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A comparative study on the application of various artificial neural networks to simultaneous prediction of rock fragmentation and backbreak

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ABSTRACT

In blasting operation, the aim is to achieve proper fragmentation and to avoid undesirable events such as backbreak. Therefore, predicting rock fragmentation and backbreak is very important to arrive at a technically and economically successful outcome. Since many parameters affect the blasting results in a complicated mechanism, employment of robust methods such as artificial neural network may be very useful. In this regard, this paper attends to simultaneous prediction of rock fragmentation and backbreak in the blasting operation of Tehran Cement Company limestone mines in Iran. Back propagation neural network (BPNN) and radial basis function neural network (RBFNN) are adopted for the simulation. Also, regression analysis is performed between independent and dependent variables. For the BPNN modeling, a network with architecture 6-10-2 is found to be optimum whereas for the RBFNN, architecture 6-36-2 with spread factor of 0.79 provides maximum prediction aptitude. Performance comparison of the developed models is fulfilled using value account for (VAF), root mean square error (RMSE), determination coefficient (R^2) and maximum relative error (MRE). As such, it is observed that the BPNN model is the most preferable model providing maximum accuracy and minimum error. Also, sensitivity analysis shows that inputs burden and stemming are the most effective parameters on the outputs fragmentation and backbreak, respectively. On the other hand, for both of the outputs, specific charge is the least effective parameter.

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1. Introduction

Backbreak is one of the undesirable phenomena in the blasting operation. In other words, a blast without any unwanted effects can be evaluated as a successful activity, and in such activity, a large proportion of the available energy has been consumed in the right direction, i.e. rock fragmentation. Rock fragmentation can be considered as the main objective of the blasting operation. Size distribution of the rock fragments is very important on the overall mining and processing plant economics (Michaux and Djordjevic, 2005; Monjezi et al., 2009). On the other hand, the blasting operation usually is accompanied by various unwanted phenomena such as backbreak. Backbreak is the fractured zone beyond the last blasting row (Jimeno et al., 1995). Occurrence of this phenomenon is an indication of wasting potential explosive energy. Moreover, it has some other hazardous effects such as slope instability. Therefore, remedial measures should be presented for diminishing and/or omitting backbreak. The effective blast design parameters are (1) blasting pattern components, (2) rock mass geomechanical properties, and (3) explosive specifications (Thornton et al., 2002; Zhu et al., 2007, 2008). Implementation of a suitable blasting pattern, as a controllable parameter, is very important in preventing backbreak and achieving proper fragmentation (Monjezi and Dehghani, 2008). Gates et al. (2005) pointed out that the backbreak is increased when inappropriate delay timing is applied. Many researchers believe that excessive burden is the main cause of the backbreak and producing oversize rock fragments (Konya and Walter, 1991; Konya, 2003). To date, several empirical models have been developed to predict the blasting results. However, complicated nature of the problem due to multiplicity of the effective parameters has caused development of simplified prediction models with limited number of independent

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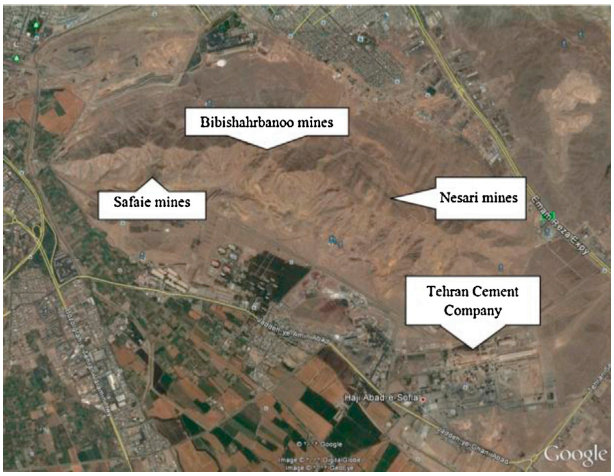


Fig. 1. Tehran cement company limestone mines.

variables. The simplification assumptions are the main cause of poor performance of the empirical models. Moreover, simultaneous prediction of backbreak and fragmentation is not possible using previously developed models. In order to overcome shortcomings of the empirical models, artificial intelligence (AI) based methods can effectively be applied to solving complicated problems. Some of the most popular AI paradigms are artificial neural network (ANN), fuzzy inference system (FIS) and genetic algorithm (GA).

