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ORIGINAL ARTICLE

Multiple regression, ANN and ANFIS models for prediction of backbreak in the open pit blasting

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Abstract Backbreak is one of the undesirable effects of blasting operations causing instability in mine walls, falling down the machinery, improper fragmentation and reduction in efficiency of drilling. Backbreak can be affected by various parameters such as the rock mass properties, blasting geometry and explosive properties. In this study, the application of the artificial neural network (ANN), an adaptive neuro-fuzzy inference system (ANFIS) for prediction of backbreak, was described and compared with the traditional statistical model of multiple regression. The performance of these models was assessed through the root mean square error, correlation coefficient (R^2) and mean absolute percentage error. As a result, it was found that the constructed ANFIS exhibited a higher performance than the ANN and multiple regression for backbreak prediction.

Keywords Blasting · Backbreak · ANFIS · ANN · Multiple linear regression

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1 Introduction

Although the main purpose of blasting in open-pit mines is rock breakage and finally facilitating in loading operations, the other effects of blasting such as ground vibration, fly rock and backbreak should be considered. Backbreak can be defined as breakage behind the last row of blast holes [1]. This phenomenon may cause instability in mine walls, falling down the machinery, improper fragmentation and reduction in efficiency of drilling [2]. Several factors leading to backbreak have been described by various researchers. Konya and Walter [1] described some of the causes for backbreak such as excessive burden, and stiff benches, long stemming depth on stiff benches and improper timing delay. Gate et al. believed that a combination of factors in the blasting such as overstemming of the shot holes and short timing delays in the firing sequence may lead to severe backbreak. Moreover, the adverse geological structure appears to have exacerbated the excessive backbreak [3].

Backbreak can be affected by various parameters such as the rock mass properties, blasting geometry and explosive properties. Due to multiplicity of effective parameters and complexity of interactions among them, the application of new techniques such as artificial intelligence (AI) may be useful to solve this problem. AI can be defined as computer emulation of the human thinking process. The main feature of this concept is the ability of self-learning and self-predicting some desired outputs. The learning may be done in a supervised or an unsupervised way. Neural network and fuzzy logic are the basic areas of artificial intelligence concept. Neural networks are composed of simple elements operating in parallel. These elements are inspired by biological nervous systems. As in nature, the network function is determined largely by the connections among elements. This technique has the ability of generalizing a solution from the pattern presented to it during training. Once the network is trained with a sufficient number of sample datasets, for a new input of relatively similar pattern, predictions can be done on the basis of previous learning [4, 5].

The usage of artificial intelligence has been applied widely in most of the fields of science and technology by several researchers [6–18].

The aim of the present work is to predict backbreak caused by blasting in Sangan iron mine of Iran. The multiple linear regression, artificial neural network (ANN) and adaptive neuro-fuzzy inference system (ANFIS) were applied for backbreak prediction.

2 Methods of modeling

2.1 Multiple linear regression

Multiple regression, a time-honored technique going back to Pearson's 1908 use of it, is employed to predict the variance in an interval dependency, based on linear combinations of interval, dichotomous, or dummy independent variables. The general purpose of multiple regression is to learn more about the relationship between several independent or predictive variables and a dependent or criterion variable. The multiple regression equation takes the form $y = b_1x_1 + b_2x_2 + \cdots + b_nx_n + c$. $b_1, b_2,\ldots, b_n$ is a regression coefficient representing the amount of the dependent variable y that changes when the corresponding independent variables changes by 1 unit. c is constant, where the regression line intercepts the y-axis, representing the amount of the dependent variable y when all the independent variables are 0 [19].

2.2 Artificial neural network

The modern view of artificial neural networks began with pioneering work of McCulloch and Pitts in the 1940s, who showed that networks of artificial neurons could, in principle, compute any arithmetic or logical function. Their work is often acknowledged as the origin of the ANN field. The first practical application of ANN came in the late 1950s, with the invention of the perceptron network and associated learning rule by Rosenblatt. Rosenblatt et al. built a perceptron network and demonstrated its ability to perform pattern recognition. This early success generated a great deal of interest in neural network research. Unfortunately, it was later shown that the basic perceptron network could solve only a limited class of problems. Neural networks became popular in the late 1980s and, more recently, in the 1990s [20]. ANNs are information processing structures which emulate the architecture and operational mode of the biological nervous tissue. Any ANN is a system made of several basic entities (named neurons) which are interconnected and operate in parallel transmitting signals to one another in order to achieve a certain processing task. One of the most outstanding features of ANNs is their capability to simulate the learning process. They are supplied with pairs of input and output signals from which general rules are automatically derived so that the ANN will be (in certain conditions) capable of generating the correct output for a signal that was not previously used [21].

