# A comparative study on the application of Regression-PSO and ANN methods to predict backbreak in open-pit mines

Masoud Shamsoddin Saeed[1], Hossein Jalalifar[1], Hamed Shamsoddini[1], Mohammad Darbor[2]

**1- Department of Petroleum Engineering, Shahid Bahonar University of Kerman, Kerman, Iran**
**2- Department of Mining Engineering, Sahand University of Technology, East Azarbaijan, Iran**

* Corresponding Author: *darbor@sut.ac.ir*

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**Angouran mine**

**Abstract**

One of the most challenging safety problems in open-pit mines is backbreak during blasting operation. Prediction of backbreak is very important for a technically and economically successful mining operation. To avoid backbreak, different parameters such as physicomechanical properties of rock mass, explosives properties, and geometrical features of the blasting pattern should be considered. This paper presents a new solution of multiple linear regression (MLR), particle swarm optimization algorithm (PSO), and artificial neural networks (ANNs) to estimate the backbreak induced by bench blasting, based on major controllable blasting parameters. Angouran mine in Iran was considered and blasting pattern parameters for 73 operations were collected for this study. In addition, back-break was measured in each operation. Considering the previous investigations and also collected data from the mine, burden, spacing, hole length, stemming, charge per delay, RQD, number of rows, and powder factor were selected as input parameters. In order to find better solutions, the constructed models were implemented in PSO algorithms. Also, the prediction of backbreak was investigated using ANNs. According to the obtained results, the PSO algorithm is a suitable tool for optimizing models and obtaining a more accurate prediction of backbreak. Among the presented empirical models, the optimized exponential model with PSO algorithm with an RMSE (0.31) and R2 (0.87) shows better results in the prediction of backbreak and it is suitable for practical use in Angouran mine. Considering the sensitivity analysis, among the input parameters, length of stemming and charge per delay have shown the most and the least effect on the backbreak, respectively. The results of ANNs showed that multilayer networks are more powerful and efficient than single-layer in the prediction of backbreak.

## 1- NTRODUCTION

Backbreak due to blasting operation has a significant impact on slope stability. This undesirable phenomenon can be defined as the limit of damaged rocks beyond the last row of production holes (Jimeno et al. 1995). Bauer (1982) noted that, if backbreak is not controlled, a decrease in the overall pit-slope angle would definitely be necessary which in turn causes an increase in the stripping ratio. Greater amounts of loose face rock would be produced and planned safety berms would be less effective. Because of the destructive consequences of backbreak, there would be a considerable increase in the total production costs (Scoble et al. 1997). In order to identify parameters that may influence the intensity of backbreak, many studies have been performed by various researchers (Jenkins, 1981; Konya and Walter 1991; Monjezi and Dehghani 2008).

According to Konya (2003) excessive burden and stemming can be considered as the main cause of backbreak. Whereas, Gate et al. (2005) believe that the delay timing and the number of rows in a blast round are the most important parameters in generating backbreak. Backbreak has a key role in the stability of mine walls (Jimeno et al. 1995). According to Bauer (1982), flattening of pit slopes results in the increase of the stripping ratio would be unavoidable if the phenomenon is persevered. Backbreak can also inversely be influential to the drilling and blasting performance of the affected blocks. Keeping in mind the adverse consequences of the event and the decrease of mine production costs due to that it is necessary to apply remedial measures to diminish backbreak (Tawadrous 2006).

To avoid backbreak, different parameters such as physicomechanical properties of rock mass, explosives properties, and geometrical features of the blasting pattern should be considered. In the past, empirical models were developed for the blast design aiming to arrive at requirements such as proper fragmentation, decreasing backbreak, suitable muck pile profile, reducing boulders, etc. However, in such models, there is no straightforward way of predicting backbreak. Also, in the empirical models, only some of the effective parameters of blasting operation are accounted for.

Previously developed empirical models regarding backbreak show poor performance. It is due to the complicated nature of such problems because of the presence of various involved parameters with no clear interrelation. In such a condition, the application of new techniques of pattern recognition like artificial neural networks (ANNs) and genetic algorithms (GAs) are recommended (Khandelwal and Singh 2006; Kahraman et al. 2006; Monjezi et al. 2010).

So, with considering the above shortcomings of available empirical methods, a new solution of multiple linear regression (MLR), particle swarm optimization algorithm (PSO), and artificial neural networks (ANNs) may suitably cover all the requirements of predicting backbreak. In some research, Ghasemi et al. (2016) proposed linear PSO and quadratic PSO forms for approximating backbreak resulting from bench blasting. He found that the quadratic form of PSO can perform better compared to the linear one.

In this study, for optimizing pattern parameters of the blasting operation of Angouran Lead and Zinc open-pit mine in Iran, aiming to minimize backbreak, a new combined MLR-ANN–PSO model was developed, which was not considered in the past such a combined model. The study aims to predict the backbreak induced by blasting using Regression-PSO and ANN methods for better assessment.

