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APPLICATION OF NEURAL NETWORKS FOR THE PREDICTION OF ROCK FRAGMENTATION IN CHADORMALU IRON MINE

ZASTOSOWANIE SIECI NEURONOWYCH DO PROGNOZOWANIA STOPNIA ROZDROBNIENIA SKAŁ W KOPALNI RUD ŻELAZA W CHADORMALU

Most open-pit mining operations employ blasting for primary breakage of the in-situ rock mass. Inappropriate blasting techniques can result in excessive damage to the wall rock, decreasing stability and increasing water influx. In addition, it will result in either over and/or under breakage of rocks. The presence of over broken rocks can result in decreased wall stability and require additional excavation. In contrast, the presence of under broken rocks may require secondary blasting and additional crushing. Since blasting is a major cost factor, both cases (under and over breakage) create additional costs reflected in the increase of the operation and maintenance of the machinery. Quick and accurate measurements of fragment size distribution are essential for managing fragmented rock and other materials. Various fragmentation measurement techniques are available and are being used by industry/researchers but most of the methods are time consuming and not precise. An ideally performed blasting operation enormously influences the overall mining cost. This aim can be achieved by proper prediction and attenuation of fragmentation. Prediction of fragmentation is essential for optimizing blasting operation. Poor performance of the empirical models for predicting fragmentation has urged the application of new approaches. In this paper, artificial neural network (ANN) method is implemented to develop a model to predict rock fragmentation size distribution due to blasting in Chadormalu iron mine, Iran. In the development of the proposed ANN model, ten parameters such as UCS, drilling rate, water content, burden, spacing, stemming, hole diameter, bench height, powder factor and charge per delay were incorporated. Training and testing of the model was performed by the back-propagation algorithm using 97 datasets. A four-layer ANN was found to be optimum with architecture of 10-7-5-1. A comparison has made between measured results of fragmentation with predicted results of fragmentation by ANN and multiple regression model. Sensitivity analysis was also performed to understand the effect of each influencing parameters on rock fragmentation.

Keywords: Fragmentation; blasting operation; ANN; Chadormalu iron mine

W większości kopalń odkrywkowych stosuje się prace strzałowe w celu wstępnego rozbicia skał górotworu *in situ*. Niewłaściwe prowadzenie prac strzałowych spowodować może nadmierne uszkodzenie

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skał, obniżając stabilność górotworu i powodując zwiększony napływ wód. Ponadto, prowadzić może do nadmiernego lub niedostatecznego rozdrobnienia skał. Obecność nadmiernie rozdrobnionych skał spowodować może zmniejszenie stabilności ścian i wymaga dodatkowego odgruzowania. Z kolei obecność niedostatecznie rozdrobnionych skał powoduje konieczność ponownego wykonania prac strzałowych celem rozdrobnienia dalszego skały. Z uwagi na to, że prace strzałowe stanowią zasadniczy element kosztów, obydwa przypadki (niedostateczne lub nadmierne rozdrobnienie skał) mogą pociągać za sobą dodatkowe koszty, odzwierciedlone w zwiększonych kosztach eksploatacji sprzętu. Szybkie i dokładne pomiary rozkładu wielkości fragmentów skał są niezbędne dla zapewnienia właściwej gospodarki rozdrobnionymi skałami i pozostałymi materiałami. Istnieje wiele metod pomiarów i są one szeroko wykorzystywane przez badaczy oraz w przemyśle, jednakże większość metod okazuje się czasochłonna i niewystarczająco dokładna. Idealne przeprowadzenie prac strzałowych w znacznym stopniu przyczynia się do ograniczenia kosztów prowadzenia prac górniczych. Cel ten osiągnąć można poprzez odpowiednie prognozowanie i kontrolowanie stopnia rozdrobnienia. Prognozowanie konieczne jest dla optymalizacji prowadzenia prac strzałowych. Niska skuteczność metod empirycznych wykorzystywanych do prognozowania stopnia rozdrobnienia skał stanowi zachętę do stosowania nowego podejścia. W artykule przedstawiono zastosowanie metody sztucznych sieci neuronowych (ANN) do opracowania modelu prognozowania rozkładu wielkości skal rozdrobnionych w wyniku prac strzałowych w kopalni Chadormalu, w Iranie. W opracowanym modelu ANN uwzględniono dziesięć parametrów: wytrzymałość skały na ściskanie jednoosiowe (UCS), prędkość wiercenia, zawartość wody, rodzaj nadkładu, rozstawienie, rodzaj przybitki, wysokość ławy, rodzaj materiału wybuchowego oraz wielkość ładunku w stosunku do zwłoki czasowej. Uczenie i testowanie modelu odbywa się przy użyciu algorytmu propagacji wstecznej (*back-propagation*) z wykorzystaniem 97 baz danych. Stwierdzono, że optymalna sieć złożona jest z czterech warstw a jej architekturę opisać można jako 10-7-5-1. Wyniki pomiarów stopnia rozdrobnienia porównano z wyniki prognoz stopnia rozdrobnienia przeprowadzonych przy pomocy sieci neuronowej w oparciu o metodę regresji wielokrotnej. Przeprowadzono analizę wrażliwości dla lepszego zrozumienia wpływu poszczególnych parametrów na stopień rozdrobnienia skały.