The suggested method in this study is the utilization of multi-layer perceptron neural network. Multi-layer networks have been applied successfully to solve some difficult and diverse problems by training them in a supervised manner with a highly popular algorithm known as the error back-propagation algorithm. This algorithm is based on the error-correction learning rule. Error back-propagation learning consists of two passes through the different layers of the network, i.e., a forward pass and a backward pass. In the forward pass, an activity pattern (input vector) is applied to the neurons of the network, and its effect propagates through the network layer by layer. Finally, a set of outputs is produced as the actual response of the network. During the forward pass, the synaptic weights of the networks are all fixed. During the backward pass, on the other hand, the synaptic weights are all adjusted in accordance with an error-correction rule. Specifically, the actual response of the network is subtracted from a desired (target) response to produce an error signal. This error signal is then propagated backward through the network, against the direction of synaptic connections [22].

2.3 Adaptive neuro-fuzzy inference system

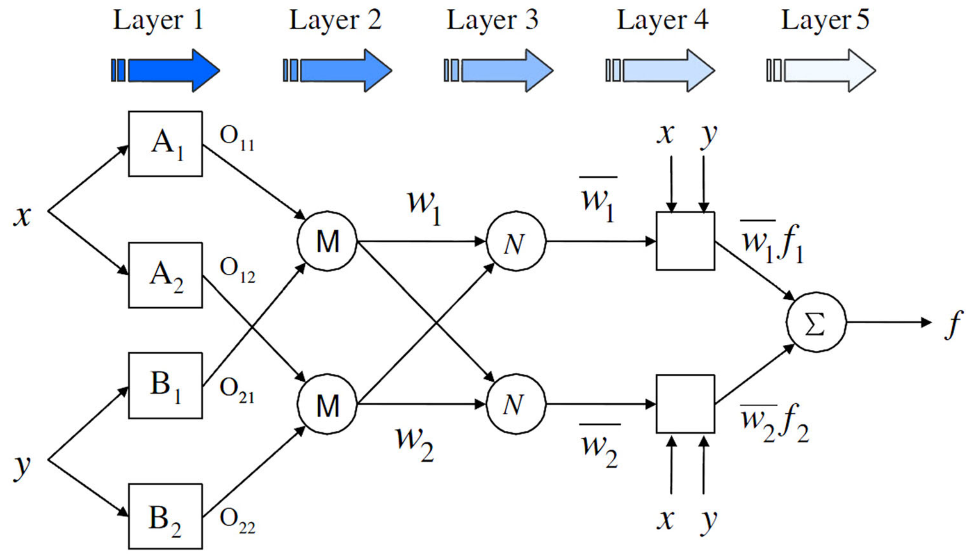
The ANFIS is a fuzzy Sugeno model put in the framework of adaptive systems to facilitate learning and adaptation [6]. Such framework makes the ANFIS modeling more systematic and less reliant on expert knowledge. For simplicity, we assumed that the fuzzy inference system has two inputs x and y and one output f. For the first-order Sugeno fuzzy model, a typical rule set with two fuzzy if–then rules can be expressed as [23]:

$$\text{Rule 1: If } (x \text{ is } A_1) \text{ and } (y \text{ is } B_1) \text{ then: } f_1 = p_1x + q_1y + r_1 \tag{1}$$

$$\text{Rule 2: If } (x \text{ is } A_2) \text{ and } (y \text{ is } B_2) \text{ then: } f_2 = p_2x + q_2y + r_2 \tag{2}$$

where p_1, q_1, r_1, p_2, q_2, r_2 are linear and A_1, A_2, B_1 and B_2 are non-linear parameters. The corresponding equivalent ANFIS architecture is shown in Fig. 1. The entire system architecture consists of five layers, i.e., a fuzzification

Fig. 1 Architecture of ANFIS



layer, a product layer, a normalized layer, a defuzzification layer, and a total output layer. The functions of each of these layers can be described as follows:Layer 1 is the fuzzification layer. In this layer, every node i in this layer is an adaptive node with a node function:

$$O_{1,i} = \mu_{A_i}(x), \quad \text{for } i = 1,2 \text{ or} \qquad O_{1,i} = \mu_{B_{i-2}}(y), \quad \text{for } i = 3,4 \tag{3}$$

where x (or y) is the input to node i and A_i (B_{i-2}) is the linguistic label (small, large, etc.) associated with this node function. In other words, $O_{1,i}$ is the membership grade of a fuzzy set A. The most commonly used membership functions is Gaussian membership function as it is non-linear and smooth and its derivation is continuous [11, 15, 16, 19]. The Gaussian membership function is given by:

$$f(x,\sigma,c) = \mathrm{e}^{\frac{-(x-c)^2}{2\sigma^2}}, \quad \text{where } 2\sigma^2 > 0 \tag{4}$$

where c and σ are the MF's centre and width, respectively. The parameters in this layer are referred to the premise parameters.