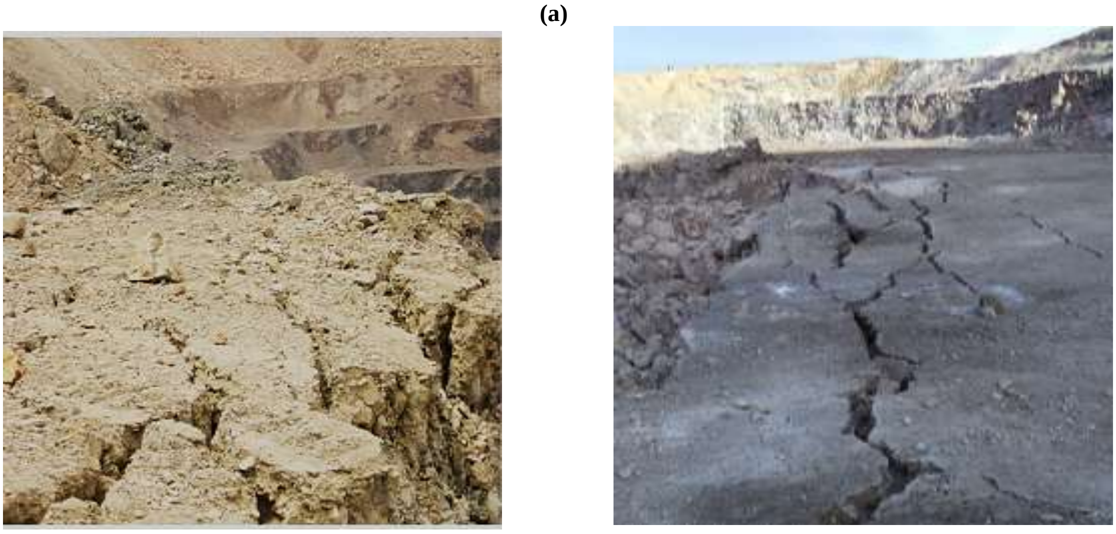
## 2- Case study and data collection

In this study, a site investigation was conducted at the Angouran mine. Angouran lead and zinc open-pit mine with a production capacity of 800 thousand tons per year and the remaining amount potential over 12 million tons with the average grade 3%-6% of lead and the average grade 25%-30% of zinc is one of the largest metal mines in Iran and also is one of the most economical leads and zinc mines in the world. Angouran mine is located in Zanjan province, 125 km SW of Zanjan, and in a region with an average altitude of 3000 m. The geographical coordinates of the Angouran mine are $40^{\circ}36'$ longitude and $20^{\circ}47'$ latitude. The geographical location of the Angouran mine has been shown in Fig. 1.


**Fig. 1- a) Geographical location of Angouran mine, b) A view of the Angouran mine**

Blasting operations at the Angouran mine utilize blast holes of 102-177 mm, explosive material of ammonium nitrate/fuel oil (ANFO; specific gravity of 0.85–0.95 gr/cm$^3$), vertical blast holes, and a delay timing of 5 ms. In this mine, the blast holes are stemmed with drill cutting. One of the most important problems of blasting operations in the Angouran mine is backbreak causing damage to the pit walls (see Fig. 2). It is well known that backbreak (damage) is influenced by several rock parameters as well as blast design. Therefore, after going through these parameters, the most influential parameters in backbreak, including burden, spacing, stemming length, hole length, powder factor, a charge per delay, rock quality designation (RQD), and a number of rows were measured in the Angouran mine. Table 1 shows variations of the input and output parameters and their range. In total, the aforementioned parameters of 73 blasting events were obtained to construct the predictive models.

**(a)**



**(b)**

**Fig. 2-. a) A sample of blasting and b) The undesirable backbreak after blasting in the Angouran mine**

**Table 1-. Statistical information of input and output parameters**

| Category | Parameter | Symbol | Range | Average | St. deviation |
|---|---|---|---|---|---|
| Input | Hole diameter (mm) | D | 102 – 177 | - | - |
| | Hole length (m)/ Burden (m) | H/B | 1.67 - 2.86 | 2.43 | 0.35 |
| | Spacing (m)/ Burden (m) | S/B | 1.00 - 1.29 | 1.20 | 0.04 |
| | Stemming (m) | ST | 3.30 – 4.20 | 3.78 | 0.23 |
| | Charge per delay (kg/ms) | CHD | 2100 – 15900 | 7728 | 3508 |
| | Powder factor (kg/m$^3$) | PF | 401 – 860 | 568 | 90 |
| | No. of row | NoR | 2 – 4 | - | - |
| | RQD (%) | RQD | 35 – 60 | 47 | 8 |
| Output | Backbreak | BB | 3.80 – 7.80 | 5.03 | 0.92 |

## 3- Materials and methods

### 3-1- Multiple linear regression analysis (MLRA)

Simple regression analysis can show how a single dependent variable is affected by the values of one independent variable. This method only concerns the $X_i$ variable as a predictor (i.e., independent variable) and the Y variable as an outcome (i.e., dependent variable). Thus, if two or more predictors are used for the simple regression analysis, each predictor can separately show an individual relationship with the outcome variable. Another anomaly of simple regression analysis is that it cannot predict the most significant *X* variable among independent variables (Cohen et al. 2003).

A multiple linear regression model is generally expressed by the relationship between a single outcome variable (Y) and some explanatory variables ($X_i$), given as:

$$\bar{Y} = a + b_1X_1 + b_2X_2 + \ldots + b_nX_n \qquad (1)$$

where the term $\bar{Y}$ is the predicted value of $Y$ (estimated from $X_i$), $a$ is the intercept, and $b_i$ is the partial regression coefficients. The multiple regression presents two different overlaps: the overlap for the combined effect and the overlap for the individual effect.

### 3-2- Artificial neural network (ANN)

The artificial neural network is an information-processing system. In this system, the information is processed by several interconnected simple elements that are known as neurons, positioned in the network's separated layers. The best neural network is the multi-layer perceptron (MLP) which is composed of three separate layers: input, output, and the intermediate or the hidden layers (Dreyfus 2005). The difficulty level of the problem determines the number of the hidden layers and neurons (Monjezi et al. 2012).

Neural network performance is dependent on the topology or architecture of the network including the number of the hidden layer(s) and the number of neurons in the hidden layer(s). The network should be trained with enough input-output patterns that are known as the training pairs (Maulenkamp and Grima 1999). The training is terminated once the error reaches the specified error and the optimum model is then specified. Several algorithms have been recommended for the training purpose of the neural network. The back-propagation (BP) algorithm is the most powerful technique for MLP networks as mentioned by many scholars (Tonnizam Mohamad et al. 2012; Singh et al. 2001; Monjezi et al. 2013). In feedforward BP ANNs, artificial neurons are organized by layers and send their signals forward. In this algorithm, based on the difference between the predicted and actual network outputs, the weights of the inter-neuron connections are adjusted (Kosko 1994). This procedure is known as learning or training. The difference between predicted and actual outputs is known as a network error. The obtained error is propagated back through the network and updates the individual weights which are named backward pass. The process is repeated until the error is converged to a defined level such as root mean square error (RMSE) (Simpson 1990).

