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Arch. Min. Sci. **67** (2022), 1, 107-121

Electronic version (in color) of this paper is available: http://mining.archives.pl

DOI: https://doi.org/10.24425/ams.2022.140705

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PREDICTION OF BACKBREAK IN THE BLASTING OPERATIONS USING ARTIFICIAL NEURAL NETWORK (ANN) MODEL AND STATISTICAL MODELS (CASE STUDY: GOL-E-GOHAR IRON ORE MINE NO. 1)

Backbreak is an undesirable phenomenon in blasting operations, which can bedefined as the undesirable destruction of rock behind the last row of explosive holes. To prevent and reduce its adverse effects, it is necessary to accurately predict backbreak in the blasting process. For this purpose, the data obtained from 66 blasting operations in Gol-e-Gohar iron ore mine No. 1 considering blast pattern design Parameters and geologic were collected. The Pearson correlation results showed that the parameters of the hole height, burden, spacing, specific powder, number of holes, and the uniaxial compressive strength had a significant effect on the backbreak. In this study, a multilayer perceptron artificial neural network with the 6-12-1 architecture and six multiple linear and nonlinear statistical models were used to predict the backbreakin the blasting operations. The results of this study demonstrated that the prediction rate of backbreak using the artificial neural network model with R^2 = 0.798 and the rates of MAD, MSE, RMSE and, MAPE were0.79, 0.93, 0.97 and, 11.63, respectively, showed fewer minor error compared to statistical models. Based on the sensitivity analysis results, the most important parameters affecting the backbreak, including the hole height, distance between the holes in the same row, the row spacing of the holes, had the most significant effect on the backbreak, and the uniaxial compressive strength showed the lowest impact on it.

Keywords: Blasting; Backbreak; Artificial neural network; Statistical models; Gol-e-gohar iron ore mine

1. Introduction

In blasting operations, various types of undesirable phenomena such as fly rock, ground vibration, air blast, and especially back break are observed, the occurrence of which should be prevented. To identify the parameters that may affect the occurrence of back break, studies have

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been conducted by various researchers. A review of related articles shows the effect of various parameters in causing back break. These parameters can be divided into three groups:

A. Geometric parameters of explosion model design

From the first group, parameters such as burden, stemming, powder factor, latency between rows, and stiffness ratio have the greatest impact on the back break phenomenon [1]. Konya and Walter showed that a high stiffness ratio reduces back break, and they also concluded that with increasing burden and stemming, back break increases [2]. Belroarmstrong (2002) conducted a detailed experimental study and modeling and found that ground vibration (which is said to be related to back break) was independent of the burden, They proved that the ground vibration depends on the degree of fracture of the rock mass around the blast hole at the time of the explosion [3]. Gate et al. found that insufficient delay between rows was the main cause of the back break phenomenon. They also stated that with the increase of blast rows, the probability of back break also increases [4]. The use of controlled blasting models such as line drilling, presplitting, cushion blasting, and intermittent air powder factor in the last row of blast holes is an effective way to reduce wall damage and back break in open-pit mines. introduced controlled blasting methods to reduce back break and pit wall damage [2,5-9]. Janwarujwa used intermittent air powder factor in an open-pit coal mine and found that this method was very useful in reducing back break [10]. Aghajani et al. used controlled presplitting blasting with large pit diameter to reduce back break in Sarcheshmeh copper mine [11]. Singh et al. also used controlled blasting method in an open-pit mine in India to reduce back break [12].

B. Properties of explosives

Properties of explosives include explosive type, density, strength, and coupling ratio (ratio of diameter of powder to hole diameter), all of which are controllable. Different explosives produce different blasting pressures; for example, the pressure produced by ANFO explosion and other permitted explosives is lower than dynamite. Low-density explosives produce low detonation pressures. Bahandari showed that the lower the blast hole pressure, the less damage is caused by back break [13]. Wilson and Moxon proved that a mixture of salt and sawdust reduced the strength of ANFO [14]. Enayatollahi and Aghajani used a mixture of salt and ANFO as explosives for controlled blasting and reduced back break. One of the most effective parameters on the back break intensity is the coupling ratio, which indicates the degree of direct contact of the explosive with the walls of the blast hole [15]. Iverson et al. assessed the extent of blast damage caused by fully coupled blasting powder and showed that back break could be reduced by reducing coupling ratio [16].