Layer 2 is the product layer. Each node in this layer is a fixed node whose output is the product of all the incoming signals. The output of this layer is given by:

$$O_{2,i} = w_i = \mu_{A_i}(x)\mu_{B_i}(y), \quad i = 1,2 \tag{5}$$

Layer 3 is a normalized layer. Each node in this layer normalizes the weight functions obtained from the previous product layer. The normalized output is computed for the ith node as the ratio of the ith rule firing strength to the sum of all rule firing strengths is as follows:

$$O_{3,i} = \bar{w}_i = \frac{w_i}{w_1 + w_2}, \quad i = 1,2 \tag{6}$$

Layer 4 is the defuzzification layer. Every node i in this layer is an adaptive node with a node function:

$$O_{4,i} = \bar{w}_i f_i = \bar{w}_i(p_i x + q_i y + r_i) \tag{7}$$

where $\bar{w}_i$ is a normalized firing strength from layer 3 and $\{p_i, q_i, r_i\}$ is the parameter set of this node. Parameters in this layer are referred to consequent parameters.

Layer 5 is the output layer. The single node in this layer is a fixed node. The overall output, which is the summation of all incoming signals, is computed by a fixed node. Overall output is given by:

$$\text{Overall output} = O_{5,1} = \sum_i \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{8}$$

The hybrid learning algorithm of ANFIS proposed by Jang is a combination of the steepest descent and least squares estimate learning. The ANFIS uses a two-pass learning algorithm, i.e., forward pass and backward pass. In forward pass, the premise parameters are not modified and the consequent parameters are computed using the least squares estimate learning algorithm. In backward pass, the consequent parameters are not modified and the premise parameters are computed using the gradient descent algorithm. Based on these two learning algorithms, ANFIS adapts the parameters in the adaptive network. From the architecture, it is clear that the overall output of the ANFIS can be represented as a linear combination of the consequent parameters as:

$$\begin{aligned} f &= \frac{w_1}{w_1 + w_2} f_1 + \frac{w_2}{w1 + w2} f_2 \\ &= \bar{w}_1 f_1 + \bar{w}_2 f_2 \\ &= \bar{w}_1(p_1 x + q_1 y + r_1) + \bar{w}_2(p_2 x + q_2 y + r_2) \\ &= (\bar{w}_1 x)p_1 + (\bar{w}_1 y)q_1 + (\bar{w}_1)r_1 + (\bar{w}_2 x)p_2 \\ &\quad + (\bar{w}_2 y)q_2 + (\bar{w}_2)r_2. \end{aligned} \tag{9}$$

In forward pass, the signals move in a forward direction to layer 4 and the consequent parameters are computed,

Fig. 2 Location of Sangan iron mine

while in the backward pass, the error rates are propagated backward and the premise parameters are updated by the gradient descent method [24].

3 Case study

The case study was carried out in Sangan iron mine 16 km away from north Sangan and 300 km away from southeast of Mashhad, Iran (Fig. 2). Geographically, it is located at 60°16′ longitude and 34°24′ latitude. The Sangan iron deposit is located in Central Iran zone. In this zone, igneous activity starting in the Eocene period and reaching to its highest point during the middle Eocene for exposed volcanic rocks and Oligo-Miocene for plutonic rocks in many parts of Iran. The iron host rock is carbonate of the Cretaceous. Various rock types which can be recognized in the Sangan Mine consist of Sarnosar granite, siltstone, sandstone and quartzite complex, north skarn unit, shale and siltstone, south skarn unit and volcanic complex. The iron ores in Sangan were grouped into the high grade massive iron zone, low grade dispersive iron zone, oxidized zone and sulfide zone. The total geological reserve of the Sangan iron ore mine is approximately estimated 1.2 billion tons. Sangan iron mine is under developing and the mineral processing plant is designed to produce 2.6 million tons of iron pellets per year in the phase 1 of the project [25].

