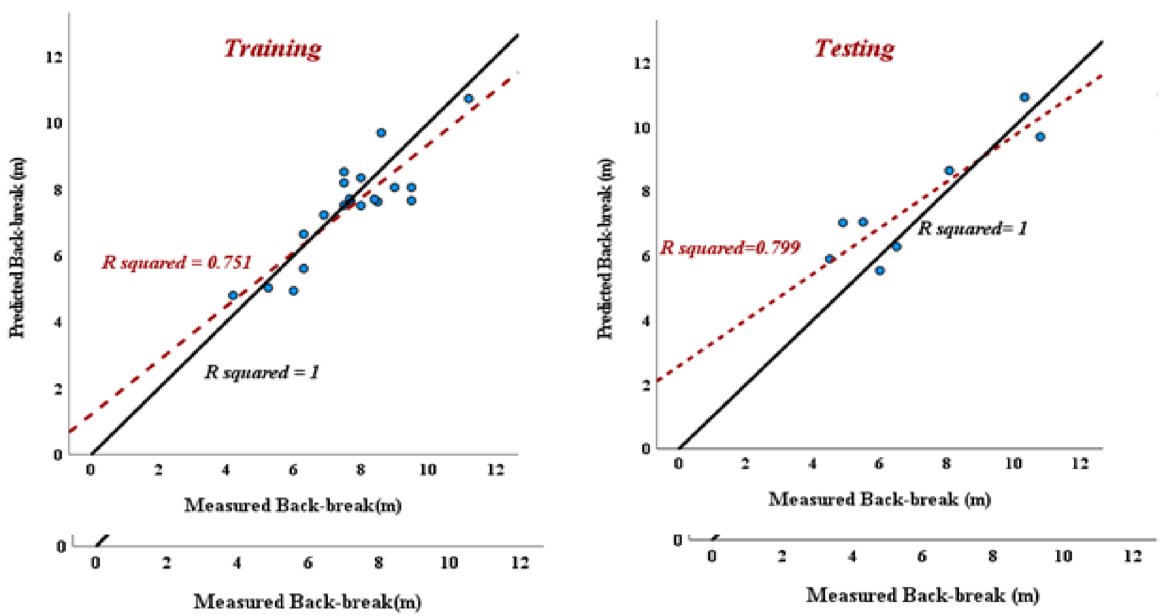
Table 5. Evaluation indicators of statistical models' performance in training and testing phases

NO	Model	Training			Testing		
		R^2	RMSE	MAPE	R^2	RMSE	MAPE
1	L R	0.772	0.808	8.748	0.834	1.064	15.043
2	P(Z)	0.751	0.812	8.662	0.799	1.175	17.108
3	**PSM-NIC**	**0.798**	**0.741**	**7.355**	**0.887**	**0.868**	**12.124**
4	Log	0.751	0.864	9.705	0.878	1.011	13.721
5	Exp	0.774	0.780	7.816	0.837	1.086	14.987

Linear Regression (LR), Polynomial with Integer Coefficients (P(Z)), Polynomial Statistical Model with Non-Integer Coefficients (PSM-NIC), Logarithmic (Log), Exponential (EXP).