C. Characteristics of rock mass and discontinuities

Physical and mechanical properties of rock mass and discontinuities are density, porosity, dynamic compressive strength, dynamic tensile strength, rock shear strength and orientation, roughness, spacing of joints, and properties of discontinuities fillers; these parameters are uncontrollable and have a critical impact on muck pile induced blasting damage. Bahandari and Badal stated that homogeneous rock with high compressive and tensile strength properties will not be crushed as much as low strength rock around the blast hole. Closed or filled discontinuities lead to fewer back breaks than open discontinuities. The direction of the discontinuities has a major effect on the blasting results for the braces and the presence of a suspended rock in the braces. They stated that when the blasting is in the direction of the inclination of the discontinuities, the back break increases significantly [17]. Jia et al. used numerical modeling and concluded that joints with a slope angle greater than the friction angle can be considered one of the most important factors of back break. In the past, most experimental methods were used to design the explosion model. Due to the number of parameters affecting the blasting model and also the complexity of the relationships between these parameters, the use of experimental methods is not suitable for this purpose [18]. To solve this problem, new techniques such as artificial neural networks (ANN) are used [19]. ANN is one of the most intelligent tools used to simulate complex problems, especially in the field of mining engineering. For example, Malenkamp and Grima presented a model for predicting uniaxial compressive strength of rock using neural networks [20]. Dehgani and Manjezi predicted back break at the Golgohar mine using neural networks [21]. Dehghani and Ataiepour studied PPV in Sarcheshmeh copper mine using neural network technique [22]. The ANN method was used as one of the powerful artificial intelligence tools to predict back break due to blasting in Golgohar iron ore mine No. 1. Also, using statistical analysis, various models were developed to predict back break, and finally, the performance of each model was evaluated.

2. Case study

Gol-e-gohar iron ore mining area with six anomalies and reserves of more than 1.2 billion tons is one of the most important and largest iron ore reserves in Iran. This mine is located in Kerman province, 55 km southwest of Sirjan city. The study area of Gol-e-gohar mine No. 1 is one of the six anomalies of the mining area, which has a geological reserve of 313 million tons based on exploratory activities, and according to economic factors, 280 million tons can be extracted. The final cavity of this mine is in the form of an oval with dimensions of approximately 3000 m* 800 m, including 26 stairs with a height of 15 m, and the overall slope of the mine walls is 38 to 45 degrees. The above mine contains three different types of ores based on mineralogical compositions and their location inside the mineral mass. These three types of minerals are called bottom magnetite, oxidized magnetite, and upper magnetite, and waste rocks include a variety of schist (quartz schist, talc schist, mica schist, and graphite schist), gneiss, skarn, and dolomite.

Bottom magnetite: This ore with a very low amount of waste and a high percentage of magnetite (up to about 80% of the magnetic product) and about 9% of low magnetite rock has a sulfur content of about 0.3 to 0.6%. Sulfur is mostly found in the form of pyrite and is easily transported to the waste in magnetic separation experiments.

Oxidized magnetite: Oxidized zone rocks contain an average of 12% of hematite and goethite. In general, the concentrate obtained from this rock has a lower amount of iron than the concentrate produced from magnetite rock (62% iron vs. 69% in magnetite rock).

Upper magnetite: This ore is in limited areas above the mineral mass and formed about 3% of the total tonnage of the mineral mass; the extraction of this type of magnetite has been completed.

Figs 1 and 2 show the relative position and tonnage of six anomalous reserves of Golgohar iron ore complex and its communication routes along with the plan of the final boundary of the studied mine, and Fig. 3 shows the back break phenomenon.

Fig. 1. The location the Gol-e-Gohar iron ore mine and its pathways, along with the last mining plan

