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ORIGINAL PAPER

Burden prediction in blasting operation using rock geomechanical properties

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Abstract Burden prediction is a vital task in the production blasting. Both the excessive and insufficient burden can significantly affect the result of blasting operation. The burden which is determined by empirical models is often inaccurate and needs to be adjusted experimentally. In this paper, an attempt was made to develop an artificial neural network (ANN) in order to predict burden in the blasting operation of the Mouteh gold mine, using considering geomechanical properties of rocks as input parameters. As such here, network inputs consist of blastability index (BI), rock quality designation (RQD), unconfined compressive strength (UCS), density, and cohesive strength. To make a database (including 95 datasets), rock samples are used from Iran's Mouteh goldmine. Trying various types of the networks, a neural network, with architecture 5-15-10-1, was found to be optimum. Superiority of ANN over regression model is proved by calculating. To compare the performance of the ANN modeling with that of multivariable regression analysis (MVRA), mean absolute error (E_a), mean relative error (E_r), and determination coefficient (R^2) between predicted and real values were calculated for both the models. It was observed that the ANN prediction capability is better than that of MVRA. The absolute and relative errors for the ANN model were calculated 0.05 m and 3.85%, respectively, whereas for the regression analysis, these errors were computed 0.11 m and 5.63%, respectively. Moreover, determination coefficient of the ANN model and MVRA were determined 0.987 and 0.924, respectively. Further, a sensitivity analysis shows that while BI and RQD were recognized as the most sensitive and effective parameters, cohesive strength is considered as the least sensitive input parameters on the ANN model output effective on the proposed (burden).

Keywords Burden · Blasting · Artificial neural network · Statistical model · Mouteh gold mine

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Introduction

In the mining engineering, rock fragmentation should be performed with minimum cost and side effects (e.g., ground vibration, air blast, flyrock). To achieve this goal, an appropriate blast design should be applied for the blasting operation (Adhikari 1999).

Since all blast parameters including spacing, stemming, subdrilling, and delay timing are dependent on the selected burden, proper calculation and/ or prediction of the proposed burden can guarantee successfulness of the entire operation. Phenomena such as flyrock, air blast, and improper fragmentation may occur if the burden is too small, whereas high burden results in incidents like ground vibration, undesirable fragmentation, insufficient displacement, toe problem, backbreak, uneven faces, etc. In the extreme case, if burden is too high, sufficient displacement and swelling would not occur, and unfavorable phenomenon of fragment interlocking will happen (Hustrulid 1999).

To determine burden, parameters such as hole diameter, rock mass characteristics, explosive properties, required fragmentation and displacement, etc. have to be considered. In this regard, various empirical models have been

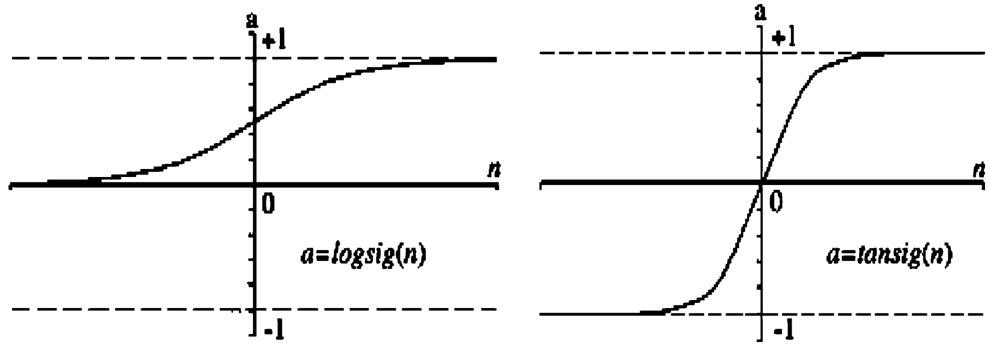


Fig. 1 Sigmoid transfer functions (Demuth et al. 1996)

developed in which just one or two of the effective parameters have been involved causing the models inefficient (Jimeno et al. 1995; Ash 1973).

To overcome shortcomings of the empirical models and to obtain more realistic and precise results, new methods such as fuzzy inference systems, artificial neural networks (ANNs), and genetic algorithm may effectively be applied (Tawadrous 2006; Monjezi et al. 2007). The ANN technique, as a branch of the "artificial intelligence", has been developed since the 1980s. This technique is considered to be one of the most appropriate means for solving complex systems where the number of effective parameters is high (Khandelwal et al. 2004).