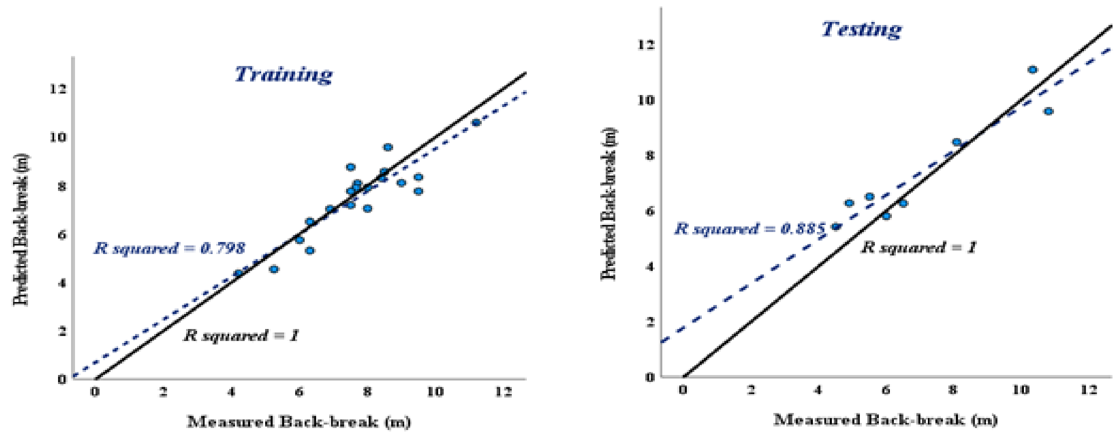


(a) Linear statistical model

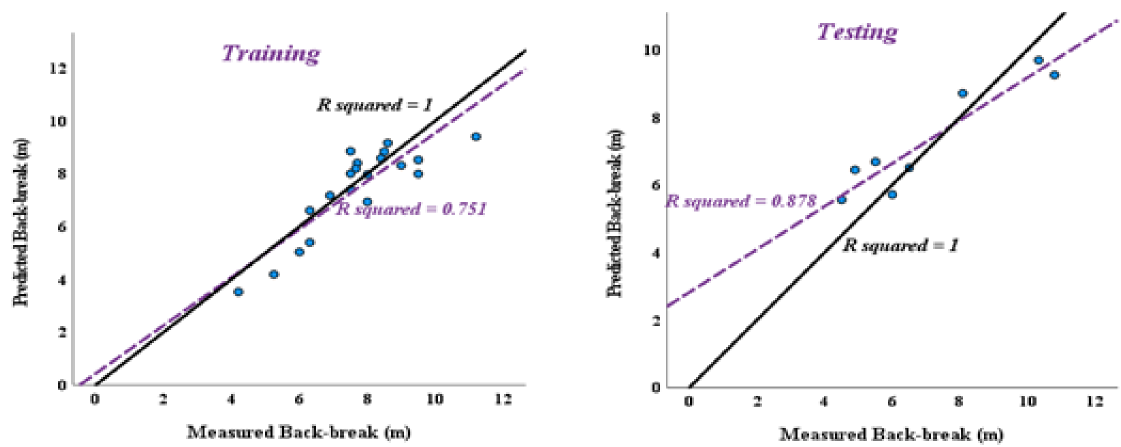


(b) Polynomial statistical model with integer coefficients

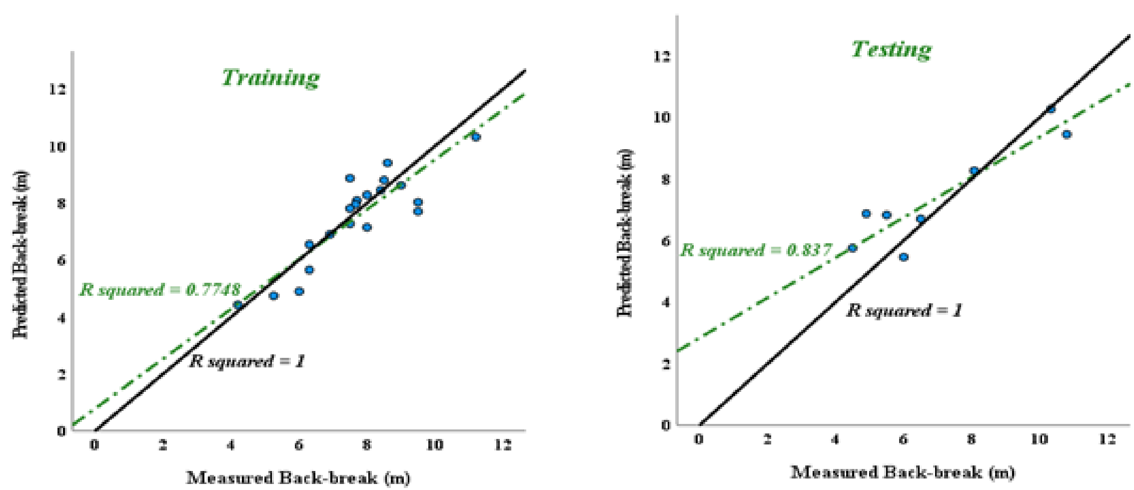
Figure 5. Measured and predicted back-break values for the training and testing datasets



(c) Polynomial statistical model with non-integer coefficients



(d) Exponential statistical model



(e) logarithmic statistical model

Figure 5. Cont.