ANN has capability of learning, evoking and generalizing from the given patterns (Cheng and Ko, 2006). Its high performance in solving complicated problems has made this technique so applicable. Various applications of the ANN method in rock engineering have been reported in the literature (Cai and Zhao, 1997; Yang and Zhang, 1997a, 1997b; Maulenkamp and Grima, 1999; Benadros and Kaliampakos, 2004; Ermini et al., 2005). Also, several researchers have implemented the method in the field of mine blasting (Khandelwal and Singh, 2005, 2006, 2007, 2009; Bakhshandeh et al., 2010; Kulatilake et al., 2010; Khandelwal, 2010, 2012; Monjezi et al., 2010).

In this paper, an attempt has been made to simultaneously predict backbreak and fragmentation due to blasting operation in the Tehran Cement Company limestone mines using ANN method.

2. Case study

Tehran Cement Company limestone mines, i.e. Bibishahrbanoo, Nesari and Safaie, are located at the southeast of Tehran. These mines are under development and have total proved limestone deposits of 41.3 million tons. From the geological point of view, these mines are situated in the sedimentary rocks of Cretaceous period. The limestone layers with an eastwest extension have 75° dip to the north. Limestone is the main exposure layer in the area while in some parts black shale and cream marl are also observed. The Nesari mine is located 10 km northeast of Tehran Cement Company. Layers of dolomite and dolomitic limestone are observed in this mine in a narrow strip formation. Safaie Mountain is also located in the northwest of Bibishahrbanoo Mountain (Fig. 1).

The blasting pattern specifications of limestone mines are presented in Table 1. Mean fragment size of 45 cm is suitable for the mine primary crusher.

The controllable parameters of burden, spacing, stemming, bench height, specific charge and specific drilling are considered as inputs to develop an ANN model for predicting backbreak and rock fragmentation as the model outputs. Fig. 2 shows the undesirable backbreak after blasting in mines.

It is noted that, for determining fragmentation quality, image processing method is employed. As such, 80% passing size (D80) is considered as the fragmentation evaluation index. Variations of the input and output parameters are given in Table 2. In this study, 103 datasets are collected from practical blasting operations of the mines. The available datasets are grouped into training and testing datasets. For this, using sorting mechanism, 10% of the datasets are kept apart for testing and evaluating of the simulations.

3. Statistical analysis

Multivariate regression analysis (MVRA) is an extension of regression analysis, which was firstly employed by Pearson in 1908 (Yilmaz and Yuksek, 2009). This method can easily be used for determining the linear and/or nonlinear relationship between dependent predictive and independent criterion variables. The main form of MVRA is

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n \quad (1)$$

where $\beta_1, \beta_2, \ldots, \beta_n$ are the coefficients of regression model; β_0 is a constant value; Y is the dependent variable; and $x_1, x_2, \ldots, x_n$ are the independent variables.

Two MVRA models are developed to predict backbreak and fragmentation considering input parameters given in Table 2.

Eqs. (2) and (3) show mathematical formulations of the developed models for predicting backbreak and fragmentation, respectively. Also, statistical details of the MVRA models are summarized in Table 3.

$$BB = 0.494B + 1.082S + 0.015H + 1.203T - 0.056SC + 23.576SD - 8.501 \quad (2)$$

$$Fr = 0.371B + 0.215S - 0.012H + 0.182T - 0.025SC + 6.45SD - 1.959 \quad (3)$$

4. Basis of artificial neural network

ANN is a subsystem of AI. This computational system is a simulation of human brain (Maulenkamp and Grima, 1999). Original ANN was introduced by McCulloch and Pitts (1943), and since then it was popular and applicable to various fields of science and technology to solve complicated problems. Capabilities of the technique are calculating arithmetic and logical functions, generalizing and transforming independent variables to the dependent variables, parallel computations, nonlinearity processing, handling imprecise or fuzzy information, function approximation and pattern recognition.

