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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.

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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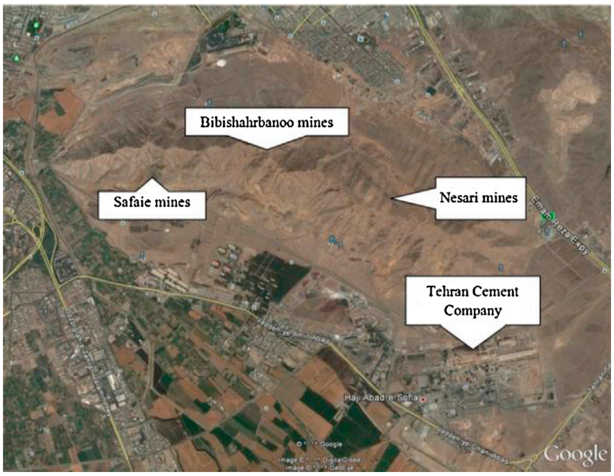

Fig. 1. Tehran cement company limestone mines.

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

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n \tag{1}$$

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.

$$BB = 0.494B + 1.082S + 0.015H + 1.203T - 0.056SC + 23.576SD - 8.501 \tag{2}$$

$$Fr = 0.371B + 0.215S - 0.012H + 0.182T - 0.025SC + 6.45SD - 1.959 \tag{3}$$

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).