7. Firefly Algorithm

The Firefly Algorithm is an optimization method recently developed by Yang at the University of Cambridge. This algorithm is inspired by the social behaviors of fireflies. The Firefly Algorithm is depicted in Figure 6. In this algorithm, the search process is based on the light intensity (I) of the fireflies, with all fireflies being attracted to those with greater luminosity. Initially, the number of fireflies (n), as well as the values of β0 (initial attractiveness), γ (attraction constant), α (a parameter influencing the number of iterations), the maximum number of generations (k), and the objective function f(x), must be determined. In the second step, a loop is defined to assess and compare light intensities based on the attractiveness value β0 Consequently, n fireflies repeatedly solve the optimization problem. $X_{i,k}$ represents the position of the i-th firefly at the k-th generation iteration, and its corresponding objective function value is f $(X_{i,k})$. Each firefly has a specific value, β, which represents its attractiveness and describes its ability to attract other fireflies [32, 33]. To establish a relationship for β, a function of the distance between two members (r_j = X_i- X_j) must be defined, which is inversely proportional to r. Yang provided the following exponential function for β (10 relation):

$$\boldsymbol{\beta = \beta_0 e^{-\gamma r^2}} \tag{10}$$

In this equation, β0 and γ are predefined components in the algorithm, representing the maximum attractiveness value and the attraction coefficient, respectively. Each firefly in the group is described by its light intensity and the parameter li, which is inversely related to the function f $(X_{i,k})$. Initially, all fireflies are randomly distributed in the search space S. For an effective search in the search space S, it is assumed that each particle i continuously changes its position, and all particles move towards the one with higher light intensity. If no brighter firefly is found, the next movement of the particle will be random. This algorithm incorporates three components: α, β, and γ, which control the position of each firefly: The maximum attractiveness value (β0) lies within the range [0, 1] and indicates the attractiveness when r = 0. The attraction coefficient (γ) controls the changes in attractiveness as the distance between two related members increases. When γ → 0, there is no change, implying that it remains constant. Conversely, when γ → ∞, the search becomes completely random within the solution space. According to Yang's studies, the performance of this algorithm has been evaluated on a set of 14 continuous optimization problems. All problems were tested with a fixed number of iterations, and the results showed that the best value for α is 0.01, which provides the best performance.The algorithm follows three general rules: All fireflies are of the same gender. Therefore, they are attracted to a firefly with a higher light intensity. The attractiveness of each member is a function of its light intensity, and the farther a firefly is from the others, the lower its light intensity becomes. If no brighter firefly is found, the movement will be entirely random. The light intensity of each member is determined by the objective function value, and this intensity is proportional to the objective function's value.

The distance between two members i and j, located at positions X_i and X_j, is calculated according to 11 equations:

$$\boldsymbol{r_{ij} = \|X_i - X_i\|} \tag{11}$$

The new position of each member i is determined using the 12 relations.

$$\boldsymbol{X_i^{t+1} = X_i^t + \beta_0 e^{-\gamma r^2}\left(X_j^t - X_i^t\right) + \alpha\varepsilon} \tag{12}$$

For most cases, ε∈[0,1] and β0 = 1, and the attraction coefficient γ∈ [0,1] varies. X_i^t represents the current position of the i-th firefly, the second part of the equation represents the light intensity, and the third part describes the random movement of the firefly i. The value of α is between 0 and 1, and ε represents a vector containing a random number generated from Gaussian functions.