ANN is trained using a set of real inputs and their corresponding outputs. For a better approximation, sufficient number of datasets is required. Performance of the trained model is checked with part of the available data known as testing datasets. To find out the best possible network, various topologies are constructed and tested. The process of model training-testing has to be continued until the optimum model with minimum error and maximum accuracy is achieved. ANN training-testing (Monjezi and Dehghani, 2008) is illustrated in Fig. 3.

A neural network has a layered structure, and each layer contains processing units or neurons. Problem effective variables are placed in the input layer, whereas objectives or dependent variables are put in the last (output) layer. The computation components (black box) of the system are the neurons of hidden layers. All of the layers are connected to each other by weighted connections. Fig. 4 shows a typical ANN structure. Each neuron is connected to the neurons in the subsequent layer. However, there is no connection between the neurons of the same layer (Demuth and Beale, 1994).

Table 1
Blasting pattern specifications of limestone mines.

Main explosive type	Secondary explosive type	Blasting hole pattern	Bench height (m)	Hole diameter (mm)	Rows per blast	Holes per row
ANFO	Emulation	V-cut (staggered)	15	76	1–4	10–15

Fig. 2. The undesirable backbreak after blasting in mines.

Table 2
Basic statistics of inputs and output parameters.

Burden B (m)	Spacing S (m)	Hole height H (m)	Stemming T (m)	Specific charge SC (kg/m^3)	Specific drilling SD (m/m^3)	Back break BB (m)	Fragmentation Fr (m)
1.8–4.5 (3.02)	1.7–4.3 (3.35)	2.5–28.5 (17.8)	1.6–3 (2.8)	1.96–28.68 (8.303)	0.063–0.226 (0.109)	1–4 (2.41)	0.37–1.76 (0.82)

Note: Numbers in parentheses represent the average values.

In the training process, the interconnections among the neurons are initially assigned specific weights. The network would be able to perform a function by adjusting the initial weights.

A single neuron containing multiple inputs ($x_1, \cdots, x_n$) and a single output (y) is shown in Fig. 5. In the process of ANN training, an initial arbitrary value (weight) is assigned to the connections and then to combine all of the weighted inputs and generate the neuron output, and the following equation is applied:

$$O = \sum x_i w_i + b \tag{4}$$

where x_i is the inputs, w_i is the connection weights, and b is the bias.

To map a neuron net output to its actual output, an activation function f has to be selected. The transfer function can be expressed as

$$y = f(O) = f(\sum x_i w_i + b) \tag{5}$$

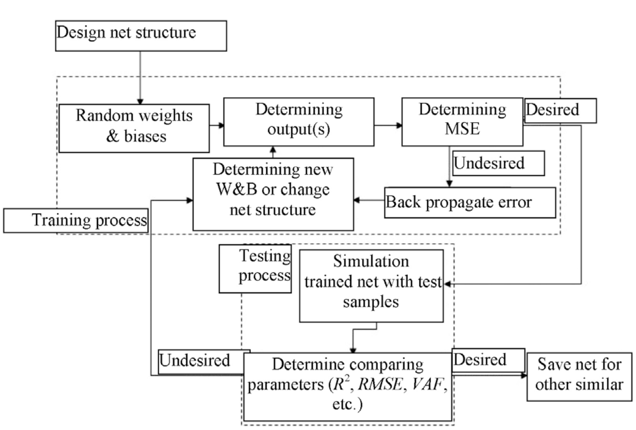


Fig. 3. Artificial neural network training-testing process.