Słowa kluczowe: stopień rozdrobnienia, prace strzałowe, sztuczna sieć neuronowa (ANN), kopalnia rudy żelaza Charnomalu

1. Introduction

Fragmentation is the process of breaking the solid in situ rock mass into several smaller pieces capable of being excavated or moved by material handling equipment. Rock blasting is the rock excavation technique most widely used among the various sectors of the mining and construction industries because of its efficiency and relative low cost.

There are a number of controllable as well as uncontrollable parameters that govern the fragmentation of rock. The controllable parameters can be controlled by effective blast designing and use of appropriate explosive for blasting. While the uncontrollable parameters as the name suggests cannot be controlled. But certain measures have to be taken to minimize the effects of these parameters in rock blasting in order to attain an optimum rock fragmentation (Karakus et al., 2010).

The rock fragmentation obtained as an outcome of blasting operations is said to be optimum, when it contains maximum percentage of fragments in the desired range of size. The desired size usually means the size that is demanded and can be effectively utilized by the consumers for further operations devoid of any processing. The desired size for different consumers is different. The significance of optimum rock fragmentation is, to fulfill the varying demands of different consumers for assorted sizes of rock fragments, to reduce the cost of crushing and grinding or pelletization operations, and finally uphold the economics of mining. For this the rock must be fragmented in such a way that further processing (usually termed as Milling) is not required.

In surface mine and quarries, the main objective is to extract the largest possible quantity of material with the least possible expenditure. The desired material may include ore, coal, aggregates for construction and also the waste rock required to remove the above mentioned useful materials. The blasting operations must be carried out so as to provide the required quantity and quality of material for production in such a way that the overall profits of the operation are maximized. In-situ rock is reduced in size by blasting and crushing it into the required size or by further grinding it into a fine powder suitable for mineral processing. Large blocks requiring secondary breakage, or an excess of fines, can result from poorly designed blasts or due to adverse geological conditions. A well designed blast should produce rocks of shapes and sizes that can be accommodated by the available loading and hauling equipment and crushing plant with little or no need for secondary breakage (Bhandari, 1997). Optimizing the fragmentation is also important for the purposes of safety and ease of loading.

One of the fundamental requirements for being able to optimize blasting is the ability to predict fragmentation. An accurate blast fragmentation model allows mine management to regulate the fragmentation size for different downstream processes (mill processing versus leach, for instance), and to make real time adjustments in blasting parameters to account for changes in rock mass characteristics (hardness, fracture density, fracture orientation, etc).