### 3-3- Particle Swarm Optimization (PSO)

Kennedy and Eberhart (1995) introduced particle swarm optimization (PSO) as a population-based algorithm. The cognitive and social behavior of the swarm is the principal of the PSO. The PSO receives many advantages such as: (1) being a fast and easy algorithm to understand and implement and (2) needing little memory for computation and having few parameters to adjust in comparison with genetic algorithm. The PSO consists of a swarm of particles that search for the best position, including the best personal (pbest) and global (gbest) positions, based on its best solution (Monjezi et al. 2013; Abdi and Giveki 2013). In other words, during each iteration, each particle moves in the direction of its best pbest and gbest positions. The position and velocity of a particle during its moving process can be determined as follows:

$$V_{new} = w \times V + C_1.r_1(p_{best} - X) + C_2.r_2(g_{best} - X) \qquad (2)$$

$$X_{new} = X + V_{new} \qquad (3)$$

where $C_1$ and $C_2$ are two positive acceleration constants; V and X denote current velocity and position of particles, respectively, while $V_{new}$ and $X_{new}$ denote new velocity and position of particles, respectively; w denotes the inertial weight; and $r_1$ and $r_2$ denote the random numbers in (0, 1). Learning more about the PSO can be found in many studies (Eberhart and Shi 2001; Zhang et al. 2007; Yagiz and Karahan 2011; Babanouri et al. 2013; Momeni et al. 2015). PSO has been successfully applied in several areas such as rock and geotechnical engineering. Day by day, the number of researches being interested in PSO increases rapidly. For instance, Gordan et al. (2016) developed a combination of PSO and ANN for predicting factor of safety (FOS). Their result demonstrated that the PSO can be used as a powerful algorithm to optimize the ANN. In another study, presented by Ghasemi et al. (2016), it was also found that PSO is a reliable algorithm to design the ANFIS. Kalatehjari et al. (2014) presented a new method for solving slope stability using PSO and concluded that the developed model is less restricted than the conventional methods.

## 4- Prediction of backbreak

In the present paper, MLR, ANN, and PSO are used to develop a precise and acceptable equation to predict backbreak induced by quarry blasting. To develop the MLR, ANN, and PSO, eight effective parameters on the backbreak including H/B, S/B, ST, D, RQD, NoR, PF, and CHD were adopted as inputs of the models, while backbreak was set as an output parameter.

### 4-1- Prediction of backbreak by MLR

To predict backbreak in the first stage, the correlation among main variables was tested by Pearson correlation coefficient. The correlation coefficient shows the intensity of the linear relationship as well as the type of relationship (direct or inverse). The range of variables is fluctuating between -1 and +1. If the value of this coefficient is 0, it means that there is no linear relationship between the two variables. The Pearson correlation coefficient can be obtained from eq. (4). Table 2 shows the main variables correlation matrix of this study.

$$Corr(y,x) = \frac{\sum(y_i - \bar{y})(x_i - \bar{x})}{\sqrt{\sum(y_i - \bar{y})^2 \sum(x_i - \bar{x})^2}} \tag{4}$$

where $y_i - \bar{y}$ is the deviation of each observation $y_i$ from the mean of the variable y and $x_i - \bar{x}$ is the deviation of each observation $x_i$ from the mean of the variable x.

**Table 2-. Pearson correlation coefficients matrix for effective parameters on backbreak**

| Variables | BB | H/B | D | ST | PF | S/B | CH | RQD | NoR |
|---|---|---|---|---|---|---|---|---|---|
| BB | 1.000 | | | | | | | | |
| H/B | -0.722 | 1.000 | | | | | | | |
| D | 0.709 | -0.877 | 1.000 | | | | | | |
| ST | 0.520 | -0.688 | 0.711 | 1.000 | | | | | |
| PF | -0.351 | 0.341 | -0.362 | -0.260 | 1.000 | | | | |
| S/B | -0.309 | 0.293 | -0.211 | -0.450 | 0.174 | 1.000 | | | |
| CHD | 0.224 | -0.157 | 0.206 | 0.212 | 0.502 | -0.056 | 1.000 | | |
| RQD | -0.203 | -0.276 | 0.347 | 0.262 | 0.034 | 0.064 | 0.034 | 1.000 | |
| NoR | -0.021 | 0.033 | 0.029 | -0.004 | 0.392 | 0.084 | 0.482 | 0.037 | 1.000 |

In this study, 73 datasets are collected from practical blasting operations of the Angouran mine. The available datasets are grouped into modeling and testing datasets. For modeling, 60 data points were used whereas remaining (i.e., 13 data points) data were taken into account for testing the models.

In the assumptions of multiple regressions, the relationship between variables is assumed to be linear and the residuals normally distributed. To obtain the linear equation related to backbreak, all the parameters are shown in Table 2 as the input, and the measured backbreak as the output was analyzed by SPSS software. For the backbreak prediction equation, 5 has been obtained as the multiple linear regression. From equation 5 it was found that some parameters showed less effect on the backboard and could be omitted. However, all parameters even in a low value of coefficients are presented here.

$$\begin{aligned} BB = 10.255 - 0.943(H/B) + 0.21(D) \\ - 0.249(ST) \\ - 0.001(PF)\ldots \\ -1.454(S/B) + 0.0004(CH) \\ - 0.054(RQD) \\ - 0.061(NoR) \end{aligned} \tag{5}$$

Regression model coefficients for research variables and co-linear variables of the model are presented in Table 3. The values of the variance inflation factor and the tolerance show that there is no co-linear problem in considered variables. Also, the regression statistical characteristics and variance analysis is presented in Table 4.

### 4-2- Prediction of backbreak by Multiple Non-linear Regression Analysis

In many cases, the linear model predicts a good approximation. But we know that the relationships between the variables are rarely linear, and these relationships may be non-linear. Therefore, in addition to the linear models, various nonlinear models fitted with the same data used in the linear models. For this purpose, four models including polynomial, power, exponential, and logarithmic are selected. The relationships and determination coefficient of the mentioned models are listed in Table 5.