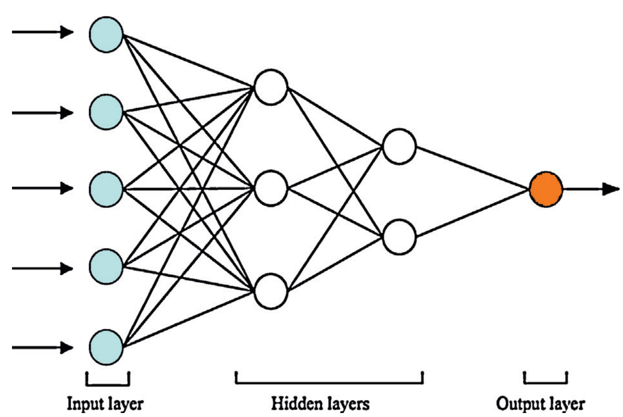


Fig. 4. Artificial neural network structure.

Applying Eq. (5) to the neuron initial summation output resulting from Eq. (4), the neuron final output within a range of [0, 1] or [−1, 1] is achieved depending on the type of applied transfer function. It is noted that a single activation function should be selected for the neurons of a particular layer. Type of the activation function is fully dependent on nature of the problem to be solved. Also their respective graphic presentations are shown in Table 4. During

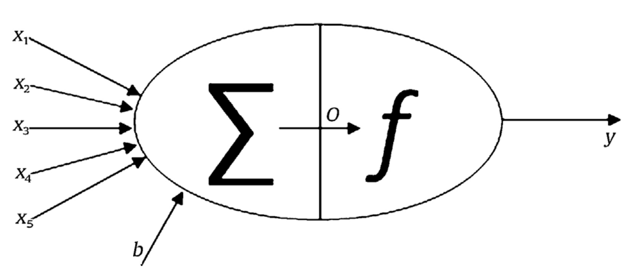


Fig. 5. Neuron structure.

Table 3
Linear regression coefficients for backbreak and fragmentation.

Independent variables	Regression coefficient		Standard error	
	Backbreak	Fragmentation	Backbreak	Fragmentation
Constant	−8.501	−1.959	7.746	1.882
B	0.494	0.371	0.804	0.194
S	1.082	0.215	0.868	0.213
H	0.015	−0.012	0.035	0.009
T	1.203	0.182	0.72	0.178
SC	−0.056	−0.025	0.049	0.014
SD	23.576	6.45	19.33	4.756

the training process, network tries to decrease difference between predicted and real values.

To do so, a specific algorithm is selected by which connection weights and biases are repeatedly updated until the minimum error is provided. There are various types of training algorithms, such as back propagation and radial basis (Demuth and Beale, 1994).

4.1. Back propagation neural network

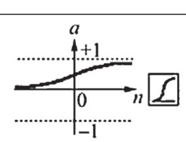
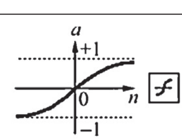
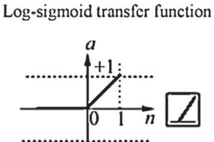
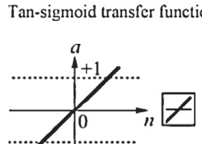
Back propagation neural network (BPNN) normally has a multi-layer structure with one or more nonlinear hidden layer and a linear output layer. It is widely used as a predicting tool in various fields of geo-sciences. Generally, in BPNN four transfer functions are used as presented in Table 4. These networks can be used to make nonlinear and/or linear correlation between input(s) and output(s).

Various types of functions, such as Newton and gradient descent, can be used for training BPNNs. In the simplest form, weights and biases are frequently updated to decrease performance function. Two different techniques (incremental method and batch method) are implemented in the learning process of the ANN. In the incremental method, weights and biases are upgraded after each input entrance to net but in the batch method upgrading process is done after entrance of all inputs. Generally, performance function is considered as the mean square error (*MSE*), which is calculated by the following equation (Demuth and Beale, 1994; Benadros and Kaliampakos, 2004):

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - y_i')^2 \tag{6}$$

where N is the number of input–output datasets.