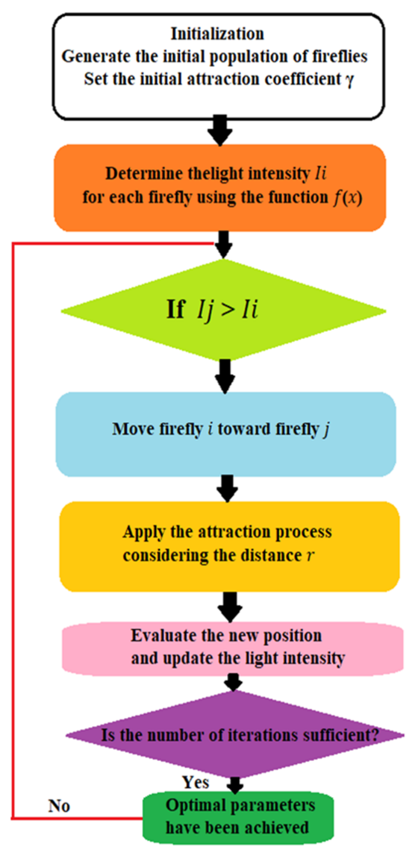


Figure 6. Flowchart of the firefly algorithm

8. Optimization of Most Accurate Statistical Model for Predicting Backlash using Firefly Algorithm

To optimize the blast pattern for minimizing back-break in the Gol-e-Gohar iron ore mine using the Firefly Algorithm, defining an objective function is essential. In this regard, statistical models are utilized to formulate the objective function. Generally, statistical indicators are responsible for analyzing and evaluating the objective function, with the primary goal of providing an appropriate model for process optimization. Once the objective function is defined within the Firefly Algorithm, the optimization process begins. The Firefly Algorithm includes a set of control parameters that influence the optimization process, which can be adjusted to modify its behavior. Ultimately, after 30 program executions and 100 iterations per execution, the final values of these parameters and the optimized blast pattern are obtained, as illustrated in Tables 5 and 6. As shown in Table 4, the number of fireflies (npop) represents the number of blast patterns collected during the research. Following the determination of the control parameters for the Firefly Algorithm, the optimization process was performed over 100 iterations to minimize back-break. Figure 7 illustrates the convergence of the optimal solution achieved by the Firefly Algorithm. The best objective function result is observed after 100 iterations, with the optimal blast pattern achieving the best outcome in the 6th iteration, where the back-break value was reduced to 3.5 meters.

Table 5. Parameters used in the firefly algorithm

Parameters	Symbol	Value
Maximum Number of Iterations	Maxit	100
Number of fireflies	Npop	28
Light absorption coefficient	γ	1
Attractiveness at Zero Distance	β	0.7
Convergence Coefficient	α	0.2
Space Width	δ	0.02
Power of Absorption Coefficient	m	2

Table 6. The optimal explosion pattern obtained by the Firefly algorithm for back break optimization

No.		Symbol	Initial value		Optimized values
			Min.	Max.	
1	Bench Height (m)	H	10	18	16
2	Burden (m)	B	2.5	7	5
3	Spacing (m)	S	3.5	9.5	6
4	Stemming (m)	ST	3	6	4.5
5	charge per delay (kg)	Q	4000	27000	12000
6	Number of holes in the last row	NOH	6	26	10
7	Back Break (m)	BB	3.8	11.2	3.5

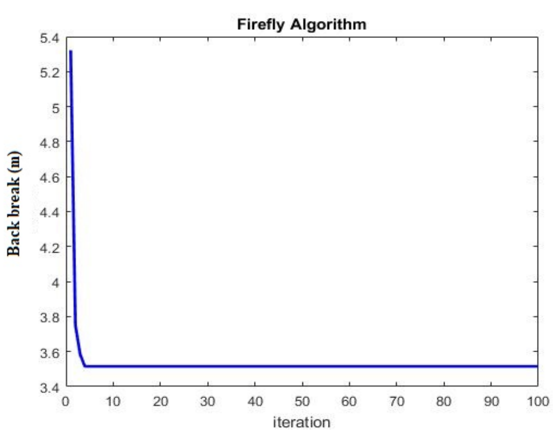


Figure 7. Convergence of the objective function results using the firefly algorithm for optimizing back break

9. Conclusions

In this work, the prediction and optimization of blast-induced back-break were investigated using various approaches, including multiple linear and non-linear regression as well as the Firefly Algorithm (FA) optimization technique. The primary objective was to assess the impact of different parameters on back-break in Mine No. 1 of the Gol-e-Gohar complex. To achieve this, a comprehensive database was compiled, incorporating real back-break occurrences and the key influencing parameters from 28 blasting events conducted at the mine. Initially, multiple regression analysis was employed to develop various empirical models for back-break prediction. Subsequently, the most suitable model was implemented within the Firefly Algorithm framework to refine the accuracy of the predictions. The following key findings were obtained:

1. Variable selection for modeling and prediction:

In the first phase, Pearson correlation analysis was performed to examine the relationships between the collected input variables, including (bench height, blast hole length, burden, spacing, stemming, total charge, specific charge, specific drilling, number of blast holes, number of blast rows, rock density, uniaxial compressive strength, joint spacing, , Number of holes in the last row and the Geological Strength Index). Based on the correlation strength and their influence on back-break, six key parameters (Bench height, Burden, Spacing, Stemming, charge per delay, and Number of holes in the last row were) selected as the primary input variables for modeling and optimization.