In the past, several empirical models have been developed to predict rock fragmentation. In most of the models the average fragment size, X_{50}, is calculated and some of the models describe the whole fragment size distribution. The most frequently used model by the industry to predict blast fragmentation is the Kuz-Ram model developed by Cunningham (Cunningham, 1983, 1987). It is based on the average fragment size, X_{50}, derived by Kuznetsov (1973), and a Rosin- Rammler distribution. Since Kuz-Ram model is an empirical model that was derived from blasting hard rock as well as under-estimates the fine end of the distribution, Thornton et al. (2001) from Julius Kruttschnitt Mineral Research Centre (JKMRC) developed a model for estimating ROM size distribution of soft rock types. JKMRC recognizes that fragmentation during blasting occurs due to two mechanisms and models each separately, the crushed zone model (CZM) and the two component model (TCM). Other models that developed for predicting the rock fragmentation by blasting are KCO, Kou-Rustan, CK, SveDeFo Model (Ouchterlony, 2005; Kou & Rustan, 1993; Chung & Katsabanis, 2000; Jimeno et al., 1995). However, these models have limited applications at the present time because:

1. The input parameters are not the most useful for the engineer to determine and data for these parameters are not available throughout the rock mass.
2. Even if the input parameters are known, the models still do not consistently predict the correct fragmentation. This is because the models capture some but not all of the important rock and blast phenomena.
3. The models do not allow for 'tuning' at a specific mine site (Kemeny et al., 2002).

Moreover, the evaluation of the fragmentation of the run of mine by sieving is generally not possible due to high cost and the disruption it causes in the production cycle (Sanchidrian et al., 2006). Therefore, indirect methods, such as digital images processing and analysis systems have been in use in blasting research (Siddiqui et al., 2009; Ozkahraman, 2006; Sudhakar et al., 2006). The programs such as GoldSize, WipFrag, Split-Engineering and others can be used for fragmentation assessment. In the present paper, Split-Desktop system is used to assess the rock fragmentation. In this, interruption of production processes is not required, as well as results can be achieved in a very short time, allowing timely adjustments to production methods. In case of large blocks or large volumes of rock, screening is just too prohibitive, and optical methods are the only available alternative (Maerz & Zhou, 2000).

Artificial Neural Network (ANN) has been proved to be of widespread utility in engineering applications due to its excellent ability of non-linear pattern recognition, generalization, self-organization and self-learning (Kulatilake et al., 2010). Sonmez et al. (2006) used ANN to estimate modulus of intact rock. Gholamnejad and Tayarani (2010) applied ANN to predict penetration rate of tunnel boring machine and found very good results. Guo (2010) used ANN in order to get the iron-ore grade estimation.

2. Split Desktop software

Split Desktop is an image processing program to determine the size distribution of rock fragments at various stages of rock breaking in the mining and processing of mineral resources. The Split Desktop software has five major steps. The first step is for the user to acquire images from the field and download these images onto the computer. The source of these images can be a muck pile, haul truck, leach pile, draw point, waste dump, stockpile, conveyor belt, or any other location, where clear images of rock fragments can be obtained. The second part of the program concerns the automatic delineation of the fragments in each of the images that are acquired. The third part of the program allows editing of the delineated fragments to ensure high quality results. The fourth part of the program involves the calculation of the size distribution based on information from the delineated fragments. Finally, the fifth part of the program concerns the plotting or export of the size distribution results (Fig. 1) (Lowery et al., 2000).

3. Case study

Chadormalu iron open pit mine is located in 120 km northeast of Yazd city in central Iran. This mine is formed from north and south anomalies. Chadormalu mine has approximately 400 million tons of resource and 320 million tons of reserves which is spread between northern and southern ore bodies with average Fe-and P-Content of 55.2% and 0.9% respectively. Magnetite, Hematite and Apatite are the three major components, whereas phosphorous act as a disturbed element based on the ratio of Hematite to Magnetite. Iron ore deposit of the mine has been divided into oxidized and non-oxidized parts. The Oxidized part consists mostly of Magnetite.