**Table 3-. Regression coefficients and co-linear variables of model**

| Dependent variables | Unstandardized Coefficients | | Standardized Coefficients | t values | Collinearity Statistics | |
|---|---|---|---|---|---|---|
| | B | Std. Error | Beta | | Tolerance | VIF |
| Constant | 10.255 | 3.214 | - | 3.190 | - | - |
| H/B | -.943 | .378 | -.357 | -2.497 | .213 | 4.691 |
| D | .021 | .006 | .529 | 3.294 | .169 | 5.934 |
| ST | -.249 | .425 | -.062 | -.585 | .386 | 2.592 |
| PF | -.001 | .001 | -.086 | -.886 | .463 | 2.160 |
| S/B | -1.454 | 1.742 | -.065 | -.835 | .723 | 1.383 |
| CH | 3.848E-5 | .000 | .146 | 1.549 | .488 | 2.050 |
| RQD | -.054 | .009 | -.465 | -6.279 | .791 | 1.264 |
| NoR | -.061 | .121 | -.039 | -.506 | .724 | 1.381 |

**Table 4-. The regression statistical characteristics and variance analysis**

| Model summary | | | | | |
|---|---|---|---|---|---|
| R | R Square | Adjusted R Square | Std. Error of the Estimate | Durbin-Watson | Numbers |
| .882[a] | .778 | .744 | .4716 | 1.591 | 60 |
| Variance analysis | | | | | |
| Model | Sum of Squares | df | Mean Square | F | Sig. |
| Regression | 39.841 | 8 | 4.980 | 22.397 | .000[b] |
| Residual | 11.340 | 51 | .222 | | |
| Total | 51.182 | 59 | | | |

**Table 5-. The relationships and determination coefficient of the developed models**

| Model | Equation | determination coefficient |
|---|---|---|
| Polynomial | $BB = \begin{pmatrix} 7.291 - 0.917(H/B) + 7.9 \times 10^{-5}(D)^2 - 0.005(ST)^3 \dots \\ -0.29(S/B)^5 + 9.2 \times 10^{-7}(NoR)^8 \end{pmatrix}$ | 0.70 |
| Power | $BB = 10^{\begin{bmatrix} 1.234 - 0.09(H/B) + 0.002(D) - 0.031(ST) - 8.7\times10^{-5}(PF)\dots \\ -0.125(S/B) + 3.5\times10^{-6}(CH) - 0.005(RQD) - 0.004(NoR) \end{bmatrix}}$ | 0.79 |
| Exponential | $BB = exp\begin{pmatrix} 0.317 + 2.385(H/B)^{-3.266} - 9.463(D)^{-0.532} + 0.805(ST)^{-3.98} + 0.338(PF)^{-2.015} \dots \\ +1.081(S/B)^{-0.294} + 0.289(CH)^{-1.707} + 8.258(RQD)^{-0.573} - 0.177(NoR)^{-0.575} \end{pmatrix}$ | 0.80 |
| Logarithmic | $BB = \begin{bmatrix} 8.168 - 2.548 \times LN(H/B) + 2.341 \times LN(D) - 0.937 \times LN(ST) - 0.619 \times LN(PF) \dots \\ -1.582 \times LN(S/B) + 0.342 \times LN(CH) - 2.450 \times LN(RQD) - 0.365 \times LN(NoR) \end{bmatrix}$ | 0.79 |

Performance comparison of the developed models is fulfilled using value account for (VAF), root mean square error (RMSE), determination coefficient ($R^2$) and mean absolute percentage error (MAPE).

$$R^2 = 100\left[\frac{\left(\sum_{i=1}^{N}(y_{meas}-\bar{y}_{meas})(y_{pred}-\bar{y}_{pred})\right)}{\sqrt{\sum_{i=1}^{N}(y_{meas}-\bar{y}_{meas})^2\sum_{i=1}^{N}(y_{pred}-\bar{y}_{pred})^2}}\right] \quad (6)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_{meas}-y_{pred})^2} \quad (7)$$

$$VAF = 100\left[1-\frac{var(y_{meas}-y_{pred})}{var(y_{meas})}\right] \quad (8)$$

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

where $y_{meas}$ and $y_{pred}$ are measured and predicted values and $\bar{y}_{meas}$ and $\bar{y}_{pred}$ are the average of measured and predicted values, respectively. Also, var. means the variance of values.

RMSE is routinely used as a criterion to show the discrepancy between the measured and predicted values of the network. The lower the RMSE, the more accurate the prediction. Also, the greater the VAF and the smaller the MAPE (close to zero), the more performance the model. The calculated values of these coefficients for different models are presented in Table 6. As it shows, the exponential model has the best performance to predict backbreak.

**Table 6-. The obtained values of evaluative criteria for different models**

| Model | $R^2$ | RMSE | VAF | MAPE |
|---|---|---|---|---|
| Linear | 0.78 | 0.44 | 77.85 | 0.71 |
| Polynomial | 0.70 | 0.52 | 70.36 | 1.00 |
| Power | 0.80 | 0.42 | 79.47 | 0.65 |
| Exponential | 0.84 | 0.35 | 83.24 | 0.46 |
| Logarithmic | 0.79 | 0.42 | 78.89 | 0.68 |

## 4-3- Sensitivity analysis

One of the new methods for determining the sensitivity of the output to the input parameters is the Cosine Amplitude Method (CAM) (Jong and Lee 2004). In this method, an m-dimensional space is assumed where m is the number of input parameters.

$$X = \{X_1, X_2, X_3, \ldots, X_m\} \quad (10)$$

Each of the elements, $\mathbf{X_i}$, in the data array, $\mathbf{X}$ is itself a vector of length *m*, *i.e.*

$$X_i = \{X_{i1}, X_{i2}, X_{i3}, \ldots, X_{im}\} \quad (11)$$

The cosine amplitude method (CAM) of sensitivity analysis was first introduced by Yang and Zhang (1997a). This technique was employed to find out the most effective input parameters on output parameters. In this method, all the data pairs are defined as a specific point in m-dimensional space. In this way, each of the parameters is directly connected to the outputs. The strength of this relation $R_{ij}$ is calculated by

$$R_{ij} = \frac{\sum_{k=1}^{m} X_{ik}X_{jk}}{\sqrt{\sum_{k=1}^{m} {X_{ik}}^2 \sum_{k=1}^{m} {X_{jk}}^2}} \quad i,j = 1,2,\ldots,n \quad (12)$$

where $X_i$ and $X_j$ are inputs and outputs, respectively; and m is the number of all datasets. The larger the $R_{ij}$ is, the higher the influence of relevant input. From Table 6, it can be inferred that the stemming and spacing/burden (S/B) are the most influential input parameters on the backbreak.