Table 1 The descriptive statics of the input and output parameters

Parameter	Description	Symbol	Minimum	Maximum
Inputs	Stiffness ratio	H/B	1	3.7
	Stemming length (m)	ST	0.6	4
	Specific charge (kg/m^3)	SC	0.45	1.4
	Rock density (t/m^3)	DN	2.5	4.2
	Number of rows	NR	2	12
	Charge last row (kg)	CLR	260	2,800
	Spacing to burden ratio	S/B	1	1.36
Output	Backbreak (m)	BB	0	9

In the blasting operation of the mine, the explosive used is ANFO. Blasting holes of 3.5 and 4.5 in. diameters are used in benches with 3–10 m height. The drill-hole pattern (burden × spacing), depending on the rock type, is 2 × 2.5, 2.3 × 2.7, 2.5 × 3 and 3 × 3.5 m. In the present study, a database including 42 datasets was collected from blasting operation of the Sangan iron mine, and for modeling backbreak, seven parameters were considered as the input parameters. Descriptive statistical distribution of the input and output parameters and their respective symbols are indicated in Table 1. In Table 1, charge last row (CLR) is defined as the total charge utilized in the last row.

4 Results and discussion

4.1 Data processing

In order to establish the predictive models among the parameters obtained in this study, simple regression analysis was performed at the first stage of the analysis. Figure 3 shows the correlations among the individual independent variables and the actual measured backbreak. The figures also, include the correlation coefficient (R^2) which is an indicator of correlation strength. As shown in Fig. 3, the R^2 value decreases in the order of the CLR (0.74), NR (0.55), SC (0.45), ST (0.38), H/B (0.024), S/B (0.028) and DN (0.008). Accordingly, CLR, NR, SC and ST are the most significant variables, and H/B, S/B and DN the least correlations with backbreak. It can be concluded that H/B, S/B and DN have negligible effects on the backbreak and should be excluded in regression model. As a result, four input parameters (CLR, NR, SC and ST) were considered as effective parameters on backbreak and assumed that backbreak is a function of these important input parameters.

4.2 Multiple linear regression model

Multiple regression analysis was carried out on backbreak and specific charge (SC), stemming length (ST), charge last row (CLR) and number of rows (NR). Multiple regression model to predict backbreak is given below:

$$\mathrm{BB} = 1.854\ \mathrm{SC} - 0.273\ \mathrm{ST} + 0.003\ \mathrm{CLR} + 0.076\ \mathrm{NR}$$
$$R^2 = 79\,\% \quad (10)$$

In this study, root mean square error (RMSE), correlation coefficient (R^2) and mean absolute percentage error (MAPE) indices were calculated to control the performance of the prediction capacity of predictive models developed [19, 26, 27].

Root mean square error (RMSE), a measure of the goodness-of-fit, best describes an average measure of the error in predicting the dependent variable. However, it does not provide any information on phase differences.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(A_{i\mathrm{meas}} - A_{i\mathrm{pred}}\right)^2} \quad (11)$$

where $A_{i\mathrm{meas}}$ is the ith measured element, $A_{i\mathrm{pred}}$ is the ith predicted element and n is the number of datasets.

Mean absolute percentage error (MAPE), which is a measure of accuracy in a fitted series value in statistics, was also used for comparison of the prediction performances of the models. MAPE usually expresses accuracy as a percentage:

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{A_{i\mathrm{meas}} - A_{i\mathrm{pred}}}{A_{i\mathrm{meas}}}\right| \times 100 \quad (12)$$

The RMSE and MAPE for multiple linear regression are given in Table 4. Figure 4 shows the relationship between measured and predicted values obtained from the Eq. (10).