Table 4
BPNN most usual transfer functions.

Transfer function situation	Transfer function diagram	
Hidden layers	 a=log$_{10}$sig(n) Log-sigmoid transfer function	 a=tansig(n) Tan-sigmoid transfer function
Output layer	 a=poslin(n) Positive linear transfer function	 a=purelin(n) Linear transfer function

4.2. Radial basis function neural network

Radial basis function neural network (RBFNN) is one of the efficient artificial networks. These types of the networks are mostly used for function approximation. However, they can also be applied for pattern recognition and classification. Arriving in very small errors during training process can be considered as the main advantage of RBFNN over BPNN (Haykin, 1999; Christodoulou and Georgiopoulos, 2001). Unlike BPNN, in the structure of RBFNN, there is only one hidden layer that makes computation time very less. Moreover, transfer function φ of the hidden layer is always of the Gaussian type:

$$\varphi(\boldsymbol{P}) = \exp\left(-\frac{1}{2\sigma_j}||\boldsymbol{P} - C_j||^2\right) \tag{7}$$

where $\boldsymbol{P}$ is the input vector; C_j and σ_j are the center and extension (spread factor) of Gaussian function, respectively.

As illustrated in Fig. 6a, $\varphi(\boldsymbol{P})$ reaches the maximum value (1.0) when $\boldsymbol{P}$ is equal to 0.0. In this way, when difference between values of weights and inputs is lower, the neuron output will be greater. In fact, here the amount of output of hidden layer shows the absolute difference between connection weights and inputs. In the RBFNN, the jth network output d_j (Demuth and Beale, 1994) can be calculated by

$$d_j = \sum_{j=1}^{N}\varphi_j(\boldsymbol{P})w_{ij} \tag{8}$$

where φ_j is the jth neuron output, and w_{ij} is the output layer weight.

During the training process, parameters C_j, σ_j and w_{ij} are determined by the network to provide the best approximation function. In this process, optimum number of neurons required for the hidden layer is also determined by the network. The structure of a RBFN is illustrated in Fig. 6b.

5. Results and discussion

To compare model performance of the regression analysis and ANN method, value account for (*VAF*), root mean square error (*RMSE*), determination coefficient (R^2) and maximum relative error (*MRE*) are utilized:

$$VAF = 100\left[1 - \frac{var(y - y')}{var(y)}\right] \tag{9}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y - y')^2} \tag{10}$$

$$R^2 = \left[\frac{\sum_{i=1}^{N}(y - \bar{y})(y' - \bar{y}')}{\sum_{i=1}^{N}(y - \bar{y})^2\sum_{i=1}^{N}(y' - \bar{y}')^2}\right]^2 \tag{11}$$