2. Optimization and model performance:

Among the developed empirical models, the (Polynomial statistical model with non-integer coefficients statistical model) was selected as the objective function for optimization using the Firefly Algorithm. This model demonstrated superior predictive performance compared to others, achieving a corrected coefficient of determination R^2 of 0.885 and an absolute mean percentage error of 12.124. These results indicate the model's high accuracy and suitability for practical application in Mine No. 1 of Gol-Gohar.

3. Proposed optimized blasting pattern:

The final optimized blasting design parameters were determined as follows:

- Bench height: 16 meters.
- Burden: 5 meters.
- Spacing: 6 meters.
- Stemming: 4.5 meters.
- Charge per delay: 12000 kg.
- Number of holes in the last row: 10.

Using this optimized pattern, the predicted back-break was 3.5 meters. This research highlights that hybrid regression and evolutionary optimization methods, such as the Firefly Algorithm, can provide more precise back-break predictions and significantly improve blast design optimization in mining operations.

References

[1]. Gate, Wc., Ortiz, BLT., & Florez, RM. (2005). Analysis of Rockfall and Blasting Back-break Problems. *Proceeding of the American rock mechanics conference, 5,* 671-80.

[2]. Moomivand, H., & Soltanalinejad, S. (2024). Development of a novel empirical approach to control overbreak, surface quality, and slope angle of benches following blasting. *Canadian Geotechnical Journal 62,*1-22.

[3]. Konya, CJ. (1991). Rock blasting and overbreak control. *1st ed. USA: National Highway Institute.*

[4]. Aghajani, A.B., Mansouri. H., Ebrahimi M.A.F., & Atash, A.P. (2006). Application of controlled blasting (pre-splitting) using large diameter holes in Sarcheshmeh Copper Mine. *In: Proceedings of the 8th International Symposium on Rock Fragmentation by Blasting,*388-392.

[5]. Singh, P.K., Roy, M.P., Joshi, A., & Joshi, V.P. (2009). Controlled blasting (pre-splitting) at an open-pit mine in India. *In: Proceedings of the 9th International Symposium on Rock Fragmentation by Blasting,* 481-489.

[6]. Bhandari, S. (1997). Engineering Rock Blasting Operations. *A.A.Balkema, Rotterdam.*

[7]. Wilson, J.M., & Moxon, N.T. (1988). The development of low energy ammonium nitratebased explosives. *In: Proceedings of the Australasian Institute of Mining and Metallurgy,* 27-32.

[8]. Iverson, S.R., Hustrulid, W.A., Johnson, J.C, Tesarik, D., & Akbarzadwh, Y. (2009). The extent of blast damage from a fully coupled explosive charge. *In: Proceedings of the 9th International Symposium on Rock Fragmentation by Blasting,*459-468.

[9]. Jia, Z., Chen, G., & Huang, S. (1998). Computer simulation of open pit bench blasting in jointed rock mass. *Int J Rock Mech Min Sci, 35,* 476-486.

[10]. Monjezi, M., Rezaei, M., & Yazdian, A. (2010) Prediction of back-break in open-pit blasting using fuzzy set theory. *Intell Syst Appl, 37,* 2637-2643.

[11]. Esmaeili, M., Osanloo, M., Rashidinejad,F., Aghajani Bazzazi, A., & Taji, M. (2014) Multiple regression, ANN and ANFIS models for prediction of backbreak in the open pit blasting. *Eng Comput, 30,* 549–558.

[12]. Monjezi, M., Ahmadi, Z., Yazdian Varjani, A., & Khandelwal, M. (2013). Backbreak prediction in the Chadormalu iron mine using artificial neural network. *Neural Comput Appl, 23,*1101–1107.

[13]. Monjezi, M., & Dehghani, H. (2008). Evaluation of effect of blasting pattern parameters on back break using neural networks. *Int J Rock Mech Min Sci, 45,*1446–1453.

[14]. Faradonbeh, R.S., Monjezi, M., & Armaghani, D.J. (2016). Genetic programing and non-linear regression techniques to predict backbreak in blasting operation. Eng Comput, 32, 123–133.

[15]. Monjezi, M., Amini Khoshalan, H., & Yazdian Varjani, A. (2011). Optimization of open pit blast parameters using genetic algorithm. *Int J Rock Mech Min Sci, 48(5),* 864-869.