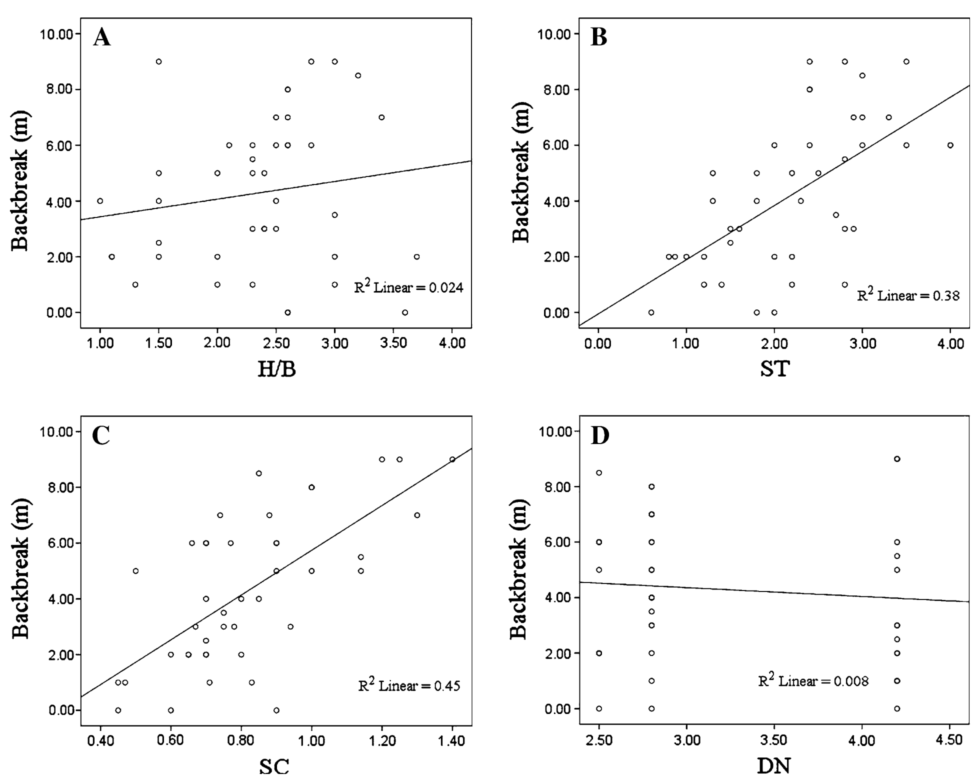
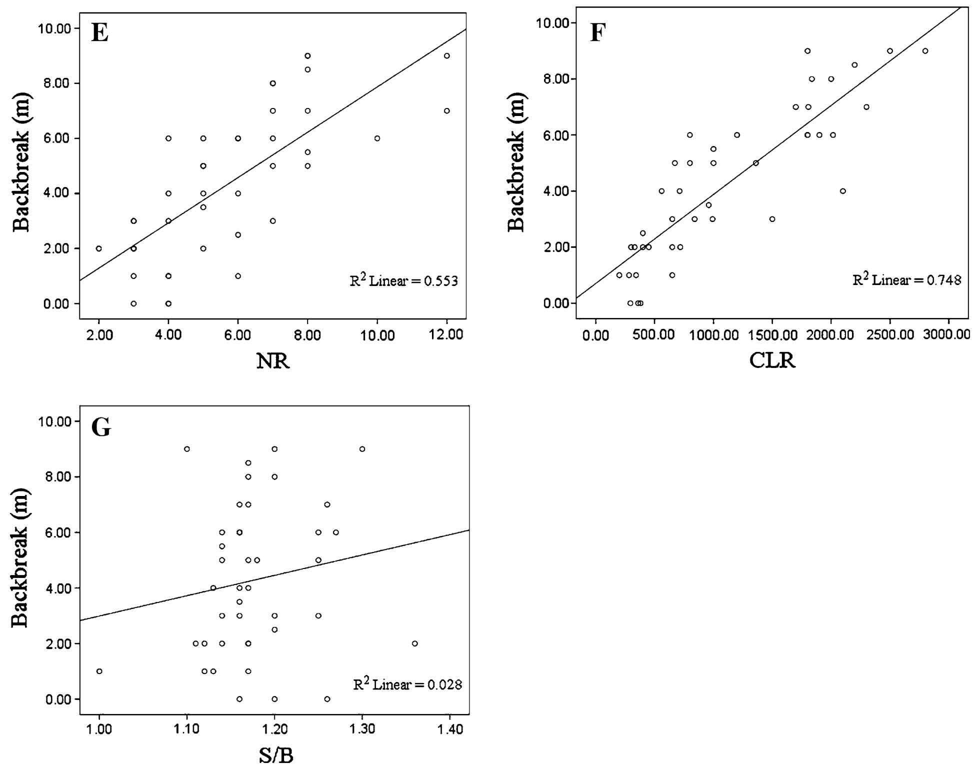


Fig. 3 The relationship between measured backbreak and the input parameters: **a** stiffness ratio, **b** stemming length, **c** specific charge, **d** rock density, **e** number of rows, **f** charge last row, **g** spacing to burden ratio