In the modeling process, generalization is made for the patterns presented during the training of the network. These patterns, known as data pairs, are composed of real input(s) and output(s) which have to be prepared before constructing the ANN model. In fact, prediction of output(s) for a new input(s) is possible only after presenting the prepared data to the network and completing model training. Suitability of the ANN modeling in geo-engineering applications is shown by solving linear and nonlinear multivariable problems (Sonmez et al. 2006). Monjezi and Dehghani (2008) and Monjezi et al. (2006) utilized the ANN model to improve the blasting pattern. Cai and Zhao (1997) used ANNs for analyzing the tunnel stability as well as designing the support system. Singh et al. (2001) and Khandelwal and Singh (2002) applied this approach for rock strength prediction and stability analysis of a waste dump. Maity and Saha (2004) used the ANN technique to assess damage in structures. Sonmez et al. (2006) used neural network modeling for rock modulus estimation whereas Qiang et al. (2008) used the same approach to predict size-limited structures in a coal mine. Chungsik and Kim (2007) predicted the tunneling performance using an integrated GIS and neural network. Using ANN model, Yong (2005) performed an underground blast stimulated ground vibration. More applications of this technique have been reported by other researchers (Singh et al. 2004; Maulenkamp and Grima 1999).

Artificial neural network

Artificial neural network is a simplified simulation of human brain. Likewise a brain structure, ANN contains elementary processing units (neurons) which are interconnected throughout the network by weighted vectors (Monjezi and Dehghani 2008). The neurons of the same layer are not connected to each other.

Although there exist various types of ANNs, the feed-forward back-propagation ANN is the most efficient one. Back-propagation multilayer neural networks consist of at least three layers, i.e., input, hidden, and output layers. This type of network has effectively been used in the field of rock mechanics, geosciences, mining engineering, etc. (Neaupane and Adhikari 2006; Neaupane and Achet 2004). The number of hidden layers and the number of respective neurons in each layer depend upon complexity of the problem under study. Normally, two-hidden layer

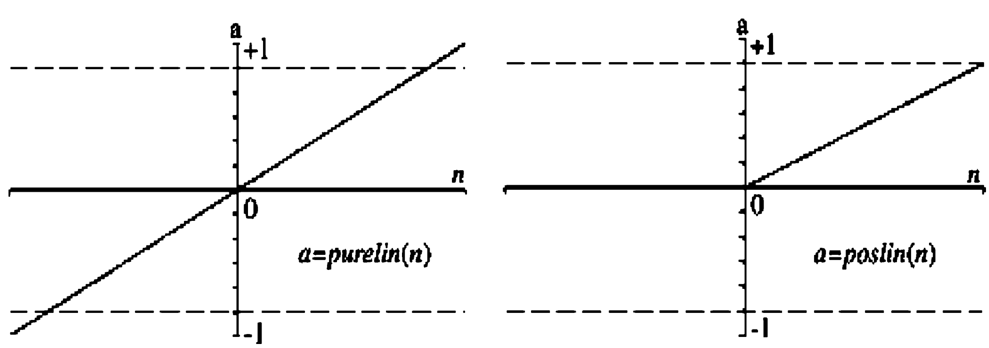


Fig. 2 Liner transfer functions (Demuth et al. 1996)

networks are considered to be proper for engineering applications (Lee et al. 2003; Gomez and Kavzoglu 2005; Ermini et al. 2005; Yesilnacar and Topal 2005). With respect to number of neurons in the hidden layers, it can be said that insufficient neurons can cause "underfitting" whereas excessive selection can result in "overfitting". In the underfitting, the required accuracy of the modeling is not achieved, whereas in the overfitting which is also called memorization, the network performance would not be reliable because instead of realizing relationship between the patterns, network just remembers the patterns (Demuth et al. 1996; Haykin 1999).

Transfer functions, known as activation functions, are used to transform the weighted sum of all input signals to a neuron and determine the neuron output intensity (Basheer and Hajmeer 2000). Nonlinear sigmoid (LOGSIG, TANSIG) and linear (POSLIN, PURELIN) functions can be used as transfer functions (Figs. 1 and 2); however, the sigmoid type is more efficient. The logarithmic sigmoid function (LOGSIG) is defined as (Demuth et al. 1996):

$$f = \frac{1}{(1 + e^{-e_x})} \tag{1}$$

where e_x is the weighted sum of inputs for a processing unit.