[16]. Monjezi, M., Amini Khoshalan H, & Yazdian Varjani, A. (2012). Prediction of flyrock and backbreak in open pit blasting operation: a neuro-genetic approach. *Arab J Geosci 5,* 441–448.

[17]. Ebrahimi, E., Monjezi, M., Khalesi, M.R., & Armaghani, D.J. (2016). Prediction and optimization of back-break and rock fragmentation using an artificial neural network and a bee colony algorithm. *Bull Eng Geol Environ, 75,* 27–36.

[18]. Saghatforoush, A., Monjezi, M., Faradonbeh, R.S., & Armaghani, D.J. (2016) Combination of neural network and ant colony optimization algorithms for prediction and optimization of flyrock and back-break induced by blasting. *Eng Comput, 32,*255–266.

[19]. Kannavena, S.K., Pradeep, T., Chandrahas, N.S., & Prasad, D.U.V.D. (2024). Prediction of Back Break Using Sensitivity Analysis and Artificial Neural Networks. *J. Inst. Eng. India Ser. D.*

[20]. Sorabi, P., Ataei, M., Alimoradi Jazi, M. R., Dehghani, H., Shakeri, J., & Habibi, M. H. (2024). Utilizing heuristic strategies for predicting the backbreak occurrences in open-pit mines, Gol Gohar Mine, Iran. *Soft Computing.*

[21]. Nabavi, Z., Mirzehi, M., Dehghani, H., & Ashtari. P. (2023). A Hybrid Model for Back-Break Prediction using XGBoost Machine learning and Metaheuristic Algorithms in Chadormalu Iron Mine. *JME, 14 (2),* 689-712.

[22]. Sirjani, A. K., Sereshki, F., Ataei, M., & Hosseini, M. A. (2022). Prediction of Backbreak in the Blasting Operations using Artificial Neural Network (ANN) Model and Statistical Models (Case study: Gole-Gohar Iron Ore Mine No. 1). *A M S, 67(1),* 107–121.

[23]. Li, C., Zhou, J., Khandelwal, M., Zhang, X., Monjezi, M., & Qiu, Y. (2022). Six Novel Hybrid Extreme Learning Machine–Swarm Intelligence Optimization (ELM–SIO) Models for Predicting Backbreak in Open-Pit Blasting. *Natural Resources Research, 31(5),* 3017–3039.

[24]. Zhou, J., Dai, Y., Khandelwal, M., Monjezi, M., Zhi Yu, Z., & Qiu, Y. (2021). Performance of Hybrid SCA-RF and HHO-RF Models for Predicting Backbreak in Open-Pit Mine Blasting Operations. *Natural Resources Research, 30 (6),*4753–4771.

[25]. Saghatforoush. A., Monjezi. M., Shirani Faradonbeh. R., & Armaghani. D.J. (2016). Combination of neural network and ant colony optimization algorithms for prediction and optimization of flyrock and back-break induced by blasting. *Eng Comput*, 32, 255–266.

[26]. Hasanipanah. M., Shahnazar. A., Arab. H., Bagheri Golzar. S., & Amiri. M. (2017). Developing a new hybrid-AI model to predict blast-inducedBackbreak. *Eng Comput,33,* 349–359.

[27]. Shirani Faradonbeh. R., Monjezi. M., & Armaghani.D.J.(2016). Genetic programing and non-linear multiple regression techniques to predict backbreak in blasting operation. *Eng Comput*, 32, 123–133.

[28]. Sari, M., Ghasmi, E., & Ataei, M. (2014). Stochastic modeling approach for the evalution of backbreak due to blasting operations in open pit mines. *Rock Mech Rock Eng*, 47, 771–783.

[29]. Mohammadnejad, M., Gholami, R., Sereshki, F., & Jamshidi, A. (2013). A new methodology to predict backbreak in blasting operation. *Int J Rock Mech Min Sci*, 60, 75–81.

[30]. Faramarzi, F., Ebrahimi Farsangi, M.A., & Mansouri, H. (2013). An RES-based model for risk assessment and prediction of backbreak in bench blasting. *Rock Mech Rock Eng, 46,* 877–887.

[31]. Caffo, B. (2019). Regression Models for Data Science in R: A companion book for the Coursera Regression Models class. *Leanpub.*

[32]. Yang, X.S. (2010). firefly algorithm, flights and global optimization. *Research and Development inIntelligent Systems,* 209-218.