Fig. 3 continued



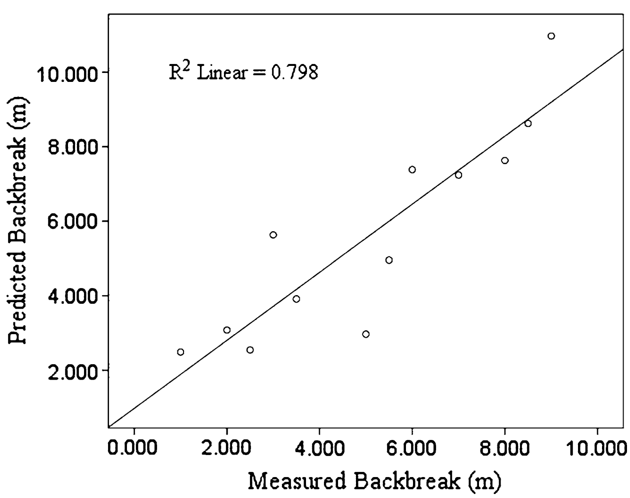


Fig. 4 Correlation coefficient for multiple linear regression model

4.3 ANN model

In this study, multi-layer perceptron neural network was used for the model as this architecture is reported to be suitable for problems based on pattern matching and pattern prediction. In designing the model for prediction backbreak, 30 datasets were used to train and the remaining 12 datasets were used to test the model. To evaluate networks with different architectures and then to determine optimum network architecture, RMSE and R^2 were calculated for various models. As shown in Table 2, the network, which had one hidden layer with the neural network architecture of 4-4-1, was considered as the optimum model for backbreak prediction. This network is shown in Fig. 5. A graphic comparison of measured and predicted backbreak is shown in Fig. 6. As seen in this figure, a good conformity exists between the measured and predicted backbreak by the ANN model.

Table 2 Networks with different architecture

No.	Transfer function	Model	RMSE	R^2
1	TANSIG-TANSIG-PURELIN	4-4-1	0.88	0.92
2	TANSIG-TANSIG-PURELIN	4-8-1	1.75	0.81
3	LOGSIG-LOGSIG-LOGSIG-POSLIN	4-9-6-1	2.81	0.12
4	TANSIG-TANSIG-TANSIG-PURELIN	4-6-6-1	0.92	0.88
5	TANSIG-TANSIG-TANSIG-POSLIN	4-12-8-1	1.05	0.89
6	LOGSIG-LOGSIG-LOGSIG-PURELIN	4-7-5-1	2.27	0.74

4.4 ANFIS model

In this work, the available datasets were divided into two subsets randomly, i.e., 30 datasets for training and 12

Fig. 5 The optimum architecture of ANN used in this study

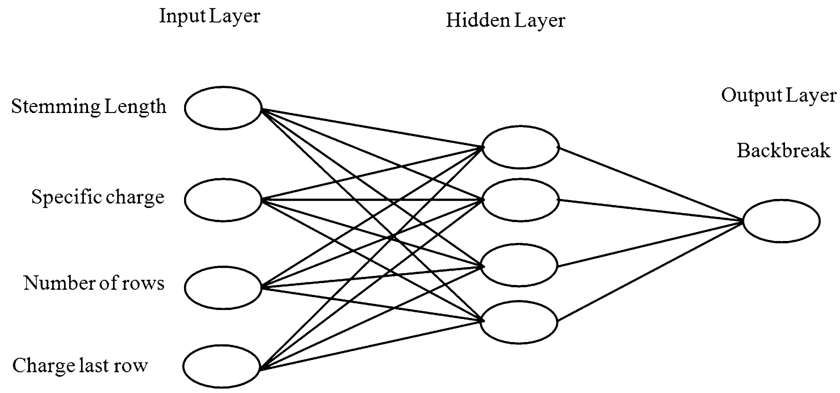
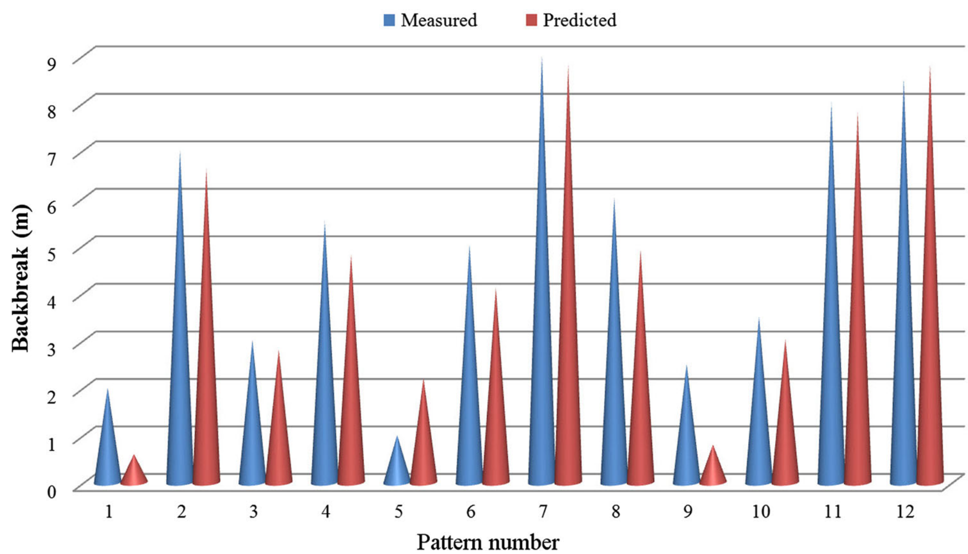


