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## PREDICTION OF BACKBREAK IN OPEN PIT BLASTING BY ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM

## PROGNOZOWANIE SPĘKAŃ SKAŁ PRZY PRACACH STRZAŁOWYCH W KOPALNIACH ODKRYWKOWYCH PRZY UŻYCIU METOD NEURONOWYCH I WNIOSKOWANIA ROZMYTEGO (ANFIS) ZASTOSOWANYCH W MODELU ADAPTYWNYM

Adaptive neuro-fuzzy inference system (ANFIS) is powerful model in solving complex problems. Since ANFIS has the potential of solving nonlinear problem and can easily achieve the input–output mapping, it is perfect to be used for solving the predicting problem. 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. In this paper, ANFIS was applied to predict backbreak in Sangan iron mine of Iran. The performance of the model was assessed through the root mean squared error (RMSE), the variance account for (VAF) and the correlation coefficient ($R^2$) computed from the measured of backbreak and model-predicted values of the dependent variables. The RMSE, VAF, $R^2$ indices were calculated 0.6, 0.94 and 0.95 for ANFIS model. As results, these indices revealed that the ANFIS model has very good prediction performance.

**Keywords:** blasting, backbreak, adaptive neuro-fuzzy inference system, Sangan iron mine

Adaptywny system wnioskowania wykorzystujący elementy sieci neuronowych i logiki rozmytej (AN-FIS) stanowi potężny narzędzie do rozwiązywania złożonych problemów. Ponieważ model ANFIS może być wykorzystywany do rozwiązywania problemów nieliniowych i umożliwia wygodne przedstawienie problemu w formie: wejście - wyjście, jest idealnym narzędziem do rozwiązywania problemów związanych z prognozowaniem. Pękanie skał w odkrywce jest jednym z niekorzystnych skutków prowadzenia prac strzałowych, powoduje niestabilność ścian, uszkodzenia maszyn i urządzeń, nieodpowiednią fragmentację skał oraz prowadzi do obniżenia efektywności wierceń. W pracy przedstawiono zastosowanie systemu ANFIS do prognozowania pękań skał w kopalni rud żelaza w Sangan (Iran). Działanie modelu zbadano na podstawie wartości błędu średniokwadratowego (RMSE), wariancji (VAF) i współczynnika korelacji

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($R^2$) obliczonego na podstawie pomiarów pęknięć skał i wartości uzyskanych z modelowania. Wartości wskaźników RMSE, VAF i $R^2$ obliczonych przy użyciu modelu ANFIS wynoszą odpowiednio 0.6, 0.94 i 0.95. Wielkości te wyraźnie potwierdzają wysoką skuteczność modelu.

**Słowa kluczowe:**  prace strzałowe, pękanie skał, system wnioskowania wykorzystujący elementy sieci neuronowych i logiki rozmytej, kopalnia rud żelaza Sangan

# 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 holes (Konya & Walter, 1991). This phenomenon may cause instability in mine walls, falling down the machinery, improper fragmentation and reduction in efficiency of drilling (Bazzazi, 2005). Several factors leading to backbreak have been described by various researchers. Konya and Walter (1991) 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. (2005) 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 have led to the severe backbreak. Moreover, the adverse geological structure appears to have exacerbated the excessive backbreak.

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, application of new techniques is necessary for solving this problem. Currently, new techniques such as artificial neural networks, fuzzy systems, maximum likelihood and genetic algorithm were utilized as tools to prediction of complex problems (Monjezi & Dehghani, 2008). Fuzzy logic concept is close to human thinking style because it uses linguistic terms. It reduces the possible difficulties in modeling and analysis of complex data and also, it is appropriate for incorporating the qualitative aspects of human experience within its mapping rules, which are to provide a way of catching information. Artificial neural networks (ANNs) have also been used to identify models of complex systems because of their high computational rates, robustness and ability to learn. For the same purpose neuro-fuzzy systems are fuzzy systems which use ANNs theory in order to determine their properties (fuzzy sets and fuzzy rules) by processing data samples. A specific approach in neuro-fuzzy is the adaptive neuro-fuzzy inference system (ANFIS) that is one of the first integrated hybrid neuro-fuzzy models (Jang, 1993), but has shown significant results in modeling nonlinear functions and is faster in convergence when compared to the other neuro-fuzzy models (Akcayol, 2004).