The forward and backward passes are repeated until the network error reaches to a specific threshold (Sonmez et al. 2006). Root mean square error (RMSE) can be utilized to evaluate network training process by considering differences between the model outputs and the real measured values. In this regard, training progress should be checked using data pairs which have already been considered for this purpose. As a matter of fact, increasing iterations can result in decreasing the error; however, excessive training can cause decreasing generalization capability. Therefore, the threshold error would be the minimum error obtained while testing the model with the test data pairs (Basheer and Hajmeer 2000).

Case study

The Mouteh goldmine is located some 270 km southwest of Tehran in the Isfahan province, with an elevation 2,000–2,300 m above sea level. Possible, probable, and measured reserves of the mine are 4,852,000, 2,283,000, and 1,191,800 tons, respectively. Gold average grade for the mine is 4 g/ton.

From geological point of view, the mine is situated in the acidic to relative basic Precambrian metamorphic rocks. Joints and fractures of this rock series contain metallic minerals such as pyrite and chalcopyrite. The host rock layers have mild dip toward northwest, while the gold zones have sharp dip toward northeast. Two main fractures with crossover inclination affect the Mouteh gold zone. In this mine, the ore is mainly deposited along the fractures in the highly weathered zones. A view of the Mouteh gold mine is shown in the Fig. 3.

Fig. 3 A view of the Mouteh gold mine

Input and output parameters

In this study, to determine the relationship between burden and geomechanical properties, parameters including rock blastability index (BI), rock quality designation (RQD), unconfined compressive strength (UCS), density (*D*), and cohesive strength (*C*) have been determined and considered as input parameters for the ANN model.

To determine BI, first joint characteristics have to be recognized. In the proposed area, three joint sets with dominantly east–west dip direction were identified (Table 1). Blastability index can be calculated using Eq. 2 (ISRM International Society for Rock Mechanics 1981).

$$\mathrm{BI} = 0.5(\mathrm{RMD} + \mathrm{JPS} + \mathrm{JPO} + \mathrm{SGI} + H) \tag{2}$$

where RMD is the rock mass description, JPS is the joint plane spacing, JPO is the joint plane orientation, SGI is the specific gravity influence, and *H* is the rock hardness.

Table 1 Identified joint sets in the Mouteh gold mine

Joint set no.	Dip (deg)	Dip direction (deg)
1	32	8
2	47	28
3	15	326

Table 2 Sample data used in the modeling

No	BI	RQD (%)	D (g/cm^3)	UCS (MPa)	C (MPa)	Burden (m)
1	49	75.4	2.64	2.9	0.2	1
2	43.75	52.3	2.5	0.2	0.02	2.2
3	47	68.8	2.64	2.5	0.1	1.6
4	56.75	91.9	2.7	3.5	0.25	1
5	62.375	98.5	2.75	3.5	0.25	1
6	48.5	75.4	2.64	2	0.1	1.2
7	45	52.3	2.6	0.4	0.05	2
8	48	68.8	2.64	2.7	0.1	1.8
9	59.25	91.9	2.7	3.27	0.25	1
10	62.375	98.5	2.75	3.5	0.3	0.4

NX size rock samples with 54 mm diameter and 108 mm length were prepared to determine unconfined compressive strength and cohesion in the laboratory. For the ANN model construction, a database including 54 datasets was considered for training and testing the ANN model. Selecting of testing datasets was performed using sorting method to maintain generality. Testing datasets were selected at a regular interval (Table 2). Also, minimum and maximum values of the relevant parameters used in the modeling are given in Table 3.

Determination of optimum network

To reach an optimum architecture, different types of networks have to be examined. For this, root mean square error is calculated for all the models, and accordingly, the model with minimum RMSE is chosen as the optimum model. RMSE is calculated by Eq. 3. For different types of the models, RMSE was calculated (Table 4).

$$\mathrm{RMSE}(A) = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(A_{i\mathrm{meas}} - A_{i\mathrm{pred}}\right)^2}. \qquad (3)$$

where $A_{i\mathrm{meas}}$, $A_{i\mathrm{pred}}$, and n are the i-th measured element, i-th predicted element, and the number of datasets, respectively (Tzamos and Sofianos 2006).

As it is seen from Table 4, the network with architecture 5-10-15-1 and LOGSIG transfer function has the minimum RMSE, hence considered to be the optimum model. Figure 4 shows a graphic presentation of the optimum network.