In Chadormalu iron open pit mine, some 300 Million tons of resource is oxidized and 100 million tons of resource is non-oxidized. The mining operation is planned for 12 million tons annual ore feed to beneficiation plant and around 1 million ton annual lump ore (high Fe content and low phosphorous) production. To get this production, there is a requirement to exploit around 30 million tons ore and waste every year.

In the blasting operation of the mine, blast holes of 165 and 251 mm diameter are drilled and charged with ANFO as the main explosive. Staggered pattern is implemented for the drill holes whereas drill cuttings are utilized as the stemming material. Detonating cord is used for the initiation as well as a trunk line.

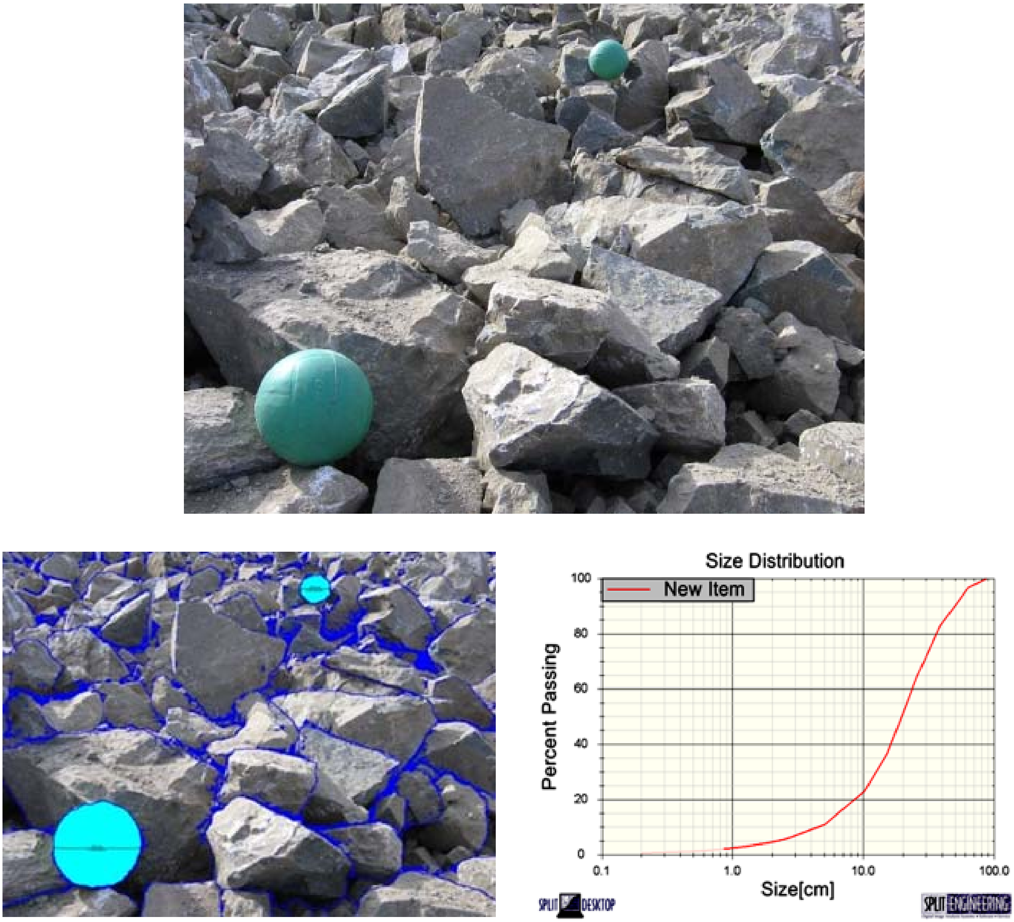

Fig. 1. Delineation of the muck pile image and its size distribution curve

4. Artificial neural network (ANN)

Nowadays, application of neural network has become a popular tool in various fields including mine blasting operations. ANN can be described either as mathematical and computational models for non-linear function approximation, data classification, clustering and nonparametric regression or as simulations of the behavior of collections of model biological neurons (Maji & Sitharam, 2008). They can learn some target values (desired output) from a set of chosen input data that has been introduced by means of input nodes, called "neurons", into a computing network system under both supervised and self-adjusted or unsupervised learning algorithms. The neurons are arranged in layers and are combined through excess connectivity. The predictive ability of the trained neural networks can be tested by using datasets which has not been used in the training of the ANN model (Wang et al., 2005). Each neuron in the layer receives an input from the node in the below layer, and each of these input variables is multiplied by separate current weight values. The weighted inputs are summed and passed an activation function that scales the output to a fixed range of values. The binary sigmoid function is most widely used for the continuous activation function which has range of 0–1. The function is defined as $f(x) = 1/(1 + \exp(x))$. The output is then distributed to all nodes in the next layer (Park & Kang, 2007). The schematic diagram of the process at each node is shown in Fig. 2.

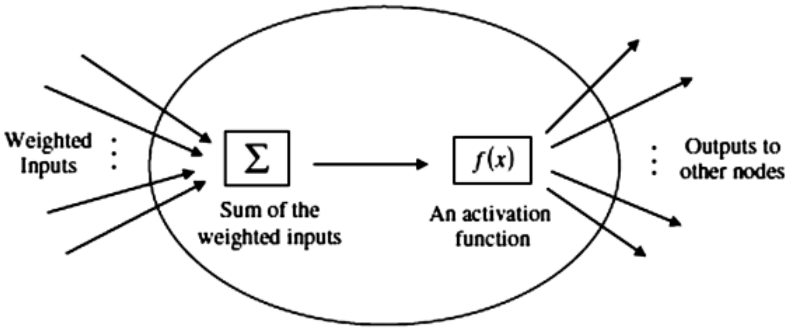

Fig. 2. The structure of a simple neuron