Modeling of tunnel boring machine performance by neuro-fuzzy method was carried out by Grima et al. (2000). Gokceoglu et al. (2004) constructed a neuro-fuzzy system to estimate the deformation modulus of rock masses. For the purpose, a database including 115 data sets was employed and a neuro-fuzzy system consisting of two inputs, one output and 18 if then fuzzy role was constructed. The results showed that the neuro-fuzzy model to predict the deformation modulus of rock masses has a considerable advantage when compared with the other prediction models. A comparative study of ANN and neuro-fuzzy for the prediction of dynamic constant of rockmass was performed by Singh et al. (2005). It was concluded that the neuro-fuzzy method performed better than ANN method model. Iphar et al. (2008) employed adaptive neuro-fuzzy

inference system to predict the ground vibrations resulting from the blasting operations in an open-pit mine. It was concluded that the proposed ANFIS-based model exhibited better prediction performance than the classical regression-based model. Prediction of the strength and elasticity modulus of gypsum using multiple regression, ANN, and ANFIS models was performed by Yilmaz and Yuksek (2009). It was showed that the constructed ANFIS model exhibits a high performance for predicting UCS and E. The performance comparison also showed that the ANFIS is a good approach for minimizing the uncertainties in the rock engineering projects. Prediction of free swelling index (FSI) using multivariable regression and adaptive neuro-fuzzy inference system was carried out by Tayebi Khorami at al. (2011). The comparative study of ANFIS and regression predictive models showed that the ANFIS significantly can be used to predict FSI when regression results do not have appropriate accuracy. Kucuk et al. (2011) constructed adaptive neuro-fuzzy inference system model for predicting the performance of impact hammer type excavator by considering rock and excavating machine properties such as block punch strength index, geological strength index system and impact hammer power. The results of ANFIS model were compared with traditional multiple linear regression model. It was found that the prediction performances of ANFIS model is better than traditional multiple linear regression model. ANFIS has also been used in the field of science and technology by many researchers (Guler & Ubeyli, 2004; Zaheeruddin & Garima, 2006; Naadimutha et al., 2007; Cakmakci, 2007; Bakhtyar et al., 2008; Wang & Elhag, 2008; Khajeh et al., 2009; Radulovic & Rankovic, 2010; Yan et al., 2010; Ata & Kocyigit, 2010; Sargolzaei & Kianifar, 2010; Yilmaz & Kaynar, 2011; Mohammadi et al., 2011).

The purpose the present study is prediction of backbreak causing by blasting in Sangan iron mine of Iran. This paper is organized as follows: In section 2, basic concepts of ANFIS are explained. Section 3 describes the field of study. Section 4 presents and discusses the results of the ANFIS model. Finally, section 5 concludes the paper.

## 2. Adaptive neuro-fuzzy inference system

### 2.1. Architecture of ANFIS

The ANFIS is a fuzzy Sugeno model put in the framework of adaptive systems to facilitate learning and adaptation (Jang, 1993). 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 (Jang et al. 1997):

Rule 1: If ($x$ is A1) and ($y$ is B1) then: $f_1 = p_1 x + q_1 y + r_1$

Rule 2: If ($x$ is A2) and ($y$ is B2) then: $f_2 = p_2 x + q_2 y + r_2$

where $p_1, q_1, r_1, p_2, q_2, r_2$ are linear and A1, A2, B1 and B2 are nonlinear parameters. The corresponding equivalent ANFIS architecture is as shown in Fig. 1. The entire system architecture consists of five layers, i.e. a fuzzification 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:

$$O_{1,i} = \mu_{A_i}(x), \qquad \text{for} \qquad i = 1, 2 \quad \text{or}$$

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

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. It other words, $O_{1,i}$ is the membership grade of a fuzzy set A. The most commonly used membership functions are Bell shaped and Gaussian membership functions as they are nonlinear and smooth and their derivatives are continuous.

The Gaussian membership function is given by

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

where $c$ and $\sigma$ 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:

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

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 $i^{th}$ node as the ratio of the $i^{th}$ rule's firing strength to the sum of all rule firing strengths as follows:

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

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

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

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, as the summation of all incoming signals, is computed by a fixed node. Overall output is given by:

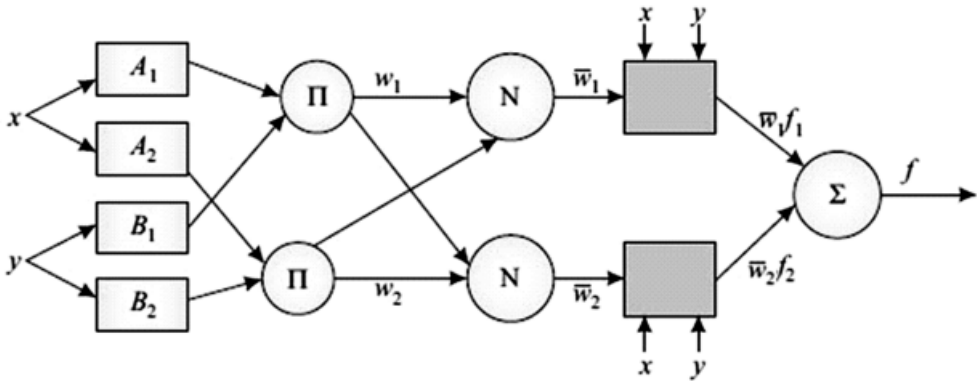$$\textit{Overall output} = O_{5,1} = \sum_i \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}$$