Multivariable regression analysis

The multivariable regression analysis (MVRA) is employed to establish a mathematical formula in order to predict the dependent variables based on the known independent variables (Jennrich 1995; Eskandari et al. 2004). This method has been utilized in different mining fields (Alvarez Grima and Babuska 1999; Finol et al. 2001; Gokceoglu and Zorlu 2004; Monjezi et al. 2009, 2010). To evaluate ANN modeling, the same input parameters were considered for regression analysis (Eq. 4):

$$\mathrm{Burden} = 1.435 - 0.056\mathrm{RQD} + 0.076\mathrm{BI} + 0.1D - 4.340C + 0.251\mathrm{UCS} \qquad (4)$$

Comparison of performances

To compare performances of both the ANN and regression models, predicted burdens were compared with the actual measured burdens. For this, mean absolute error (E_a) and

Table 3 Input and output parameters in the modeling

Type of data	Parameter	Unit	Symbol	Minimum	Maximum
Input	Rock quality designation	%	RQD	46.02	98.5
	Unconfined compressive strength	MPa	UCS	0.18	3.75
	Density	g/cm^3	D	2.2	2.96
	Cohesion	MPa	C	0.02	0.3
	Blastability index	–	BI	38.5	63.4
Output	Burden	m	B	0.4	2.2

Table 4 Calculated RMSE for different types of the models

No.	Network architecture	Transfer function	RMSE
1	5-10-1	POSLIN	0.3021
2	5-15-1	POSLIN	0.4567
3	5-10-7-1	TANSIG	0.1398
4	5-5-15-1	TANSIG	0.1756
5	5-5-10-1	PURELIN	0.5310
6	5-10-15-1	PURELIN	0.2035
7	5-10-7-1	LOGSIG	0.125
8	5-10-15-1		0.092

mean relative error (E_r) were calculated using Eqs. 5 and 6 (Monjezi and Dehghani 2008):

$$E_a = |T_i - O_i| \quad (5)$$

$$E_r = \left(\frac{|T_i - O_i|}{T_i}\right) \times 100 \quad (6)$$

where T_i, O_i, and N represent measured output, predicted output, and the number of input–output data pairs, respectively.

For the ANN model, E_a and E_r were equal to 0.05 m and 3.85%, respectively, whereas for the statistical model, E_a and E_r were equal to 0.11 m and 5.63%, respectively. Figures 5 and 6 show comparison between measured and predicted burden for both the models. According to these figures, the determination coefficient (R^2) of the ANN model is better than the statistical model.

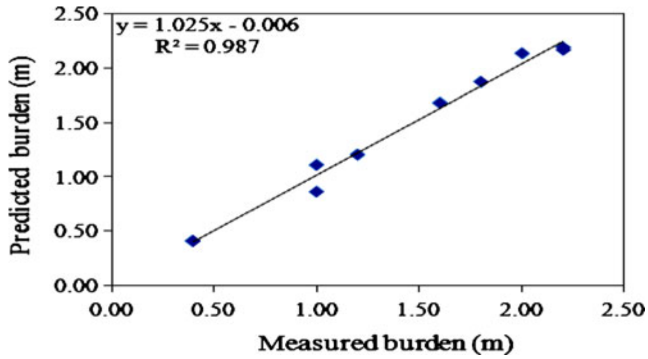


Fig. 5 Comparison between measured and predicted burden for the ANN model

Sensitivity analysis

Sensitivity analysis was carried out with the aim of determining the most effective input parameter on the output. For this, cosine amplitude method was applied (Monjezi et al. 2010; Jong and Lee 2004). In this method, all data pairs used to construct a data array X are expressed in common X-space:

$$X = \{X_1, X_2, X_3, \ldots X_n\} \quad (7)$$

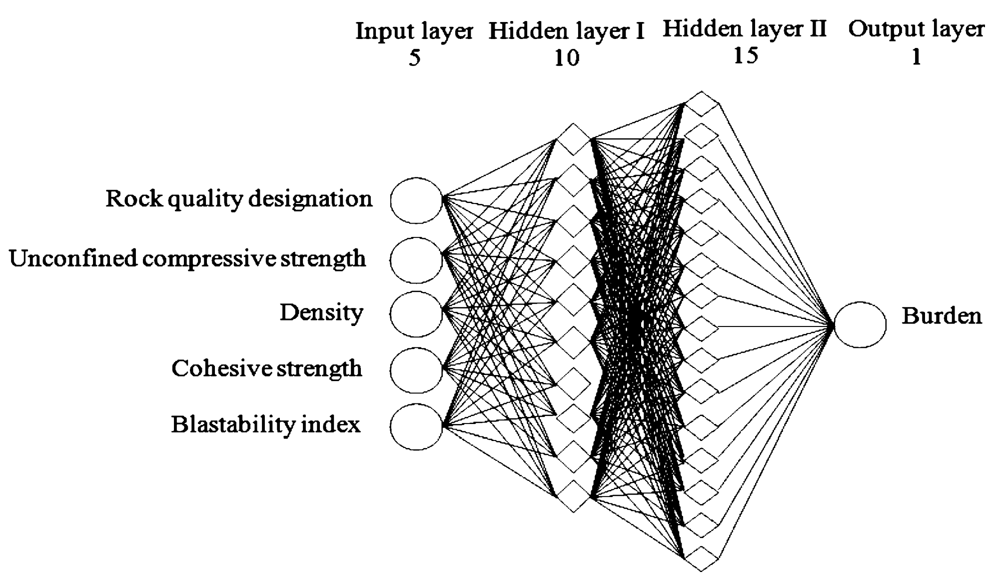
Each of the elements, X_i, in the data array X is a vector of lengths of m, that is:

$$X_i = \{x_{i1}, x_{i2}, x_{i3}, \ldots, x_{im}\}_1 \quad (8)$$

Strengths of relations (r_{ij}) between output and input parameters can be calculated using Eq. 9.

$$r_{ij} = \sum_{k=1}^{m} x_{ik}x_{jk} \Big/ \sqrt{\sum_{k=1}^{m} x_{ik}^2 \sum_{k=1}^{m} x_{jk}^2} \quad (9)$$

Fig. 4 Optimum ANN model for the burden prediction



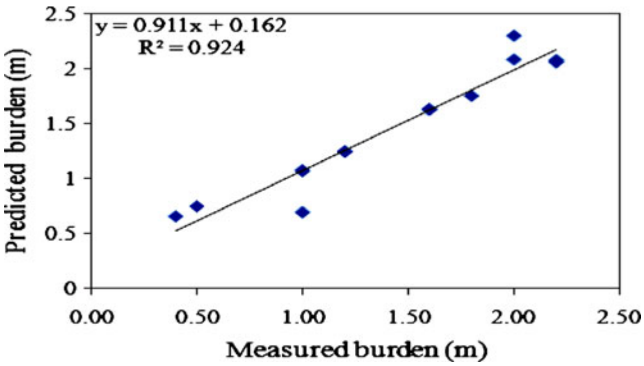


Fig. 6 Comparison between real and predicted burden for the statistical model

Figure 7 shows the strengths of relations (r_{ij}) between the input parameters and burden. As it is seen, the most effective parameters on the burden are BI and RQD. Also, cohesive strength is the least effective parameter on the burden.

Conclusion

In this paper, superiority of the artificial neural network modeling over regression analysis in predicting burden was demonstrated. A feed-forward back-propagation neural network with architecture 5-15-10-1 and RMSE of 0.092 was found to be optimum. Performance of the ANN and regression models has been evaluated by computing mean absolute error (E_a), mean relative error (E_r), and determination coefficient (R^2). For the ANN model, E_a, E_r, and R^2 were calculated 0.05 m, 3.85%, and 0.987, respectively, whereas for the regression model, E_a, E_r, and R^2 were determined 0.11 m, 5.63%, and 0.924, respectively. Further, sensitivity analysis was performed to identify the most effective parameters on the burden prediction in which blastability index and rock quality designation were observed to be the most sensitive and cohesive strength to be the least sensitive parameters.

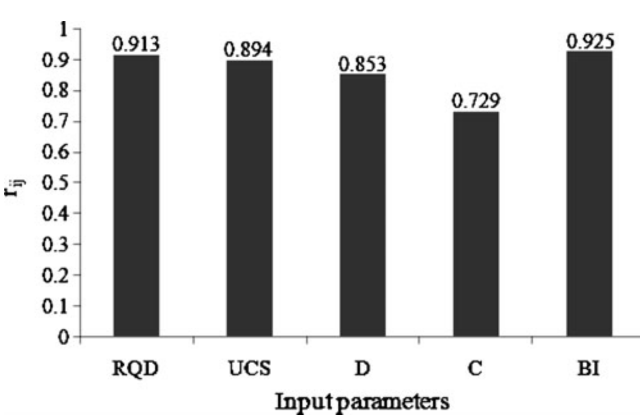


Fig. 7 Strengths of relation (r_{ij}) between the burden and input parameters

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