A network first needs to be trained before interpreting new information. Various algorithms are available for training of neural networks, but the feed forward back-propagation algorithm is the most versatile and robust technique, which provides the most efficient learning procedure for multilayer perception (MLP) neural networks. Also, the fact that the back-propagation algorithm is especially capable of solving predictive problems makes it so popular. The feed forward back-propagation neural network (BPNN) always consists of at least three layers; input layer, hidden layer and output layer (Monjezi & Dehghani, 2008). The number of hidden layers, as well as the number of neurons, in each hidden layer is dependent on the type of problem itself. Too few neurons can lead to poor network generalization known as "under fitting". On the other hand, too many neurons can contribute to "over fitting", in which case the network is actually remembering the training data instead of learning to generalize from the training data. Usually, a network with one or two hidden layers is sufficient to handle most of the complex problems in engineering applications (Lu, 2005). During training of the network, data is processed through the network, until it reaches the output layer (forward pass). In this layer the predicted output is compared to the actual or true output. The difference or error between both is processed back through the network (backward pass) updating the individual weights of the connections and the biases of the individual neurons. The input and output data are mostly represented as vectors called training pairs. The whole process is repeated for all the training pairs in the data set, until the network error converged to a threshold minimum defined by a corresponding cost function; usually the root mean squared error (RMS) or summed squared error (SSE) (Meulenkamp & Alvarez Grima, 1999).

5. Datasets

The datasets of ANN model consist of input and output parameters. The inputs used in developing the ANN model for predicting the most important parameters in fragmentation of Chadormalu iron ore mine are listed in Table 1. Input parameters such as UCS, drilling rate, water content, burden, spacing, stemming, hole diameter, bench height, powder factor and charge per delay were incorporated were implemented to predict fragmentation size as an ANN output parameter.

In this study, the input parameters of ANN model were collected from the Chadormalu iron ore mine. A database including 97 data pairs was prepared for model construction. From the collected database, 20% of datasets was selected for testing the model using a sorting system to ensure consistency of the selection.

