Arab J Geosci (2011) 4:421–425
DOI 10.1007/s12517-009-0091-8

ORIGINAL PAPER

Prediction and controlling of flyrock in blasting operation using artificial neural network

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Received: 14 July 2009 / Accepted: 3 September 2009 / Published online: 30 October 2009

Abstract Flyrock is one of the most hazardous events in blasting operation of surface mines. There are several empirical methods to predict flyrock. Low performance of such models is due to complexity of flyrock analysis. Existence of various effective parameters and their unknown relationships are the main reasons for inaccuracy of the empirical models. Presently, application of new approaches such as artificial intelligence is highly recommended. In this paper, an attempt has been made to predict and control flyrock in blasting operation of Sangan iron mine, Iran incorporating rock properties and blast design parameters using artificial neural network (ANN) method. A three-layer feedforward back-propagation neural network having 13 hidden neurons with nine input parameters and one output parameter were trained using 192 experimental blast datasets. It was also observed that in ascending order, blastability index, charge per delay, hole diameter, stemming length, powder factor are the most effective parameters on the flyrock. Reducing charge per delay caused significant reduction in the flyrock from 165 to 25 m in the Sangan iron mine.

Keywords Blasting · Sangan iron mine · Artificial neural network · Flyrock

Introduction

Flyrock, an undesirable phenomenon of the blasting operation, is defined as propelling of fragments beyond a specified boundary which can result in human injuries, fatalities, and structure damages. This phenomenon is considered to be the main cause of numerous cases of property damage and injuries in surface mining (Verakis and Lobb 2003; Lundborg et al. 1975). A detailed condition responsible for the occurrence of the incident is reviewed by Bhowmik et al. (2004). Occurrence of this incident implies that some part of the available explosive energy is wasted. Any proposed solution for controlling flyrock should assure maintaining a designated fragmentation which is an ultimate objective of a blasting operation. Since flyrock occurrence and intensity is influenced by controllable and uncontrollable parameters, in the selected solution, both the parameters should be incorporated (Langefors and Kishlstrom 1963). Controllable parameters can be changed by the blasting in charge, while uncontrollable parameters are natural and cannot be controlled (Atlas Powder Company 1987). The main controllable parameters causing flyrock are insufficient burden, improper delay timing, inadequate stemming, inaccurate drilling, and unwarranted powder factor. Whereas, poor geological and geotechnical conditions specially existence of loose rock in the upper part of the blast hole are considered to be the uncontrollable parameters affecting flyrock (Bhowmik et al. 2004; Fletcher and D'Andrea 1986; Massey and Siu 2003). The most applicable empirical methods proposed for predicting and/or controlling flyrock are by Lundborg (1974) and Roth (1979). However, presence of various concerned parameters responsible for flyrock in blasting operation and complexity of the whole process, performance of the empirical methods is not so satisfactorily. It is often difficult to predict flyrock because of the uncertainty associated with the inherent variability of blasting phenomenon (Monjezi et al. 2007). Limitations of such methods have been argued by Hustrulid (1999). The most important

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shortcomings of the available empirical methods are inability to predict flyrock within 400 m projectile distance, due sometimes to poor judgment of the rock conditions.

In view of the aforesaid restrictions of the empirical methods, solving flyrock problem requires new inventive methods such as artificial intelligence method. Artificial Neural Network (ANN), one of the most capable artificial intelligence subsystems, can arrive in a precise solution in complicated situations (Salah 2004). ANN method has been used as a speedy and precise solution for various problems in the fields of science and engineering. ANN has been used in many areas where solutions are intricate and not easily available (Kim et al. 2001; Khandelwal and Singh 2002; Monjezi and Dehghani 2008; Khandelwal and Singh 2006; Grznar et al. 2007; Tawadrous 2006).

In the present investigation, using artificial neural networks, a model was developed to predict and control flyrock due to blasting operation of Sangan iron mine, Iran. It has also been predicted most influencing parameters using sensitivity analysis.

ANN method

ANN originally was introduced by Mc Culloch and Pitts who showed ability of this technique to calculate any arithmetic or logical function. Application of ANN has been increased specially in the 1990s (McCulloch and Pitts 1988). In the artificial neural network method, concerned parameters interrelationships are derived by an inverse analysis using a real field-collected database, the larger the database, the more accurate the model results. In this way, ANN model can compute the desired output according to the input parameters. A perceptron network was built by Rosenblatt in which ANN ability was demonstrated to perform pattern recognition (Rosenblatt 1988). As a matter of fact, ANN is a sequence of layers (input-hidden-output) consisting of simple and fully connected processing elements, called neurons. The most important features of layered networks are performing nontrivial calculations, learning from examples and generalization in the training stage. The number of elements is dependent to the nature and complexity of problem to be solved. The internal layer (s) is called the hidden layer(s) because it usually has no connection to the outside world (Seiberl et al. 1998; Cigizoglu and Kis 2005). Practically, one or two hidden layers are enough for complex problems, however there is no theoretical limitation in this regard. The neurons of hidden layer(s) are responsible to properly intervene between the network input and output. Moreover, when the number of inputs is large, these neurons can extract higher order statistics (Reed and Marks 1998; Haykin 1999).