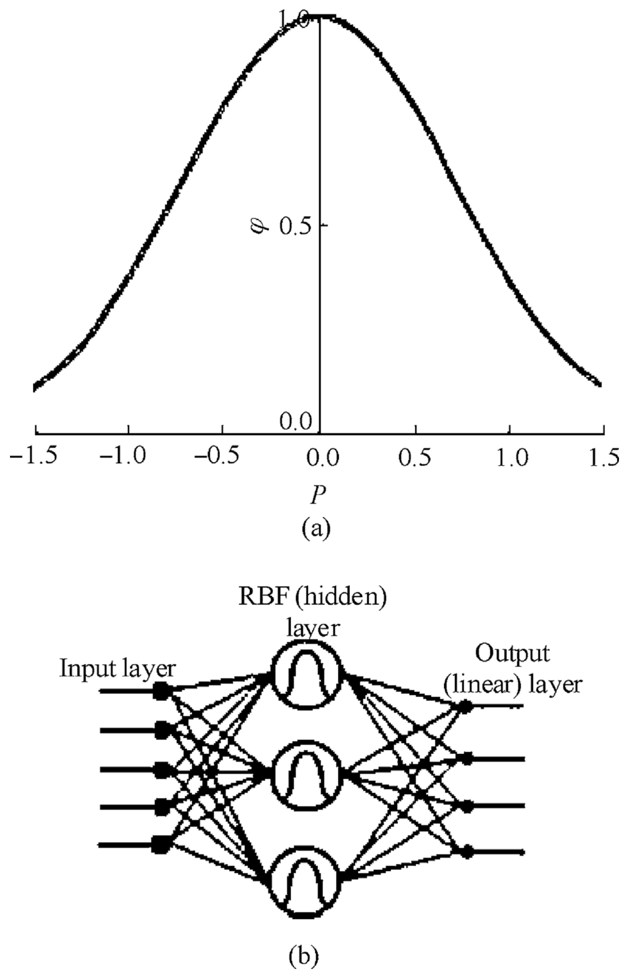


Fig. 6. (a) Radial basis transfer function (radbas) and (b) structure of a radial basis function network.

$$MRE = \max\left(100\frac{|y-y'|}{y}\right) \tag{12}$$

where y and y' are the measured and predicted values, respectively; $\bar{y}$ and $\bar{y}'$ are the average measured and average predicted values, respectively; var(·) is the variance.

Table 5 shows the performance of some of the constructed BPNN models. As it is observed from this table, BPNN model with architecture 6-10-2 gives the best result with minimum errors and maximum accuracy, and is considered as the optimum model amongst the BPNN models. Also, Table 6 shows the performance of some of the constructed RBFNN models with various spread factors. As it is seen from Table 6, the model with spread factor of 0.79 provides the best results. Furthermore, performance of the regression model is shown in Table 7. Figs. 7–9 show the correlation between predicted and measured outputs for the three methods of modeling. In Figs. 7–9, dashed line shows 1:1 slope line, where measured and predicted values will be same. From Tables 5–7 and Figs. 7–9, it is noted that BPNN modeling shows better prediction capability as compared to the other applied methods. Superiority of BPNN over RBFNN was also reported by Monjezi et al. (2010).

6. Sensitivity analysis

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

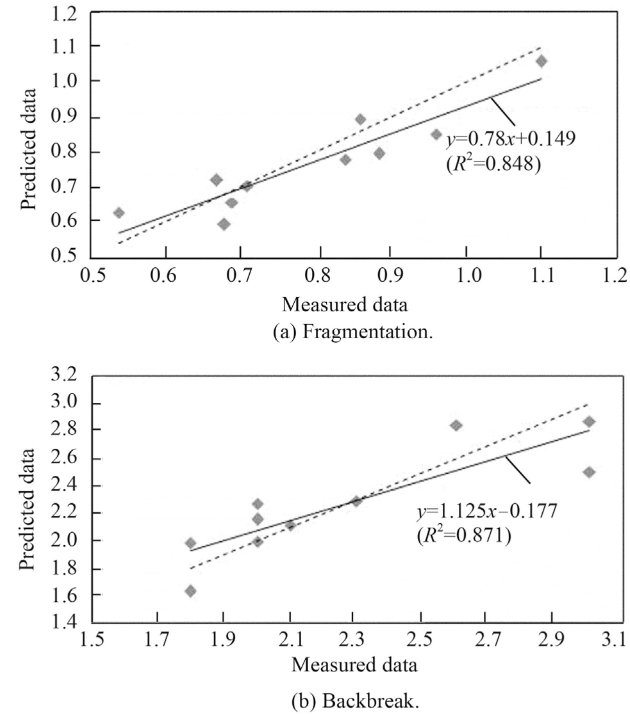


Fig. 7. The correlation of measured and predicted data with back propagation neural network.