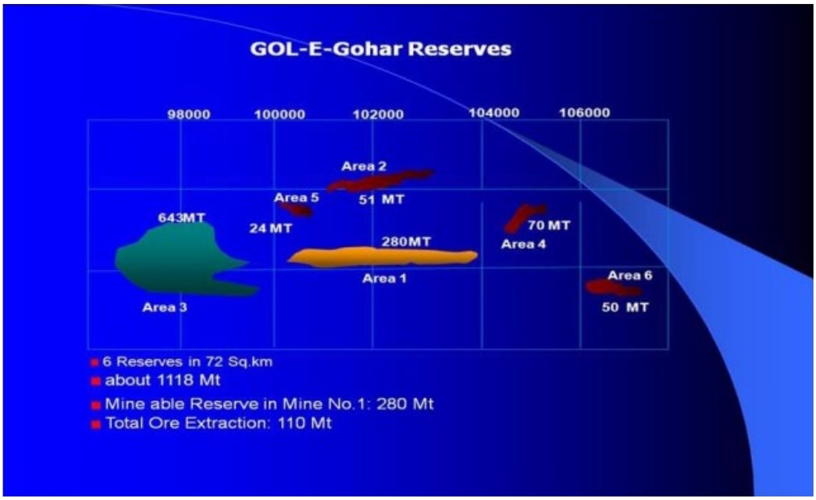

Fig. 2. Relative location and tonnage of six Golgohar anomalies

3. Data collection

In this study, the data obtained from 66 blasting operations in Gol-e-Gohar iron ore mine No. 1 considering blast pattern design Parameters and geologic were collected. The Pearson correlation results showed that the parameters of the hole height, burden, spacing, specific powder, number of holes, the uniaxial compressive strength had a significant effect on the backbreakphenomenon.

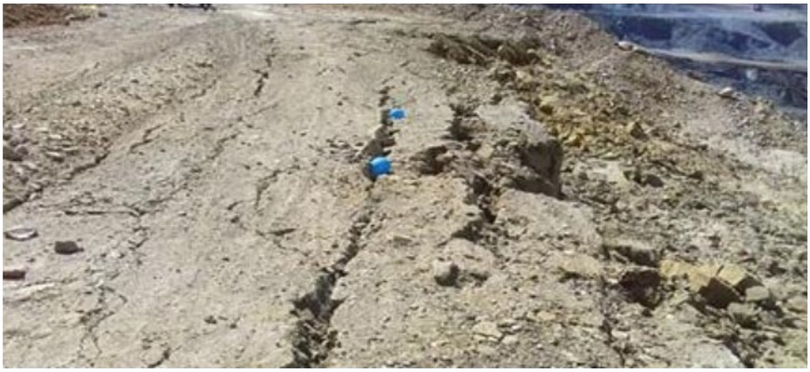

Fig. 3. The back break phenomenon in Gol-e-Gohar iron ore mine No. 1

Table 1 shows descriptive statistics of the collected data. Pearson correlation coefficient matrix for input parameters is presented in Table 2.

TABLE 1

Descriptive statistics of the collected data

No.	Parameter	Symbol	Minimum	Maximum	Mean	Std. Deviation
1	Hole height (m)	H	4	17.5	14.84	2.06
2	Burden (m)	B	2.77	8.5	547	1.16
3	Spacing (m)	S	4	10.5	6.7	1.36
4	Specific powder (kg/t)	Pf	0.12	0.57	0.36	0.11
5	Number of blast rows	N	2	5	3.3	0.79
6	Uniaxial compressive strength (MPa)	UCS	19	178	96.6	53.25
7	Back break (m)	BB	3	13	7.3	2.07

TABLE 2

Pearson correlation coefficient matrix for input parameters

	BB	H	B	S	PF	N	UCS
Back break	1						
Hole height	0.308	1					
Burden	0.467	0.153	1				
Spacing	0.491	0.161	0.959	1			
Specific powder	0.444	0.326	–0.089	–0.055	1		
Number of blast rows	–0.249	–0.166	–0.054	–0.168	0.046	1	
Uniaxial compressive strength	0.535	0.137	0.171	0.224	0.272	–0.269	1

4. Artificial neural network (ANN)

A neural network has a layered structure, and each layer contains processing units. Independent variables are placed in the input layers, while dependent variables are placed in the last layer.

The components of the neuronal system are hidden layers. All layers are connected by weighted joints. Fig. 4 shows a typical ANN structure. Each neuron is connected to the neurons of the next layer. However, there is no connection between neurons in the same layer.

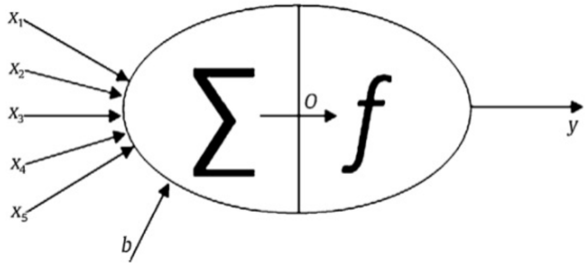

Fig. 4. Neuron structure

In the training process, special weights are first assigned to the connections of the neurons. The network can function by setting initial weights.