Fig. 6 Comparison of measured and predicted backbreak by ANN model



datasets for testing (the same as ANN model). Subtractive clustering was used to generate fuzzy inference system (FIS) structure automatically. Subtractive clustering has an auto-generation capability to determine the number and initial location of cluster centers in a set of data. This method partitions the data into groups called clusters by specifying a cluster radius, and generates a Sugeno-type fuzzy inference system (FIS) with the minimum number of rules according to the fuzzy qualities associated with each of the clusters. Hybrid learning algorithm, a combination of

Fig. 7 Model structure of the ANFIS for prediction of backbreak

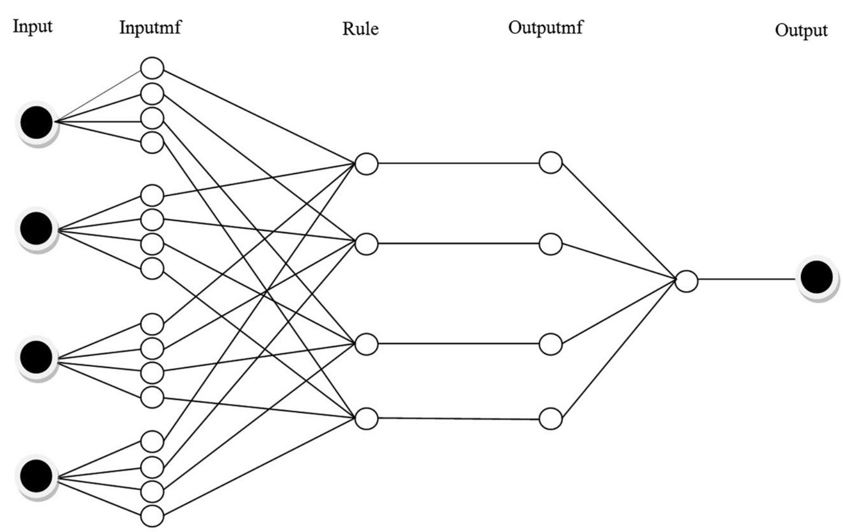


Table 3 The ANFIS information used in this study

ANFIS parameter type	Value
MF type	Gaussian
Number of MFs	4
Output function	Linear
Number of nodes	47
Number of linear parameters	20
Number of nonlinear parameters	32
Total number of parameters	52
Training RMSE	0.74

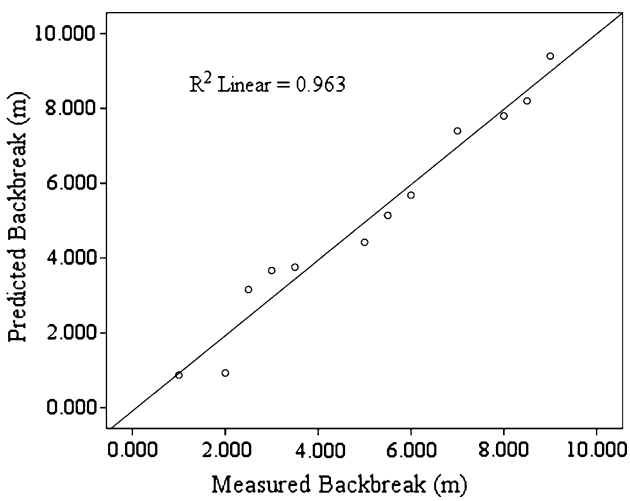


Fig. 8 Correlation coefficient for ANFIS model

Table 4 Performance indices of the models

Model	R^2	RMSE	MAPE (%)
ANFIS	0.96	0.6	13
ANN	0.92	0.88	27
Multiple linear regression	0.79	1.35	34

least squares and back-propagation gradient, was applied to identify the membership function parameters of single output, Sugeno-type fuzzy inference systems (FIS). Several models with four input parameters and one output parameter were constructed and trained. To evaluate models with different structure (FIS division) and then to determine the best model, RMSE was calculated for these models. Figure 7 shows the proposed ANFIS model for predicting backbreak which has four membership functions for each input parameter and four rules. Other parameter types and their values used for constructing ANFIS model can be seen in Table 3. Figure 8 shows the relationship between measured and predicted values obtained from the ANFIS model in testing stage. The obtained values of RMSE and MAPE, given in Table 4, indicate high prediction performances.