6. Model development

One of the most difficult tasks in neural network studies is to find optimal Network architecture which is based on determination of numbers of optimal layers and neurons in the hidden layers by trial and error approach. The assignment of initial weights and other related parameters may also influence the performance of the ANN in a great extent. However there is no well defined rule or procedure to have optimal network architecture and parameter settings where trial and error method still remains valid. This process is very time consuming (Cabalar & Cevik, 2009).

In this paper, trying various types of networks, a multilayer perceptron back propagation neural network was adopted for predicting fragmentation. As such, a database including sufficient number of data pairs was collected from blasting operation of the Chadormalu mine. To avoid the negative impacts of the absolute size of the data on the results, we used the following method for the normalization treatment between input data and output data: (actual value – the minimum)/(the maximum – the minimum) = normalized value (Zhang et al., 2009). The variables given in the Table 1 were considered as the network inputs. The optimum model architecture (10-7-5-1) is shown in Fig. 3.

TABLE 1

Description of input and output data for constructing the ANN model

Type of data	Parameter	Symbol	Range of data
Input	UCS (MPa)	C	5-250
	Drilling rate (m/min)	D.R	0.12-0.90
	Water content	W	0-1
	Burden (m)	B	4.0-7.5
	Spacing (m)	S	4.8-8.5
	Stemming (m)	T	4.0-8.5
	Hole diameter (mm)	D	165-251
	Bench height (m)	K	7.5-18.9
	Powder factor (kg/ton)	Pf	0.045-0.449
	Charge per delay (kg/d)	Cpd	5.05-210.00
Output	Fragmentation (Cm)	F	12-51

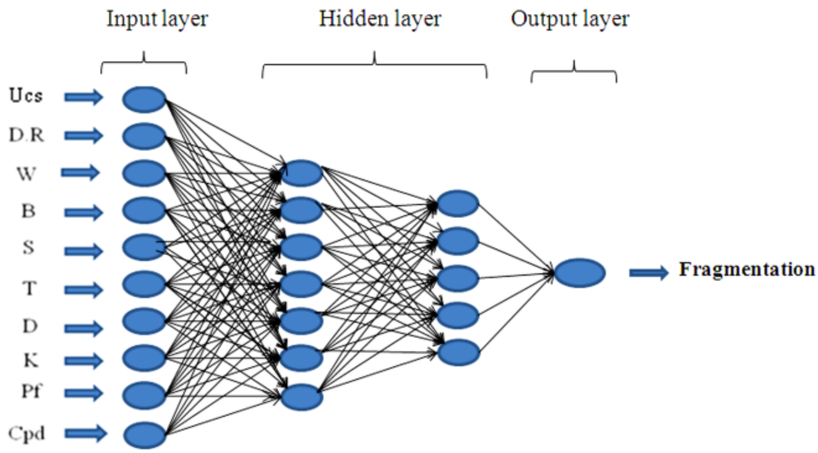

Fig. 3. The architecture of neural network model

7. Multiple regression analysis

Multiple regression analysis is used when relationship of several independent variables with a dependent variable must be determined (Monjezi et al., 2010). Using this method, a mathematical model was developed between input variables (compressive strength of rock, drilling rate, water content of block, burden, spacing, stemming, bench height, hole diameter, powder factor and charge per delay) and the output variable (Fragmentation) using software SPSS.

$$\begin{aligned} \mathrm{F} = {} & 33.388 + 0.022 \times Ucs + 6.724 \times D.R - 1.284 \times W + 8.317 \times B - 7.778 \times S \\ & + 2.642 \times T + 0.079 \times D - 1.423 \times K - 46.669 \times PF - 0.036 \times Cpd \end{aligned} \tag{1}$$