Fig. 3 shows a single neuron containing several inputs (x_1, …, x_n) and a single output (y). In the ANN training process, an initial arbitrary value (weight) is assigned to the connections, and then the equation 1 is applied to combine all weighted inputs and produce neuron output:

$$O = \sum X_i W_i + b \tag{1}$$

Where, x_i is the input; w_i is the connection weight, and b is bias. To map a neural network output to its actual output, an activation function f must be selected. The transfer function can be expressed as equation 2:

$$Y = f(o) = f\left(\sum X_i W_i + b\right) \tag{2}$$

Solving Equation 5, which includes the output, depends on the initial sum of the neurons in Equation 4. The final output of neurons in the range of [0, 1] or [–1, 1] is obtained depending on the type of transfer function applied. It is stated that a single activation function must be selected for neurons of a particular layer. The type of activation function depends entirely on the nature of the problem to be solved

ANNs are composed of interconnected biological nerve cells to calculate the output by the inputs [23]. Neural networks (NNs) were used widely in various applications and have become powerful tools for both data analysis and solving complex engineering problems [24]. The NN is an excellent alternative to math's complicated equations [25]. Multilayer Perceptrons (MLPs) can be considered as one of the most important types of NNs.

4.1. Artificial Neural Networks Models for the Backbreak Prediction

To predict the backbreak using the ANNs, the parameters affecting the backbreak were first selected for the network structure and, then simulations were performed to achieve the optimal network. In this study, to better compare the results of the NNs, the hole height, burden, spacing, specific powder, number of holes, the uniaxial compressive strength as input parameters and, the backbreak as the output parameter of the network were considered. We divided the dataset into training (70%), validation (15%), and testing parts (15%). MATLAB software was employed to train the MLP neural network. The training process involving a change in weights between different layers was performed to minimize the difference between the observed (actual) and predicted data. Fig. 3 shows the structure of the ANN model consisting of six input variables, one output variable and, two intermediate layers. Fig. 4 shows the histogram of ANN model. Changes in the mean squared error (MSE) of the ANN training are shown in Fig. 5. The ANN assigns a weight to each input and then adds a bias to these weights and passes them through the hidden layers. ANN with one hidden layer and 12 neurons on it has been selected

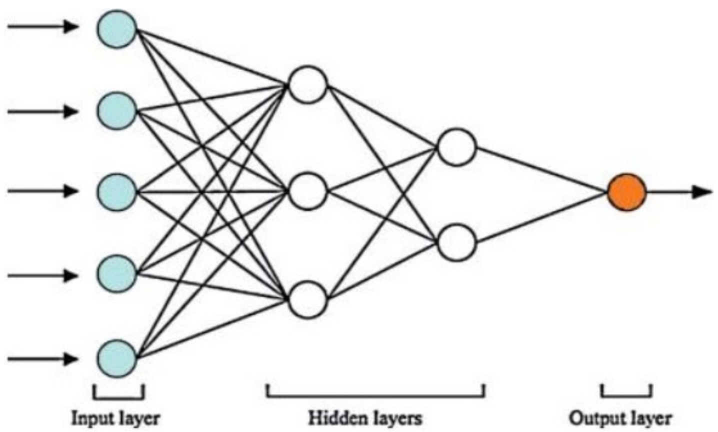

Fig. 5. Artificial neural network structure

5. Statistical Models

One of the standard methods, for data analysis in the fields of mining engineering and geoscience is multiple linear and nonlinear regression [26-28] which, are used to obtain the prediction models between several independent variables and dependent variables using existing data [29-31].The Nonlinear regression model has been used by many researchersto estimate the prediction models between different parameters [18,19].

Multiple Linear and Nonlinear Regression Models for the Backbreak Prediction

In this study, the multiple linear and nonlinear regression models were used to predict the relationship between the independent variables and the backbreak phenomenon in SPSS version 24. To develop statistical models such as ANN model, training, validation, and testing steps were implemented. The following relationships from 3 to 8 represent linearregression, powerregression, polynomial with integer coefficients, logarithmic, exponential, and polynomial with non-integer coefficients of statistical models, respectively, that are developed to predict the backbreak.