The higher the influence of the input parameter on the output, the closer the $R_{ij}$ to one. If the input parameter is not affected by the output, $R_{ij}$ is zero. Typically, the $R_{ij}$ value above 0.9 represents a significant effect on the output, and values below 0.8 represent a weak effect on output (Khandelwal and Singh 2007).

Considering that the exponential model has a more accurate prediction of backbreak, sensitivity analysis for this model was performed using the cosine amplitude method (CAM). Fig. 3 shows that the most effective input parameters on backbreak in Angouran mine include the length of stemming, spacing/burden, hole diameter, number of rows, and …, respectively. Based on sensitivity analysis, it was also found that the length of stemming and charge per delay, respectively, were the most and least effective parameters on the backbreak in this case study. Note that, the developed equations in the present research can be only used in the studied sites.

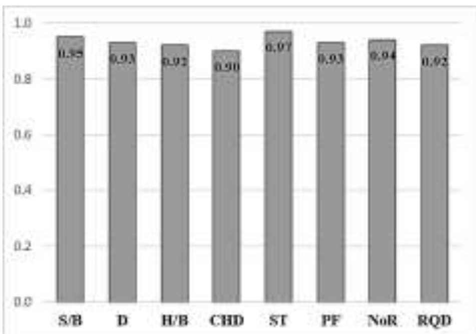



**Fig. 3-. Strengths of the relations between independent and dependent parameters**

## 4-4- Prediction of backbreak by ANN model

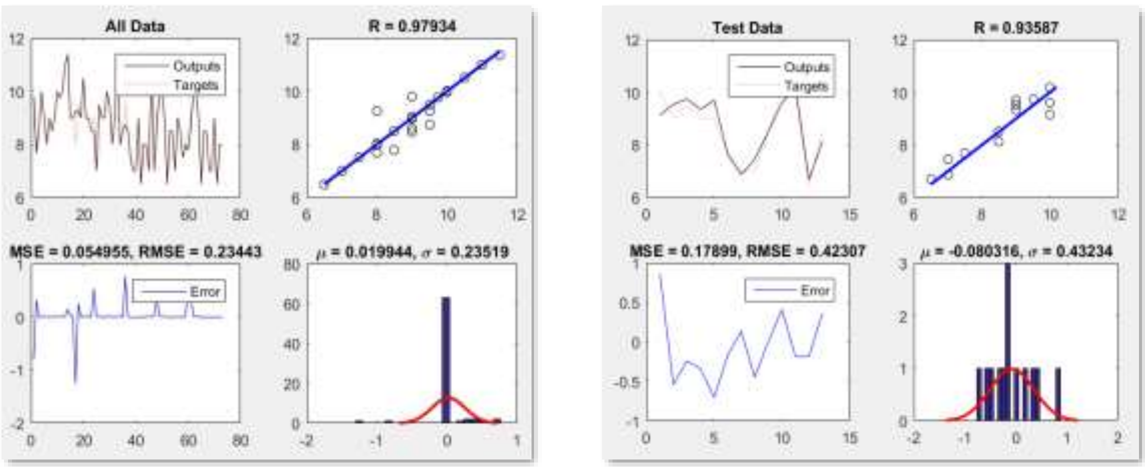
The purpose of the ANN training is to determine the values of weights to achieve the best network based on cost or objective function. Since the output value is determined corresponding to the input vector, the best learning can be considered as supervised learning. Among supervised learning algorithms, BP has been received attention in the field of engineering. Normally, the number of the hidden neuron is obtained using the trial-and-error procedure as this method was used in several ANN studies (Momeni et al. 2014). If the selected number of the hidden neuron is small, the system cannot train properly and if the selected number of the hidden neuron is large, overfitting (a network obtaining a large error) will happen in the ANN modeling. In this study, all datasets were divided randomly into training and testing datasets. The idea behind using some data for testing is to check the performance capacity of the developed model. A range of 20–30% of whole data was suggested for testing datasets in the study by Nelson and Illingworth (Rafig et al. 2001). So, in this study, 13 datasets(≅ 20%), were selected randomly for testing the model development, whereas the remaining 60 datasets were used for training the ANN models (more than 40 models). Table 7 shows several ANN models applied in this study together with their structures and performances. To evaluate the ANN model, RMSE was utilized.

As shown in Table 7, model no. 36 with eight inputs, two hidden layers (including 20 and 17 neurons) and one output (back-break) outperforms the other models. In the selected model, the value of 0.23 was obtained for RMSE. Fig. 4 displays the results of the selected model for all data and test data.

The graphs of predicted backbreak using the ANN technique against the measured backbreak for training and testing datasets are shown in Fig. 5. $R^2$ values of 0.931 and 0.942 for training and testing datasets, respectively, show that the ANN approach can predict backbreak with a high degree of accuracy.