Back-propagation networks have been gradually gaining popularity due to its robust characteristics. They are considered to be the most popular, effective, and easy-to-learn models in the complex conditions, and suitable for training multilayer feedforward networks with supervised learning techniques (Kalogirou 2000; Parker 1985; Neaupanea and Achet 2004). In the training stage, the connection weights are adjusted to reduce the output error (Simpson 1990). The training process is significantly influenced by parameters' learning rate and momentum. Larger values of the learning rate (typical values between 0 and 1) result in a more rapid learning but the weights may oscillate. On the other hand, selection of low values causes slow learning and time required for convergence to global minima would be longer. A high value of a momentum coefficient allows one to choose higher value of learning rate.

Case study

Sangan iron mine is situated 18 km northeast of Sangan city and 308 km southeast of Mashhad. It is an important iron-ore-producing mine in Iran. This mine is under development and is expected to have an initial annual production of 3.4 Mt iron ore concentrate. Sangan iron deposit is a magnetite skarn and can be classified as iron-oxide-type deposit.

In the blasting operation of the mine, undesirable flyrock phenomenon is observed. In this operation, blast holes of 76, 89, and 115 mm in diameter are vertically drilled in benches of 12 m lenght. Normally, blocks of 12×36 m are operated in each blast. ANFO is the main explosive; dynamite cartridges are used as primer, and detonating cord is utilized as initiation system. With regard to the high rock mass strength, staggered blast pattern is applied while drilling.

Input and output parameters

In this study, a database including 213 datasets was prepared using actual blasting parameters measured on the benches of the Sangan iron mine. The collected datasets partially belong to the mine records or during research work conducted by the authors. Table 1 show the input and output parameters applied for neural network modeling, its respective symbols and practical ranges. Some of the most important controllable and/or uncontrollable parameters have been selected as inputs, however the other influencing parameters with low variation such as rock density have not been considered in the analysis. To maintain statistical consistency, a sorting method was applied on the datasets.

Table 1 Input and output parameters used for neural network modeling

Type of data	Input parameter	Symbol	Range
Inputs	Burden to spacing ratio (m)	A	0.65–0.87
	Charge per delay (kg)	B	159–964.20
	Hole diameter (mm)	C	75–115
	Average hole depth (m)	D	7–18
	Stemming length (m)	E	2–10
	Specific drilling (m/m*3)	F	0.13–0.20
	Powder factor (kg/ton)	G	0.13–0.38
	SMR	H	35–60
	Blastability index	I	59.50–84
Output	Flyrock (m)	J	22.50–195.70

Network architecture

As compared with the other types of neural networks, Feedforward Back Propagation Neural Network (FBPNN) is believed to be more suitable for such type of problems based on pattern matching which is an input–output mapping problem. The closer the mapping the better is the performance of the network. An appropriate mapping between input patterns and target patterns can be attained using FBPNN enabling the network-predicting target pattern for a given input pattern. To perform a reliable mapping, all the parameters which are related to the output should be involved and provided to the network as inputs (Chandok et al. 2008). The other important point while designing of network architecture is recognizing and avoiding phenomena such as overfitting and underfitting. Overfitting occurs when a network is trained using too many training epochs result in model memorization. On the other hand, considering insufficient number of epochs cause underfitting and inaccuracy of the model results (Singh and Singh 2005; Maulenkamp and Grima 1999).

For the present study, 90% of the available datasets were randomly taken for training and the rest of them considered for testing the models. To determine optimum network, Root Mean Square of Error (RMSE; Eq. 1), mean absolute error (Ea; Eq. 2), and mean relative error (Er; Eq. 3) were calculated for various models (one and two hidden layers).

$$\mathrm{RMSE} = \sqrt{\frac{(O_\mathrm{i} - T_\mathrm{i})^2}{N}} \tag{1}$$

Where T_i, O_i, and N represent the measured output, the predicted output, and the number of input–output data pairs, respectively (Hornik 1991; Monjezi et al. 2006).

As it can be seen from Table 2, a network with architecture 9-13-1 has the minimum RMSE and therefore is considered to be the optimum model.

Model performance

Performance of a model can be evaluated by comparing predicted and measured flyrock values. A graphic comparison of the predicted and measured flyrock is shown in Figs. 1 and 2. As it is seen from these figures, a very high conformity and correlation exist between the measured and predicted values for each blasting pattern.