Fig. 1. Architecture of ANFIS

## 2.2. Hybrid learning algorithm

The hybrid learning algorithm of ANFIS proposed by Jang et al. (1997) 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 by using the least squares estimate learning algorithm. In backward pass, the consequent parameters are not modified and the premise parameters are computed by 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

$$
\begin{aligned}
f &= \frac{w_1}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2 \\
&= \overline{w_1} f_1 + \overline{w_2} f_2 \\
&= \overline{w_1} (p_1 x + q_1 y + r_1) + \overline{w_2} (p_2 x + q_2 y + r_2) \\
&= (\overline{w_1} x) p_1 + (\overline{w_1} y) q_1 + (\overline{w_1}) r_1 + (\overline{w_2} x) p_2 + (\overline{w_2} y) q_2 + (\overline{w_2}) r_2
\end{aligned}
$$

In forward pass the signals move in a forward direction to layer 4 and the consequent parameters are computed while in the backward pass, the error rates are propagated backward and the premise parameters are updated by the gradient descent method (Sumathi & Paneerselvam, 2010).

## 3. Case study

The field 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 total geological reserve of the Sangan iron ore mine is estimated to be near 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.

Fig. 2. Location of Sangan iron mine

In the blasting operation of the mine, pattern geometry is staggered and the explosive used is ANFO. Blasting holes of 3.5 and 4.5 inch 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. Drilling cuttings are used as stemming material. In the present study, a database including 42 data sets was collected from blasting operation of the Sangan iron mine and for modeling backbreak ten effective parameters were considered as the input parameters. 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.

TABLE 1

Input and output parameters for this study

| Parameter | Description | Symbol | Minimum | Maximum |
|---|---|---|---|---|
| **Inputs** | Spacing to burden ratio | S/B | 1 | 1.33 |
| | Stiffness ratio | H/B | 1 | 4 |
| | Hole diameter (inch) | D | 3.5 | 4.5 |
| | Stemming length (m) | ST | 0.6 | 4 |
| | Specific charge (kg/m$^3$) | SC | 0.45 | 1.4 |
| | Rock density (t/m$^3$) | DN | 2 | 4.7 |
| | UCS (Mpa) | UCS | 30 | 70 |
| | Number of rows | NR | 2 | 13 |
| | Charge last row (kg) | CLD | 260 | 2800 |
| | Charge last row per total charge ratio | CPT | 0.18 | 1 |
| **Output** | Backbreak (m) | BB | 0 | 9 |

Sensitivity analysis is a method for extracting the cause and effect relationship between the inputs and output parameters. The strength of the relationship between the backbreak and input parameters was analyzed by the cosine amplitude method (CAM). As seen in Fig. 3, sensitivity analysis was performed by cosine amplitude method (CAM) on fuzzy model and the most effective parameters on the backbreak were obtained: charge last row (CLR), number of rows (NR), stemming length (ST) and specific charge (SC), respectively. These effective parameters were selected as input parameters for the ANFIS model (Esmaeili, 2011).
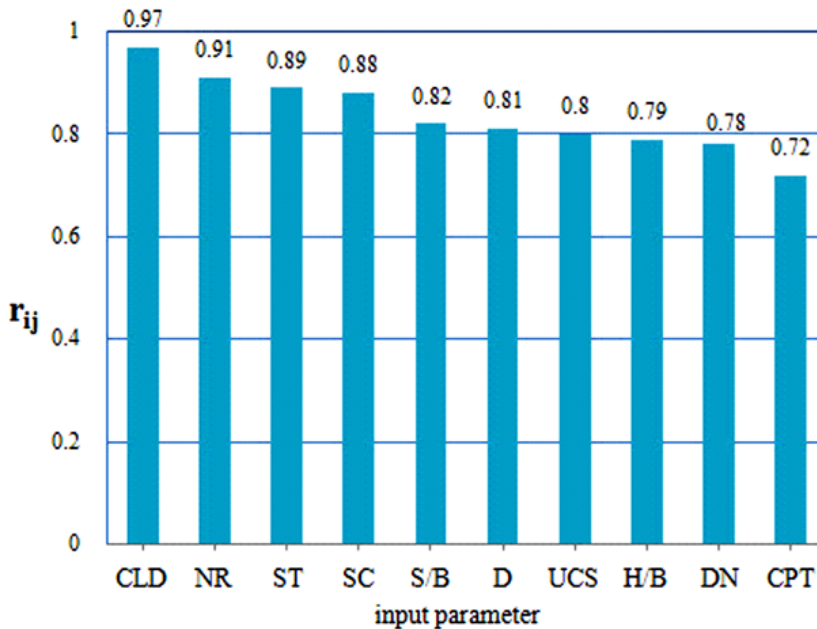