4.5 Comparison between the models

In this section, a prediction performance comparison is made among the ANFIS model, ANN model and the multiple regression model. The performance of these models was evaluated according to statistical criteria such as correlation coefficient (R^2), root mean square error (RMSE) and mean absolute percentage error (MAPE). The results of applying these models are compared in Table 4. The table clearly shows that the predictive performance of ANFIS model is obviously higher than the ANN and regression models. Correlation coefficient for measured and estimated data obtained from ANFIS, ANN and multiple regression is shown in Fig. 9. ANFIS model has the maximum value of correlation in comparison with other models. In addition, the values of estimating error for all methods have been offered in Table 4. According to this table, the minimum values of RMSE and MAPE is for ANFIS. The results of analysis show that ANFIS model has the best efficiency in comparison with ANN and multiple regression considering all criteria.

5 Conclusion

In this study, multiple linear regression, ANN and ANFIS models were utilized to predict the backbreak caused by blasting; to model backbreak, seven effective parameters were considered as the input parameters and 42 datasets were collected from Sangan iron mine of Iran. The following results could be drawn from this investigation:

- As a result of data analysis, the four input parameters including charge last row (CLR), number of rows (NR), specific charge (SC), and stemming length (ST) are significant parameters and stiffness ratio (H/B), spacing to burden ration (S/B) and rock density (DN) have insignificant effects on the backbreak and were excluded in these models.
- The RMSE, R^2 and MAPE for multiple regression were obtained as 1.35, 0.79 and 34 %, respectively. The result of the model for prediction of the backbreak showed that the equation obtained from the multiple linear regression model had an acceptable prediction performance.
- The optimum ANN architecture has been found to be four neurons in the input layer, one hidden layer with 4 neurons, and one neuron in the output layer. For the ANN model, RMSE, R^2 and MAPE were calculated as 0.88, 0.92 and 27 %, respectively. The ANN model

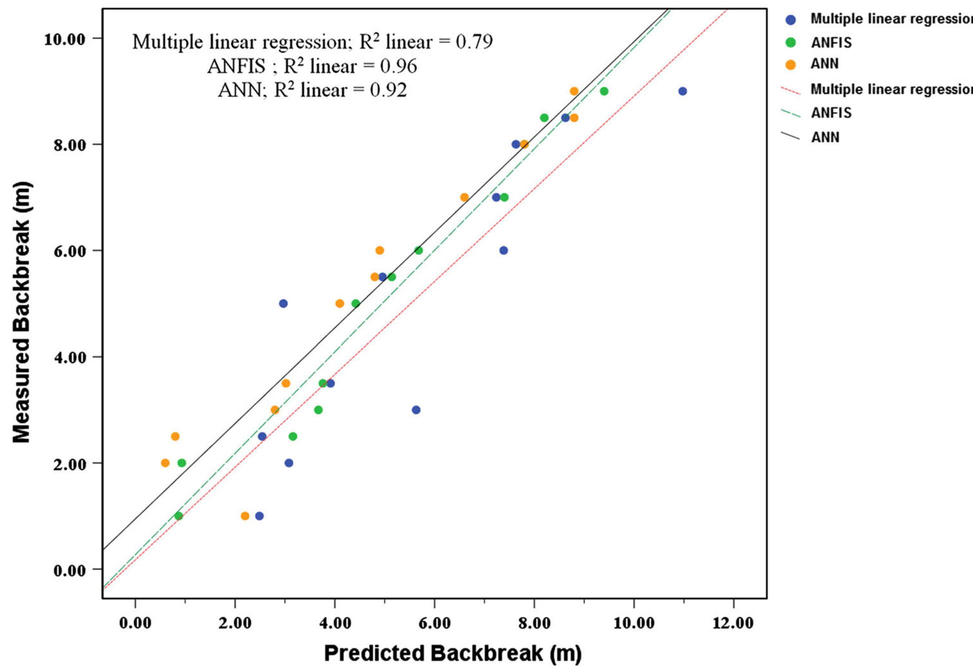


Fig. 9 Correlation coefficient between measured and predicted backbreak

revealed a more reliable prediction when compared with the multiple linear regression model.

- The RMSE, R^2 and MAPE indices were calculated as 0.6, 0.96 and 13 % for ANFIS model. It was found that the constructed ANFIS model exhibits a high performance for predicting of backbreak.
- According to the performance indicators, the prediction performance of ANFIS model was found to be better than the ANN and multiple linear regression models.
- ANFIS, ANN and multiple regression models that have been achieved are exclusively related to Sangan iron mine and in other cases rather than this mine, these models should be modified.

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