8. Evaluating model performance

To compare performance of the proposed ANN model with that of the statistical model, the testing datasets were applied in both the models and then using equations 2-4 Variance Account For (VAF), Root Mean Square Error (RMSE) and determination coefficient (R^2) were computed between measured and predicted fragmentation (Table 2). As it can be seen from Table 2 performance of the ANN model is better than that of the statistical model. Also comparison between predicted and measured values for the models is graphically illustrated in the Figs 4-6.

$$VAF = 100\left(1 - \frac{\mathrm{var}(T_i - O_i)}{\mathrm{var}(T_i)}\right) \tag{2}$$

$$RMSE = \frac{1}{N}\sqrt{\sum_{i=1}^{N}(T_i - O_i)^2} \tag{3}$$

$$R^2 = 100\left[\frac{\sum_{i=1}^{N}(O_i - \overline{O_i})(T_i - \overline{T_i})}{\sum_{i=1}^{N}(O_I - \overline{O_i})^2 \sum_{i=1}^{N}(T_i - \overline{T_i})^2}\right]^2 \tag{4}$$

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

TABLE 2

Evaluating performances of ANN and regression models using statistical indices

Index	ANN model	Regression model
VAF	93%	52%
RMSE	2.84	6.84
R^2	92.9%	53.9%

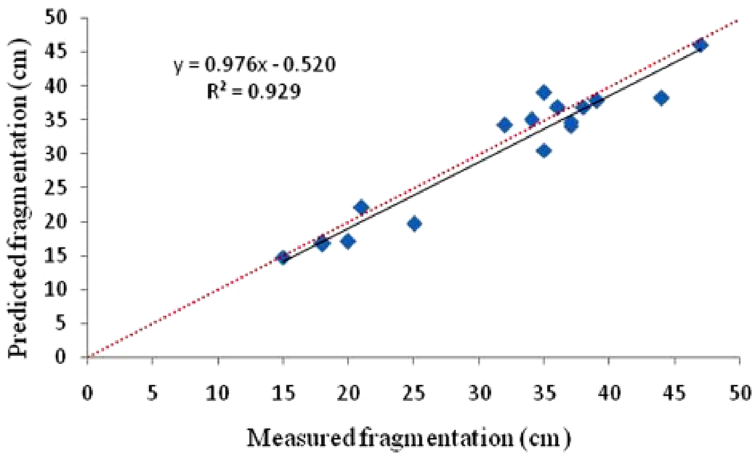

Fig. 4. Comparison between the measured and predicted fragmentation for the ANN model

9. Sensitivity analysis

Cosine Amplitude Method (CAM) was adopted to determine the effect of each individual input on the output. Identifying sensitive inputs can be helpful for the designers to carefully treat with such influential parameters in the designing process (Jong & Lee, 2004). To apply this method, all of the data pairs are expressed in common X-space. The data pairs are used to construct a data array X defined as:

$$X = \{X_1, X_2, X_3, \ldots, X_m\} \tag{5}$$

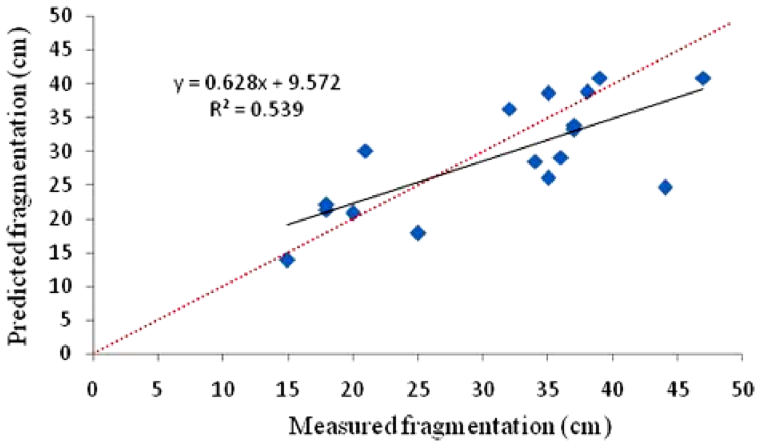

Fig. 5. Comparison between the real and predicted fragmentation for the Regression model