$$BB = 0.321 + 0.017(H) + 0.906(B) - 0.079(S) + \\ + 6.948(PF) - 0.424(N) + 0.012(UCS) \quad (3)$$

$$BB = \left[10^{(0.477+0.003(H)+0.05(B)-0.007(S)+0.32(PF)-0.024(N)+0.001(UCS))}\right] \quad (4)$$

$$BB = \left[\begin{array}{l} 2.317 + 0.181(H)^1 + 0.164(B)^2 + 0.144(S)^3 + \\ + 0.001(PF)^4 + 0.001(N)^5 + 0.006(UCS)^6 \end{array}\right] \quad (5)$$

$$BB = \left[\begin{array}{l} -1.376 + 0.247\ln(H) + 4.115\ln(B) - 0.001\ln(s) + \\ + 2.391\ln(PF) - 0.942\ln(n) + 1.086\ln(UCS) \end{array}\right] \quad (6)$$

$$BB = EXP\left[\begin{array}{l} 1.097 + 0.007(H) + 0.115(B) - 0.017(S) + \\ + 0.737(PF) - 0.055(N) + 0.002(UCS) \end{array}\right] \quad (7)$$

$$BB = \left[\begin{array}{l} 0.147 + 3.39E-13(H)^{0.095} + 0.252(B)^{1.453} + 0.006(S)^{0.221} + \\ + 0.0000013(PF)^{-0.038} + 0.686(N)^{-2.563} + 0.098(UCS)^{0.546} \end{array}\right] \quad (8)$$

Evaluation indicators of models

The analysis of the models in two stages of training and testing based on Statistical indicators the coefficient of determination (R^2), correlation coefficient (R), mean absolute error (MAD), mean square error (MSE), the root mean square error ($RMSE$), and the mean absolute percentage error ($MAPE$) was calculated by relationship from 9 to 14, respectively.

$$R^2 = 100\left[\frac{\sum_{i=1}^{N}\left(Y_{meas} - \overline{Y}_{meas}\right)\left(Y_{pred} - \overline{Y}_{\mathrm{Pr}ed}\right)}{\sqrt{\sum_{i=1}^{N}(Y_{meas} - \overline{Y}_{meas})^2 \sum_{i=1}^{N}(Y_{pred} - \overline{Y}_{pred})^2}}\right] \quad (9)$$

$$R = \sqrt{\frac{\sum_{i=1}^{n}\left(Y_{meas} - \overline{Y}_{meas}\right)^2 - \sum_{i=1}^{n}\left(Y_{meas} - Y_{pred}\right)^2}{\sum_{i=1}^{n}\left(Y_{meas} - \overline{Y}_{meas}\right)^2}} \quad (10)$$

$$MAD = \frac{\sum_{i=1}^{n}\left|Y_{meas} - Y_{pred}\right|}{n} \quad (11)$$

$$MSE = \frac{\sum_{i=1}^{n}\left(Y_{meas} - Y_{pred}\right)}{n} \quad (12)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(Y_{meas} - Y_{pred}\right)^2}{n}} \quad (13)$$

$$MAPE = \frac{\sum_{i=1}^{n} \frac{\left|Y_{meas} - Y_{pred}\right|}{Y_{meas}}}{n} \times 100 \tag{14}$$

Where, Y_{meas} and Y_{pred} represent the measured and predicted values, respectively, and also $\overline{Y}_{meas}$ and $\overline{Y}_{pred}$ denote the mean measured and predicted values, respectively, and n is the number of data.

6. Evaluating the performance of predicting the Artificial Neural Network Models and statistical models

In this study, the ANN model and the six multiple linear and nonlinear regression models were used for thebackbreak prediction, and a structure of these models that had the best results was applied. Relationships from 7 to 12 were used to evaluate the performance of the models and determine the accuracy of the developed model. Table 3 shows Evaluation indicators of training and testing of the artificial neural network model and statistical models. As shown in Table 3, the ANN model had the highest accuracy, and nonlinear regression, and polynomial with the non-integer coefficients showed the lowest accuracy for the backbreak prediction. Based on the analysis performed by the coefficient of determination in the training and testing stages, Figs 6 to 12 show the results of the superiority of the ANN models over statistical models.