**Table 7-. Several ANN models and their performance capacities applied in this study**

| Model | Transfer function | Structure | RMSE |
|---|---|---|---|
| 5 | TANSIG- TANSIG- PURELIN | 8-20-1 | 0.30 |
| 8 | TANSIG- TANSIG- PURELIN | 8-10-1 | 0.39 |
| 13 | TANSIG- TANSIG- POSLIN | 8-15-1 | 0.35 |
| 18 | LOGSIG- LOGSIG- PURELIN | 8-8-1 | 1.06 |
| 23 | LOGSIG- LOGSIG- POSLIN | 8-18-1 | 1.05 |
| 27 | LOGSIG- LOGSIG- LOGSIG- PURELIN | 8-15-12-1 | 1.10 |
| 30 | LOGSIG- LOGSIG- LOGSIG- POSLIN | 8-20-16-1 | 1.12 |
| 33 | TANSIG- TANSIG- TANSIG- PURELIN | 8-20-15-1 | 0.46 |
| 36 | TANSIG- TANSIG- TANSIG- PURELIN | 8-20-17-1 | 0.23 |
| 41 | TANSIG- TANSIG- TANSIG- POSLIN | 8-16-12-1 | 0.32 |

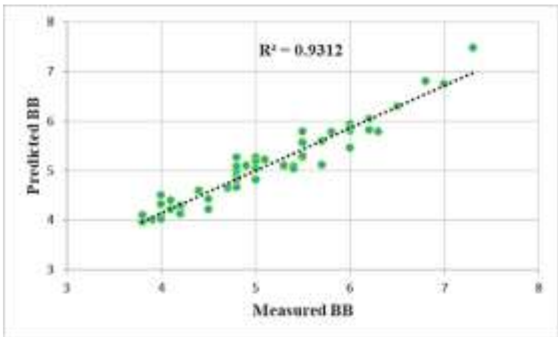



(a) (b)

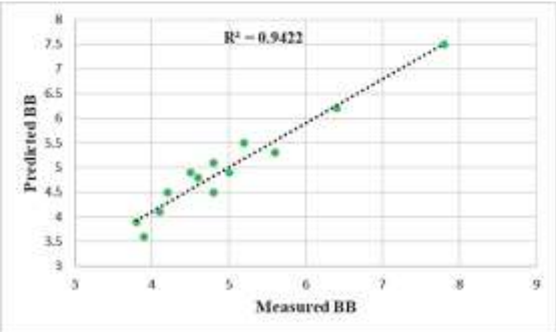
**Fig. 4-. timized ANN results, a) all data, b) test data**

### 4-5- Prediction of backbreak by PSO

As mentioned earlier, in this study, an attempt has been made to increase the performance prediction of the regression models by incorporating the PSO algorithm to develop a predictive model with a higher degree of accuracy for backbreak prediction. The followings are the modeling procedure of the hybrid Regression-PSO model in predicting backbreak.




Train




Test

**Fig. 5-. $R^2$ of measured and predicted values of back-break for training and testing datasets using ANN**

- Problem Definition: in this section, we determine the fitness function, the structure and the number of unknown variables, and the lower and upper limit of variables. For the problem at hand, the objective function is to minimize the mean square error (MSE). For instance, the problem definition for the exponential model is as follows:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\begin{bmatrix} BB^{Obs} - exp(w_1 + w_2(S/B)^{w_3} + w_4(B)^{w_5} + \\ w_6(H/B)^{w_7} + w_8(MC)^{w_9} + w_{10}(ST)^{w_{11}} + \\ w_{12}(PF)^{w_{13}} + w_{14}(NR)^{w_{15}} + w_{16}(RMR)^{w_{17}} \end{bmatrix} \quad (13)$$

- Definition of algorithm parameters: Based on the literature, the most important user specified parameters for the implementation of PSO models are particle size, inertia weight, and maximum iteration number (Sumathi and Paneerselvam 2010; Assareh et al. 2010). In this study, these parameters were determined using the trial-and-error method. It means that different values were considered for each parameter and the optimum value was determined when the fitness function presents the minimum value.

- Nonlinear different models with unknown coefficients were implemented in the PSO algorithm. For this purpose, the same data used in regression modeling was used (60 data for training and 13 data for testing). Each model was executed several times by changing the various parameters of the algorithm; this process continued until the algorithm reaches the appropriate convergence. Table 8 shows the results of evaluation indices for different models that are derived from regression modeling and the PSO algorithm.

As depicted in Table 8, better results have been achieved in the exponential model. The lack of improvement in power and logarithmic models can be concluded that these models have achieved the optimal answer by regression and no having other ability to improve.

Figs. 6 and 7 show a comparison between measured and predicted backbreak for the exponential model by PSO, training data, and testing data, respectively.

The exponential equation optimized by PSO was developed, as formulated as below:

$$\begin{aligned} \boldsymbol{BB = exp(-0.49 + 2.49(S/B)^{1.15}} \\ \boldsymbol{- 0.24(B)^{0.62}} \\ \boldsymbol{- 0.27(H/B)^{0.62}} \\ \boldsymbol{- 0.2(MC)^{-2.57}} \\ \boldsymbol{- 0.82(ST)^{0.99}} \\ \boldsymbol{+ 0.33(PF)^{-1.77}} \\ \boldsymbol{+ 9(NR)^{-0.47}} \\ \boldsymbol{+ 0.11(RMR)^{0.46}}) \end{aligned} \quad (14)$$

**Table 8-. Comparison of the obtained result of regression and regression-PSO**

| Model | $R^2$ | | RMSE | | VAF | | MAPE | |
|---|---|---|---|---|---|---|---|---|
| | regression | PSO | regression | PSO | regression | PSO | regression | PSO |
| Polynomial | 0.70 | 0.74 | 0.52 | 0.50 | 70.36 | 72.85 | 1.00 | 0.95 |
| Power | 0.80 | 0.80 | 0.42 | 0.42 | 79.47 | 79.45 | 0.65 | 0.57 |
| Exponential | 0.84 | 0.87 | 0.35 | 0.31 | 83.24 | 85.02 | 0.46 | 0.35 |
| Logarithmic | 0.79 | 0.80 | 0.42 | 0.41 | 78.89 | 78.90 | 0.68 | 0.65 |