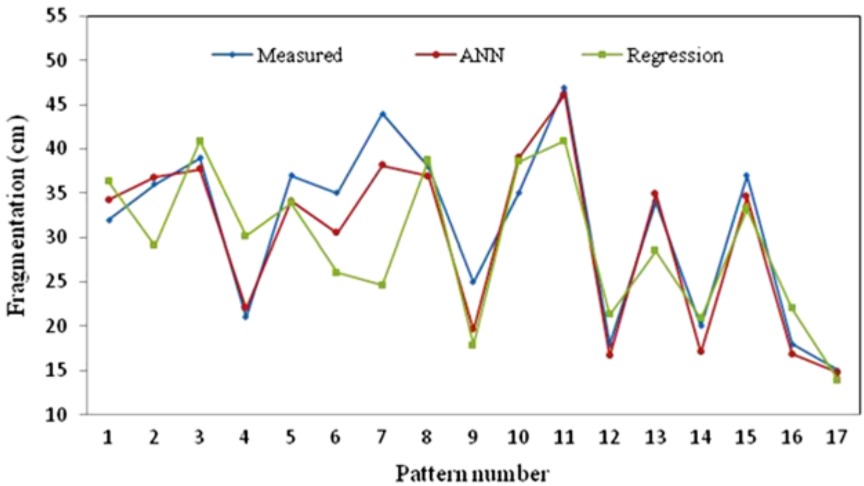

Fig. 6. Comparison of measured and predicted fragmentation

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

$$X_i = \{x_{i1}, x_{i2}, x_{i3}, \ldots, x_{im}\} \tag{6}$$

Strengths of relations (r_{ij}) between output and input parameters can be calculated using Eq. 7.

$$r_{ij} = \sum_{k=1}^{m} x_{ik} x_{jk} \Big/ \sqrt{\sum_{k=1}^{m} x_{ik}^2 \sum_{k=1}^{m} x_{jk}^2} \tag{7}$$

The r_{ij} values are shown in Fig. 7. As it can be seen from this Figure, burden and water content are the most effective and the least effective parameters on the fragmentation, respectively.

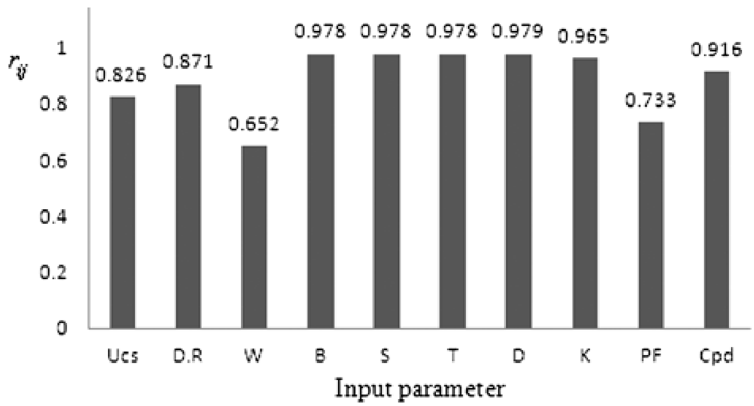

Fig. 7. The effect of input parameters on fragmentation

10. Conclusions

In this paper, application of an ANN model was performed to predict the fragmentation size of the Chadormalu iron mine. The ANN model with architecture of 10-7-5-1 was found suitable due to less RMSE error (2.84) based on trial and error mechanism. The predicted values of fragmentation by ANN model were compared with multi-variable regression model. In the regression method, determination coefficient between predicted and measured fragmentation were found 0.539, whereas determination coefficient between predicted and measured fragmentation by ANN were 0.929. Sensitivity analysis was also performed on input data sets to get the influence of each input parameter on fragmentation size. It can be said that ANN can be a better and appropriate substitute for the prediction of blast fragmentation in open pit mines.

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