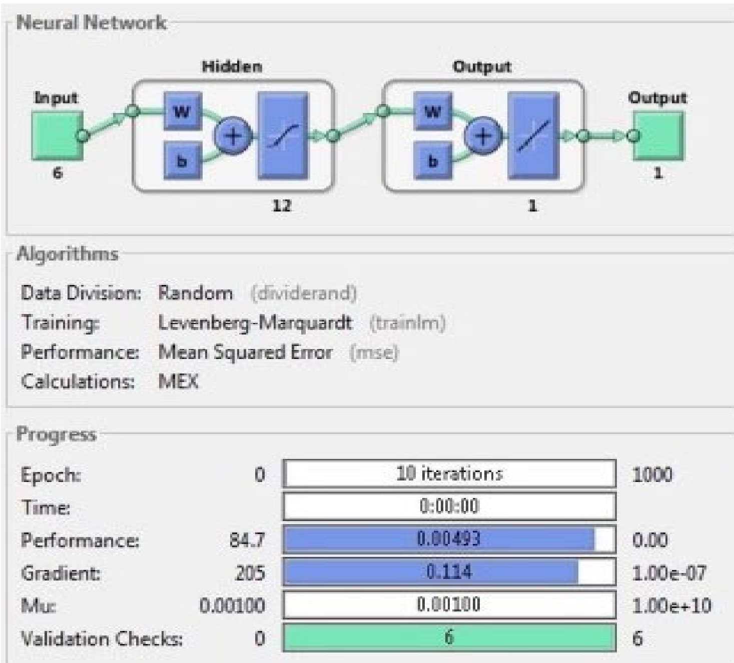

Fig. 6. The structure of the ANN model consisting of six input variables, one output variable and, two intermediate layers

TABLE 3

Evaluation indicators of training and testing of artificial neural network model and statistical models

		Training					Test				
		R	***MAD***	***MSE***	***RMSE***	***MAPE***	***R***	***MAD***	***MSE***	***RMSE***	***MAPE***
1	Ann	0.83	0.99	1.78	1.34	13.21	0.89	0.79	0.93	0.97	11.63
2	Linear regression	0.75	1.05	2.01	1.42	15.13	0.82	0.71	0.84	0.92	10.91
3	Power regression	0.74	1.29	2.51	1.59	19.02	0.81	0.94	1.30	1.14	14.07
3	Polynomial	0.64	1.36	2.77	1.66	19.93	0.58	1.03	1.65	1.28	15.09
5	Logarithmic	0.74	1.05	2.09	1.45	15.13	0.78	0.81	1.02	1.01	12.56
6	Exponential	0.74	1.16	2.18	1.48	17.06	0.82	0.78	0.95	0.97	11.80
7	Polynomial with non-integer coefficients	0.64	1.35	2.76	1.66	20.59	0.59	1.19	1.84	1.36	18.21

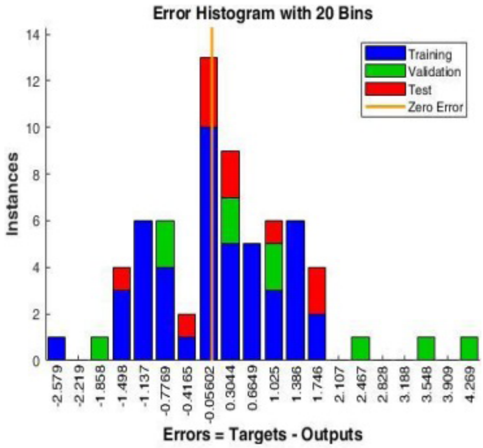

Fig. 7. Histogram of ANN model

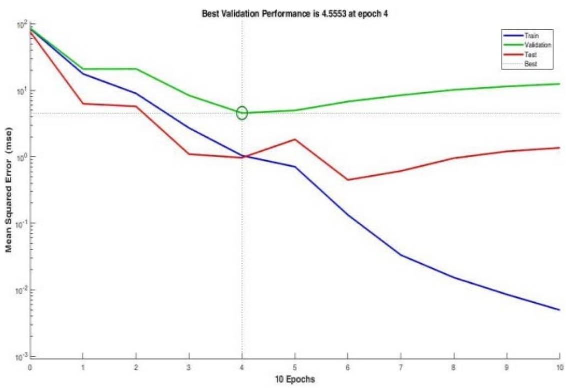

Fig. 8. Changes in the mean squared error of the ANN training

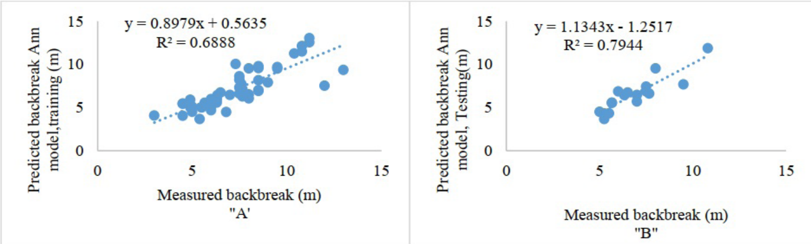

Fig. 9. Correlation of the measured back break with the predicted back break ANN model (A: Training), and (B: Testing)