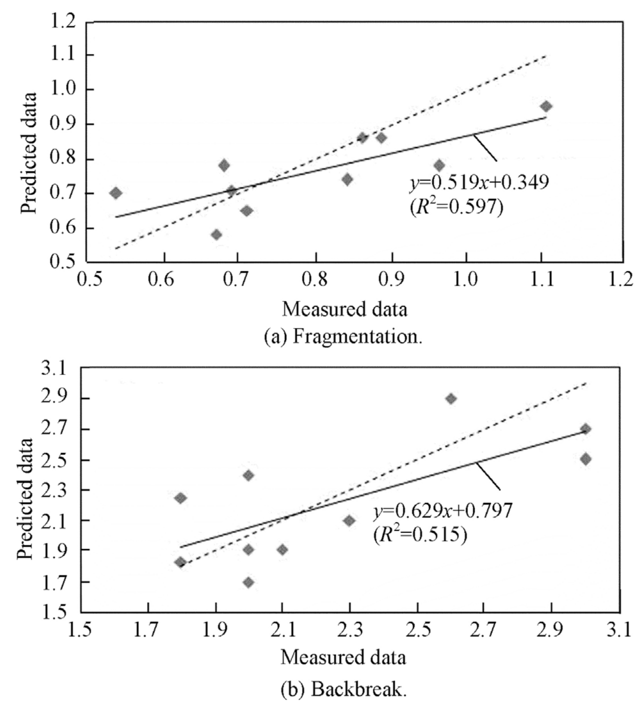


Fig. 8. The correlation of measured and predicted data with radial basis function neural network.

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

$$R_{ij} = \frac{\sum_{k=1}^{m} x_{ik}x_{jk}}{\sum_{k=1}^{m} x_{ik}^2 \sum_{k=1}^{m} x_{jk}^2} \tag{13}$$

Table 5
The calculated performance indices for back propagation neural network models.

No.	Net structure	R^2 (%)		RMSE		VAF (%)		MRE (%)	
		BB	Fr	BB	Fr	BB	Fr	BB	Fr
1	6-10-2	87.1	84.8	0.2206	0.0673	90.21	95.28	16.58	16.23
2	6-14-2	90.2	86.7	0.3052	0.1294	82.73	86.34	20.2	27.45
3	6-18-2	74.9	65.3	0.4867	0.3581	77.35	74.81	43.5	62.7
4	6-5-5-2	75.6	66.1	0.3955	0.3024	81.47	63.23	36.11	59.89
5	6-10-6-2	88.5	79.5	0.5438	0.4147	70.31	47.36	52.74	68.55
6	6-10-10-2	86.4	73.8	0.367	0.2634	85.34	80.03	27.96	33.57

Table 6
The calculated performance indices for radial basis function neural network models.

No.	Spread factor	Net structure	R^2 (%)		RMSE		VAF (%)		MRE (%)	
			BB	Fr	BB	Fr	BB	Fr	BB	Fr
1	0.7	6-36-2	48	53.6	0.461	0.249	89.55	76.12	34.1	38.46
2	0.79	6-36-2	51.5	59.7	0.3108	0.112	88.82	86.53	25	29.63
3	0.8	6-36-2	50.3	58.1	0.354	0.158	93.4	89.6	29.03	32.52

Table 7
The calculated performance indices for multivariate regression analysis model.