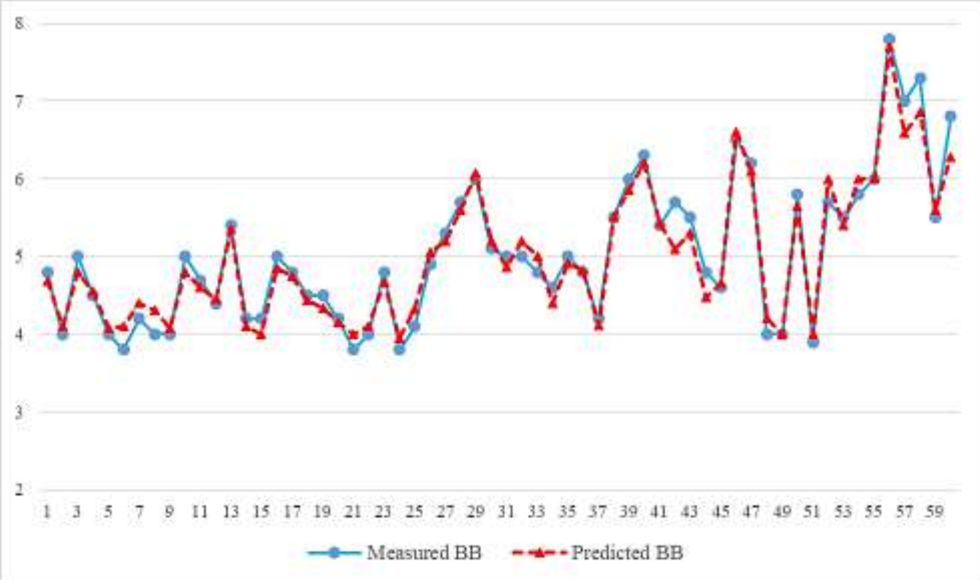



**Fig. 6-. Comparison of measured and predicted backbreak for exponential model (training data)**

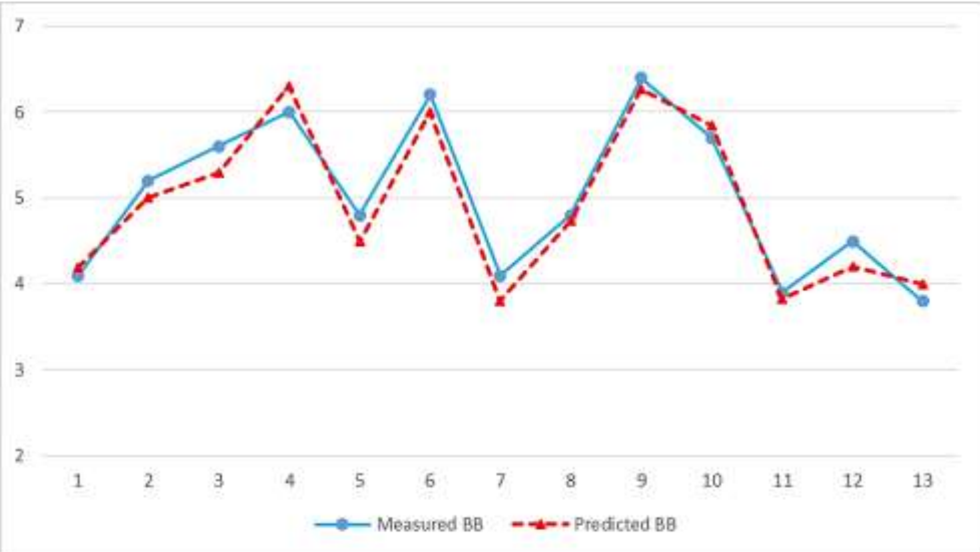



**Fig. 7-. Comparison of measured and predicted backbreak for exponential model (testing data)**

## 5- Conclusion

In this research, an attempt has been made to minimize back-break induced by blasting operations. To this aim, Angouran mine in Iran was considered and blasting pattern parameters for 73 operations were collected. In addition, back-break was measured in each operation. Considering the previous investigations and also collected data from the mine; including burden, spacing, hole length, stemming, the charge per delay, RQD, number of rows, and powder factor were selected as input parameters. Initially, using multiple regression analysis, different empirical equations were presented to predict backbreak. In order to find better solutions, the constructed models were implemented in PSO algorithms. Also, the prediction of backbreak was investigated using ANNs. After the evaluation and sensitivity analysis of the models, the following results were obtained:

- The PSO algorithm is a suitable tool for optimizing the models and more accurate prediction of backbreak.
- Among the presented empirical models, the optimized exponential model with PSO algorithm with an RMSE (0.31) and $R^2$ (0.87) shows better results in the prediction of backbreak and it is suitable for practical use in Angouran mine.
- Considering the sensitivity analysis, the most effective input parameters on backbreak in Angouran mine include the length of stemming, spacing/burden, hole diameter, number of rows, and …, respectively. Among the input parameters, length of stemming and charge per

delay have the most and the least effect on the backbreak, respectively.

- The computed values of the models' performance indices indicate that the ANN approach can be a suitable tool to predict backbreak. But it should be noted that ANNs do not show the definitive mathematical model that represents the explicit relation between inputs and outputs.
- results of ANNs show that multilayer networks are more powerful and efficient than single-layer in the prediction of backbreak.

## REFERENCE

**[1]** Abdi MJ, Giveki D (2013) Automatic detection of erythemato-squamous diseases using PSO–SVM based on association rules. Eng Appl Artif Intel 26:603–608

[2] Assareh E, Behrang MA, Assari MR, Ghanbarzadeh A (2010) Application of PSO (particle swarm optimization) and GA (genetic algorithm) techniques on demand estimation of oil in Iran. Energy 35:5223–5229

[3] Babanouri N, Karimi Nasab S, Sarafrazi S (2013) A hybrid particle swarm optimization and multi-layer perceptron algorithm for bivariate fractal analysis of rock fractures roughness. Int J Rock Mech Min Sci 60:66–74

[4] Bauer A (1982) Wall control blasting in open pits. CIM Special 30, Canadian Institute of Mining and Metallurgy, In: 14th Can, rock mechanics symposium, pp 3–10

[5] Cohen J, Cohen P, West SG, Aiken LS (2003) Applied multiple regression/correlation analysis for the behavioral sciences. Lawrence Erlbaum Associates, Mahwah

[6] Dreyfus G (2005) Neural Networks: methodology and application. Springer, Berlin

[7] Eberhart RC, Shi Y (2001) Particle swarm optimization: developments, applications and resources. In: Proceedings of IEEE International Conference on Evolutionary Computation, pp 81–86

[8] Gate WC, Ortiz BLT, Florez RM (2005) Analysis of rock fall and blasting backbreak problems. In: Proceedings of the fortieth US Rock Mechanics Symposium, paper ARMA 05-0671.