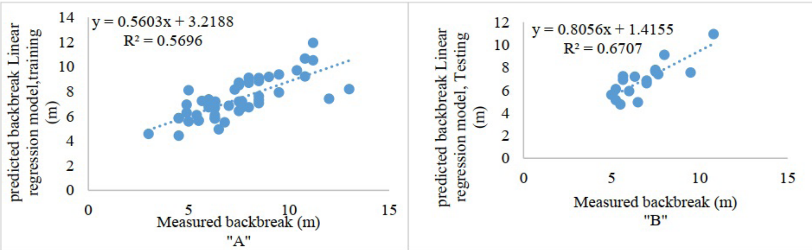

Fig. 10. Correlation of the measured back break with the predicted back break linear regression model (A: Training), and (B: Testing)

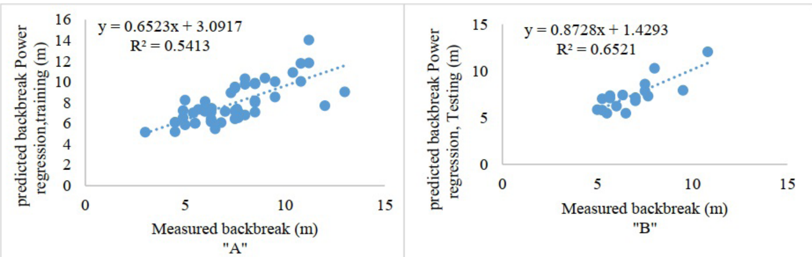

Fig. 11. Correlation of the measured back break with the predicted back break power regression model (A: Training), and (B: Testing)

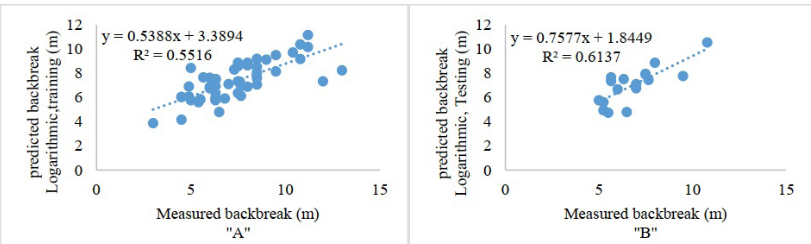

Fig. 12. Correlation of the measured back break with the predicted back break logarithmic model (A: Training), and (B: Testing)

7. Sensitivity Analysis

The last step of modeling is to assess the sensitivity analysis of the model output concerning to the input parameters. The relative effect of model input parameters on the model output (objective function) can be evaluated using sensitivity analysis. One of the methods for determining sensitivity Analysis is the cosine amplitude method (CAM)., which has been used in various studies [34]. In the CAM, an m-dimensional space where m is the number of input parameters is assumed:

$$X = \{X_1, X_2, X_3 \ldots, X_m\}$$

Each member of this input parameter, such as X, is attached to the objective function by a length vector:

$$X_i = \{X_{i1}, X_{i2}, X_{i3} \ldots, X_{im}\}$$

The effect of each of the input parameters X on the objective function can be obtained using equation 15 as:

$$R_{ij} = \frac{\sum_{k=1}^{m} X_{ik} X_{jk}}{\sqrt{\sum_{k=1}^{m} X_{ik}^2 \sum_{k=1}^{m} X_{jk}^2}} \tag{15}$$

The greater the effect of the input parameters on the outputs, the closer R_{ij} to one would be. If the input parameter does not affect the output, the value of R_{ij} is zero. Typically, a value of R_{ij} above 0.9 shows a significant effect of the input parameter on the output, and values below 0.8 indicate a weak effect of the input parameter on the output [20]. Fig. 13 shows the results of sensitivity analysis operated from for the backbreak prediction of input parameters. As shown in Fig. 13, the among the input parameters, the hole height, the distance between the holes in the same row, the row spacing of the holes had the greatest effect on the backbreak, and the uniaxial compressive strength showed the lowest effect on the backbreak.