R^2 (%)		RMSE		VAF (%)		MRE (%)	
BB	Fr	BB	Fr	BB	Fr	BB	Fr
75.1	30.1	0.672	0.291	34.77	21.73	45.32	60.22

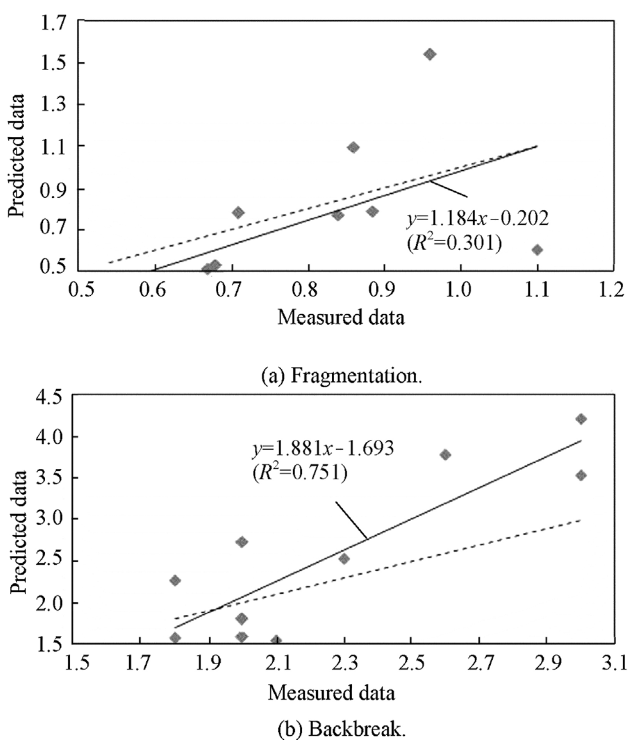


Fig. 9. The correlation of measured and predicted data with multivariate regression analysis.

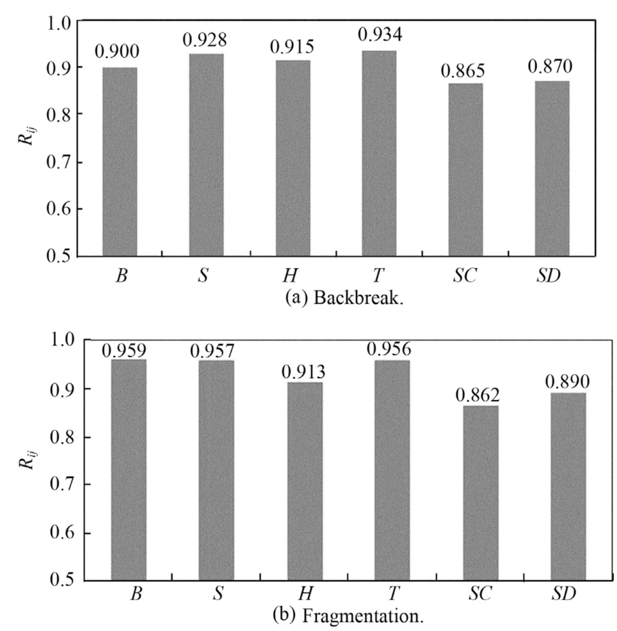


Fig. 10. Sensitivity analysis for backbreak and fragmentation.

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 is.

In Fig. 10, it can be inferred that the stemming and burden are the most influential input parameters on the backbreak and fragmentation. It is noted that for both the outputs, specific charge is the least effective parameter.

7. Conclusions

Precise prediction of backbreak and fragmentation is very crucial for success of a mining project. In this paper, an attempt is made to utilize different types of ANNs for predicting simultaneous fragmentation and backbreak in the blasting operation of Tehran Cement Company limestone mines. The ANN models are trained using a database including 103 datasets. To achieve more reliable predictive models, parameters including burden, spacing, stemming, bench height, specific charge and specific drilling are considered as the model inputs to predict outputs fragmentation and backbreak. BPNN and RBFNN are adopted for this study.

Also, regression analysis is performed between the same independent and dependent variables. For the BPNN and RBFNN modeling, networks with architectures 6-10-2 and 6-36-2 respectively are found to be optimum. Efficiency of the developed models is examined using testing datasets. Indices of *VAF*, *RMSE*, R^2 and *MRE* are calculated for predicted outputs and compared with the real outputs. It is found that performance of the BPNN model with maximum accuracy and minimum error is better than that of the RBFNN and statistical models. Also, it is observed that inputs burden and stemming are the most effective parameters on the outputs, whereas specific charge is the least effective parameter for both the outputs. At the end, it is recommended that hybrid models, combination of fuzzy logic and/or genetic algorithm with neural networks, could be applied for further research.

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