Model performance can also be represented computationally using Eqs. 2 and 3. To this, mean Ea and mean Er

Table 2 Results of a comparison between some of the Models

Transfer function	Architecture	RMSE
LOGSIG-LOGSIG-PURESLIN (L-L-P)	9-3-1	0.95
LOGSIG-LOGSIG-PURESLIN (L-L-P)	9-10-1	0.87
LOGSIG-LOGSIG-LOGSIG-PURESLIN (L-L-L-P)	9-13-20-1	2.19
TANSIG-TANSIG-PURESLIN (T-T-P)	9-20-1	1.17
TANSIG- LOGSIG-TANSIG-PURESLIN (T-L-T-P)	9-13-28-1	3.18
TANSIG-LOGSIG-PURESLIN (T-L-P)	9-13-1	0.67
LOGSIG-LOGSIG-PURESLIN (L-L-P)	9-30-1	2.42

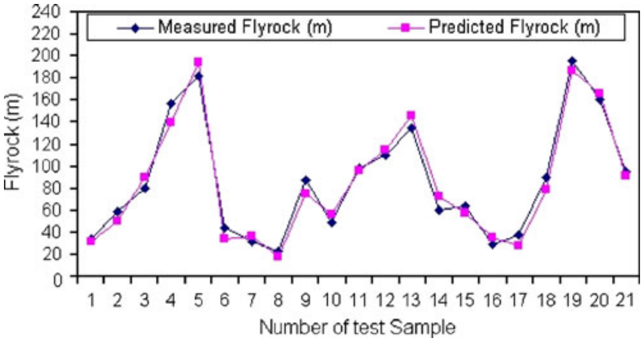

Fig. 1 Comparison of measured and predicted flyrock for different type of patterns

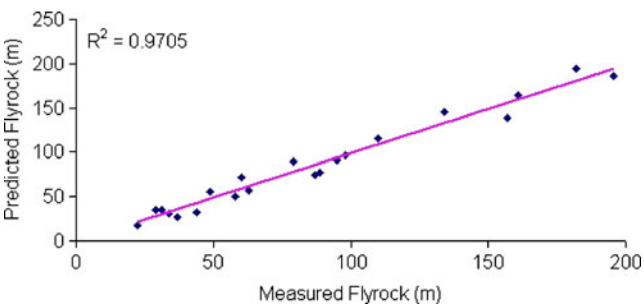

Fig. 2 Correlation between measured and predicted flyrock

can be determined. For the selected optimum model, Ea and Er were equal to 0.76 m and 1.78%, respectively.

$$E_a = |T_i - O_i|. \tag{2}$$

$$E_r = \left(\frac{|T_i - O_i|}{T_i} \right) \times 100 \tag{3}$$

Sensitivity analysis

The strength of the relations between the flyrock and the input parameters is evaluated by the cosine amplitude method (CAM; Yang and Zhang 1997). This method is used to obtain similarity relations between the involved parameters. To apply this method, all of the data pairs were expressed in common X-space. The data pairs used to construct a data array X defined as:

$$X = \{x_1, x_2, x_3, \ldots, x_i, \ldots x_n\} \tag{4}$$

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

$$x_i = \{x_{i1}, x_{i2}, x_{i3}, \ldots, x_{im}\} \tag{5}$$

Thus, each of the dataset can be thought of as a point in m-dimensional space, where each point requires m-coordinates for a full description. Each point in space has relation with results in a pair wise comparison. The strength of the relation between the dataset, X_i and X_j, is given by the Eq. 6:

$$r_{ij} = \frac{\sum_{k=1}^{m} x_{ik} x_{jk}}{\sqrt{\sum_{k=1}^{m} X_{ik}^2 \sum_{k=1}^{m} X_{jk}^2}} \tag{6}$$

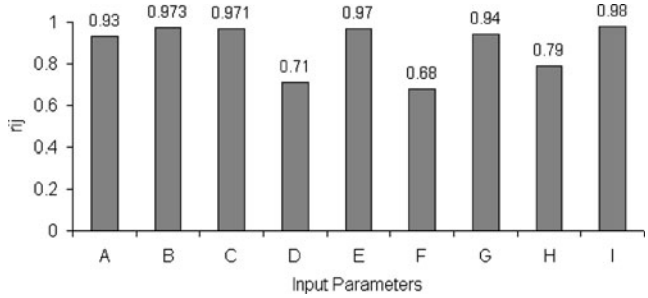

Fig. 3 Sensitivity analysis between the flyrock and each input parameters

According to strength values obtained from the application of the CAM (Fig. 3) input parameters including the blastability index, charge per delay, hole diameter, stemming, and powder factor are the most influencing parameters on flyrock.

Conclusions

In this study, ANN method was effectively used in prediction of flyrock in the blasting operation of Sangan iron mine. Learning algorithm of back propagation was found to be the most capable in network construction. In the training process, only parameters with high variation were considered as inputs and other unchanged or constant parameters such as rock density were not incorporated. In this regard, a model with architecture 9-13-1 was realized to be optimum. Application of this network showed excellent conformity between the predicted and practical measured flyrock values in the mine. According to sensitivity analysis, the most effective parameters on the flyrock are blastability index, charge per delay, hole diameter, stemming length, and powder factor. Application of the results obtained from this research work, significantly minimizes the flyrock generation from 165 m to 25 m in the Sangan Iron mine. The same results can be used in other mines having similar parameters.

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