[33]. Palit, S., Sinha, S., Molla, M., Khanra, A., & Kule, M. (2011). A crypt analytic attack on the knapsack cryp to system using binary firefly algorithm. *The Second International Conference on Computer and Communication Technology, IEEE,428–432.*

انجمن مهندسی معدن ایران
نشریه مهندسی معدن و محیط زیست
نشانی نشریه: www.jme.shahroodut.ac.ir
دانشگاه صنعتی شاهرود

بهینه‌سازی مدل‌های آماری پیش‌بینی عقب‌زدگی ناشی از انفجار معادن با استفاده از الگوریتم کرم شب تاب: یک مطالعه موردی

عباس خواجوئی سیرجانی[1*]، رقیه حیدری[1]، رامین رفیعی[1] و محمد امیری حسینی[2]

۱. دانشکده مهندسی معدن، نفت و ژئوفیزیک، دانشگاه صنعتی شاهرود، شاهرود، ایران
۲. رئیس، بخش معدن و زمین‌شناسی، مدیریت تحقیقات و فناوری گل‌گهر، سیرجان، ایران

اطلاعات مقاله

تاریخ ارسال: ۲۰۲۵/۰۲/۰۱
تاریخ داوری: ۲۰۲۵/۰۴/۱۵
تاریخ پذیرش: ۲۰۲۵/۰۵/۰۴

DOI:10.22044/jme.2025.15683.3014

کلمات کلیدی

انفجار
عقب‌زدگی
گل گهر
رگرسیون چندگانه
الگوریتم کرم شب‌تاب

چکیده

در عملیات انفجار معادن روباز، یکی از مهم‌ترین پارامترهایی که باید به‌طور دقیق و مستمر مورد بررسی و ارزیابی قرار گیرد، میزان عقب‌زدگی ناشی از انفجار است. این پدیده می‌تواند به ناپایداری دیواره‌های معدن، سقوط ماشین‌آلات معدنی، افزایش نرخ ترقیق، و ایجاد اختلال در عملیات چال‌زنی و خرج‌گذاری در مراحل بعدی منجر شود. هدف این پژوهش، پیش‌بینی و بهینه‌سازی عقب‌زدگی با استفاده از ترکیب مدل‌های آماری و الگوریتم کرم شب‌تاب است. به همین منظور، پایگاه داده‌ای شامل ۲۸ انفجار در بخش باطله سنگی معدن شماره یک سنگ‌آهن گل‌گهر گردآوری شد. پس از جمع‌آوری داده‌ها، پارامترهای ورودی شامل طول چال، بارسنگ، فاصله‌داری، گل گذاری، خرج در هرتاخیر و تعداد چال های ردیف آخر تعیین و در فرآیند مدل‌سازی مورد استفاده قرار گرفت. برای پیش‌بینی عقب‌زدگی، مدل‌سازی با استفاده از تحلیل رگرسیون چندگانه انجام شد. در میان مدل‌های توسعه‌یافته، مدل آماری چندجمله ای با ضرایب غیرصحیح با ضریب تعیین اصلاح‌شده ۰.۸۸۵ به‌عنوان بهترین مدل علمکردی شناسایی شد و در ادامه به‌عنوان تابع هدف در الگوریتم کرم شب‌تاب مورد استفاده قرار گرفت. سپس، فرآیند بهینه‌سازی با استفاده از این الگوریتم انجام شد. بر اساس نتایج به دست آمده، اجرای الگوهای عملیاتی کنونی معدن در کنار الگوهای بهینه سازی شده پیشنهادی، باعث کاهش به میزان ۴ متر از میانگین عقب‌زدگی کل ۷.۵ متر در بخش باطله سنگی شده است. یافته‌های این پژوهش نشان می‌دهد که الگوریتم بهینه‌سازی کرم شب‌تاب ابزاری کارآمد و مؤثر برای بهینه‌سازی مدل‌ها و کاهش دقیق‌تر پدیده عقب‌زدگی است. این روش می‌تواند در بهبود بهره‌وری عملیات معدن‌کاری و کاهش هزینه‌ها تأثیر قابل‌توجهی داشته باشد.

نویسنده مسئول مکاتبات: *abbas3457@gmail.com* (ع. خواجوئی سیرجانی)