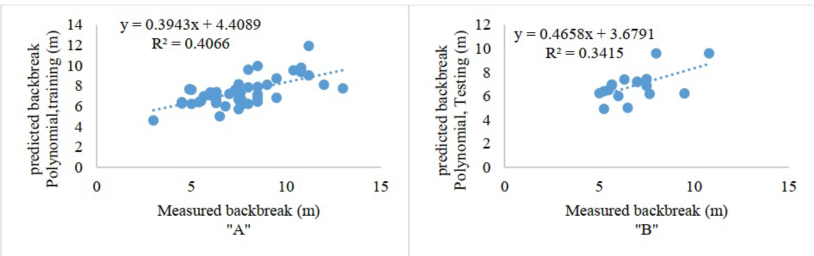

Fig. 13. Correlation of the measured back break with the predicted back break polynomial model (A: Training), and (B: Testing)

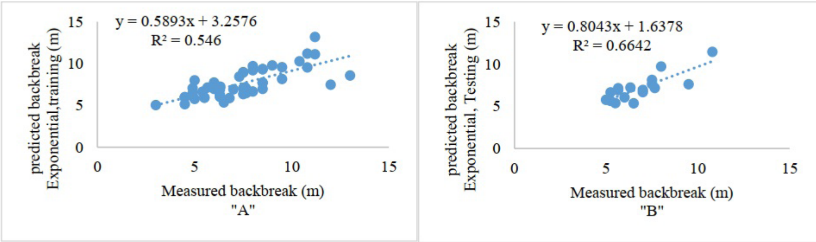

Fig. 14. Correlation of the measured back break with the predicted back break exponential model (A: Training), and (B: Testing)

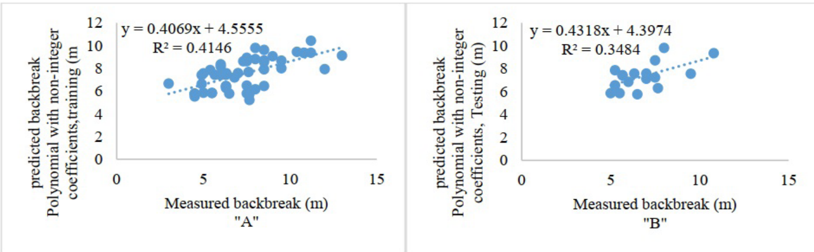

Fig. 15. Correlation of the measured back break with the predicted back break polynomial model with non-integer coefficients (A: Training), and (B: Testing)

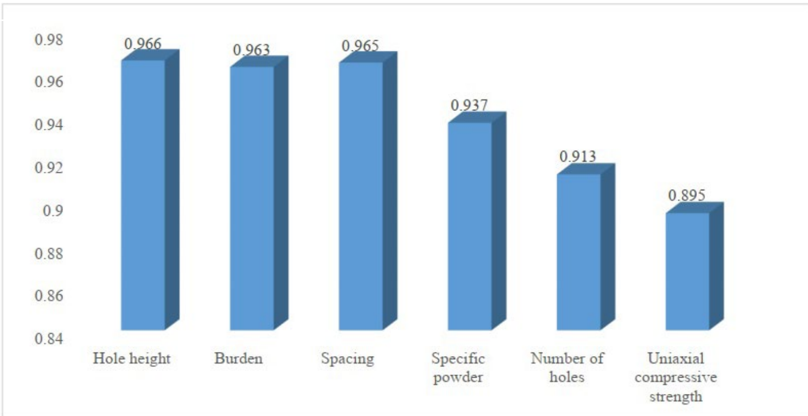

Fig. 16. The effect of input parameters on back break

8. Conclusion

The backbreak prediction in the blasting operations is very important from the technical and economic perspective. In this study, an attempt was made to apply the ANN and statistical models to predict the backbreakin the blasting operations for the Gol-e-Gohar iron ore mine No. 1. To achieve comprehensive prediction models, parameters including the hole height, burden, spacing, specific powder, number of holes, and the uniaxial compressive strength were involved in developing the models. To identify the best model in the ANN, different types of neural networks were developed and evaluated. Finally it was observed that a network with the 6-12-1 architecture was the optimal model. Also, six multiple linear and non-linear statistical models were developed for the back break prediction. Calculating the coefficient of determination (R^2), correlation coefficient (R), mean absolute error (MAD), mean square error (MSE), the root mean square error ($RMSE$), and the mean absolute percentage error ($MAPE$), showed the superiority of the ANN model over the statistical models. Additionally, the results of sensitivity analysis revealed that among the input parameters, the hole height, the distance between the holes in the same row, the row spacing of the holes had the greatest effect on the backbreak, and the uniaxial compressive strength showed the lowest effect on the backbreak.

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