[9] Ghasemi E (2016) Particle swarm optimization approach for forecasting backbreak induced by bench blasting. Neural Comput Appl 28:1855-1862

[10] Ghasemi E, Kalhori H, Bagherpour R (2016) A new hybrid ANFIS–PSO model for prediction of peak particle velocity due to bench blasting. Eng Comput 32:607-614

[11] Gordan B, Jahed Armaghani D, Hajihassani M, Monjezi M (2016) Prediction of seismic slope stability through combination of particle swarm optimization and neural network. Eng Comput 32:85-97

[12] Jenkins SS (1981) Adjusting blast design for best results. Pit and Quarry, Rotterdam, Balkema

[13] Jimeno CL, Jimeno EL, Carcedo FJA (1995) Drilling and blasting of rocks. Rotterdam, Balkema

[14] Jong YH, Lee CI (2004) Influence of geological conditions on the powder factor for tunnel blasting. Rock Mech Rock Eng 41:533-538

[15] Kahraman S, Altun H, Tezekici BS, Fener M (2006) Sawability prediction of carbonate rocks from shear strength parameters using artificial neural networks. Int J Rock Mech Min Sci 43:157–64.

[16] Kalatehjari R, Ali N, Kholghifard M, Hajihassani M (2014) The effects of method of generating circular slip surfaces on determining the critical slip surface by particle swarm optimization. Arab J Geosci 7(4):1529–1539

[17] Kennedy J, Eberhart RC (1995) Particle swarm optimization. In: Proceedings of IEEE International Conference on Neural Networks, Piscataway, pp 1942–1948

[18] Khandelwal M, Singh TN (2006) Evaluation of blast-induced ground vibration predictors. Soil Dyn Earthquake Eng 27:116–125

[19] Khandelwal M, Singh TN (2007) Evaluation of blast-induced ground vibration predictors. Soil Dynam Earthq Eng, 27:116-125

[20] Konya CJ (2003) Rock blasting and overbreak control. Washington, DC: National Highway Institute, FHWA-HI-92-001

[21] Konya CJ, Walter EJ (1991) Rock blasting and overbreak control. FHWA Report, FHWA-HI-92-001.

[22] Kosko B (1994) Neural networks and fuzzy systems: a dynamical systems approach to machine intelligence. Prentice Hall, New Delhi

[23] Maulenkamp F, Grima MA (1999) Application of neural networks for prediction of the unconfined compressive strength (UCS) from Equotip Hardness. Int J Rock Mech Min Sci 36:29–39

[24] Momeni E, Jahed Armaghani D, Hajihassani M, Amin MFM (2015) Prediction of uniaxial compressive strength of rock samples using hybrid particle swarm optimization-based artificial neural networks. Measurement 60:50–63

[25] Momeni E, Nazir R, Jahed Armaghani D, Maizir H (2014) Prediction of pile bearing capacity using a hybrid genetic algorithm-based ANN, Measurement 57:122–131

[26] Monjezi M, Ahmadi Z, Varjani AY, Khandelwal M (2013) Backbreak prediction in the Chadormalu iron mine using artificial neural network. Neural Comput Appl 23:1101–1107

[27] Monjezi M, Dehghani H (2008) Evaluation of effect of blasting pattern parameters on backbreak using neural networks. International Journal of Rock Mechanics and Mining Sciences 45:1446–1453

[28] Monjezi M, Khoshalan HA, Varjani AY (2012) Prediction of flyrock and backbreak in open pit blasting operation: a neurogenetic approach. Arab J Geosci 5(3):441–448

[29] Monjezi M, Mehrdanesh A, Malek A, Khandelwal M (2013) Evaluation of effect of blast design

parameters on flyrock using artificial neural networks. Neural Comput Appl 23:349–356

[30] Monjezi M, Rezaei M, Yazdian A (2010) Prediction of backbreak in open-pit blasting using fuzzy set theory. Expert Systems with Applications 37:2637–2643

[31] Rafig MY, Bugmann G, Easterbrook DJ (2001) Neural network design for engineering applications. Comput Struct 79:541–1552

[32] Scoble MJ, Lizotte YC, Paventi M, Mohanty BB (1997) Measurement of blast damage. Mining Engineering 49:103–108

[33] Simpson PK (1990) Artificial neural system: foundation, paradigms, applications and implementations. Pergamon, New York.

[34] Singh VK, Singh D, Singh TN (2001) Prediction of strength algorithm and artificial neural network. Sci World J, Article ID 643715.

[35] Sumathi S, Paneerselvam S (2010) Computational intelligence paradigms: theory and applications using MATLAB. CRC Press, New York

[36] Tawadrous AS (2006) Evaluation of artificial neural networks as a reliable tool in blast design. In: Proceedings of the thirty-second Annual Conference on Explosives and Blasting Techniques, Dallas, International Society of Explosives Engineering

[37] Tonnizam Mohamad E, Hajihassani M, Jahed Armaghani D, Marto A (2012) Simulation of blasting-induced air overpressure by means of artificial neural networks. Int Rev Model Simul 5(6):2501–2506

[38] Yagiz S, Karahan H (2011) Prediction of hard rock TBM penetration rate using particle swarm optimization. Int J Rock Mech Min Sci 48:427–433

[39] Yang Y, Zhang Q (1997a) Analysis for the results of point load testing with artificial neural network. In: Proceedings of the 9th International Conference on Computer Methods and Advances in Geomechanics, Rotterdam, A.A. Balkema, pp 607–612

[40] Zhang JR, Zhang J, Lok TM, Lyu MR (2007) A hybrid particle swarm optimization-back-propagation algorithm for feedforward neural network training. Appl Math Comput 185(2):1026–1037.