Fig. 3. Strengths of relation between backbreak and each input parameter (Esmaeili, 2011)

## 4.   Results and discussion

ANFIS is powerful model in solving complex problems. Since ANFIS has the potential of solving nonlinear problem and can easily achieve the input–output mapping, it is perfect to be used for solving the predicting problem (Khajeh et al., 2009). In this work, the available data sets were divided into two subsets randomly i.e. 30 data sets for training and 12 data sets for testing. 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. In this type, the default input membership function type is Gaussian type membership function, and the default output membership function type is 'linear' (Lotfi, 1995). Hybrid learning algo-

rithm, a combination of 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 models. The Fig. 4 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 training ANFIS model can be seen in Table 2.
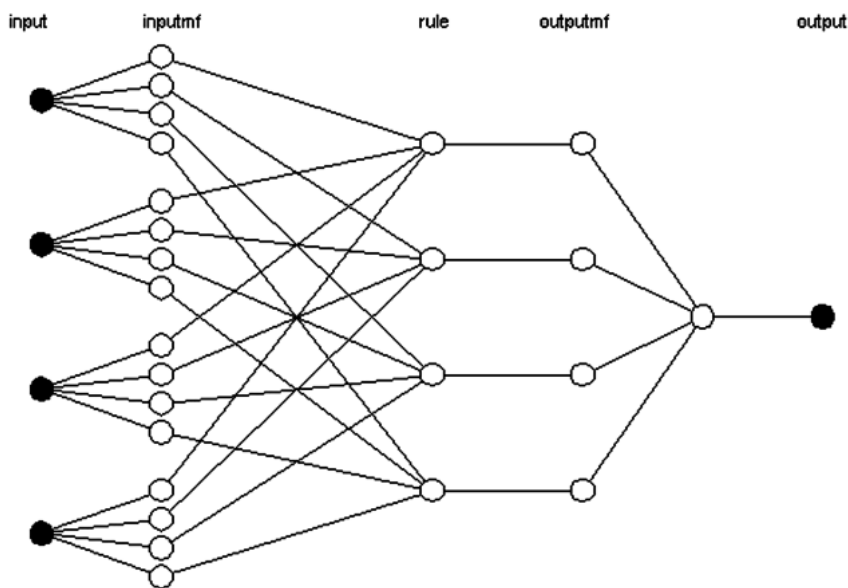


Fig. 4. Model structure of the ANFIS for prediction of backbreak

TABLE 2

The ANFIS information used in this study

| ANFIS parameter type | Value |
|---|---|
| Number of nodes | 47 |
| Number of linear parameters | 20 |
| Number of nonlinear parameters | 32 |
| Total number of parameters | 52 |
| Training RMSE | 0.74 |

After training, 12 testing data was used to validate accuracy of the ANFIS model for the prediction of backbreak. The performance of the model was evaluated according to statistical criteria such as root mean square error (RMSE), variance account for *(VAF)* (Alvarez Grima &

Babuska, 1999; Tzamos & Sofianos, 2006; Ciurana et al., 2008; Yagiz & Gokceoglu, 2010; Yan et al., 2010).

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.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(A_{i\,meas} - A_{i\,pred})^2}$$

where $A_{imeas}$ is the $i^{th}$ measured element, $A_{ipred}$ is the $i^{th}$ predicted element and $n$ is the number of data sets.

Variance account for ($VAF$) performance index is used to investigate to what degree the model can explain the variance in data.

$$VAF = 100\,\frac{1 - \mathrm{var}(A_{meas} - A_{pred})}{\mathrm{var}(A_{pred})}$$

The higher the $VAF$, the better the model performs. For instance, a $VAF$ of 100% means that the measured output has been predicted exactly (perfect model). $VAF = 0$ means that the model performs as poorly as a predictor using simply the mean value of the data.

The relation between measured backbreak and predicted values by ANFIS model is given in Fig. 5 ($R^2 = 0.95$). The $VAF$ and RMSE indices were calculated 0.94 and 0.6, respectively. These results show that the ANFIS model is a suitable tool for prediction of backbreak causing by blasting operation in Sangan iron mine.
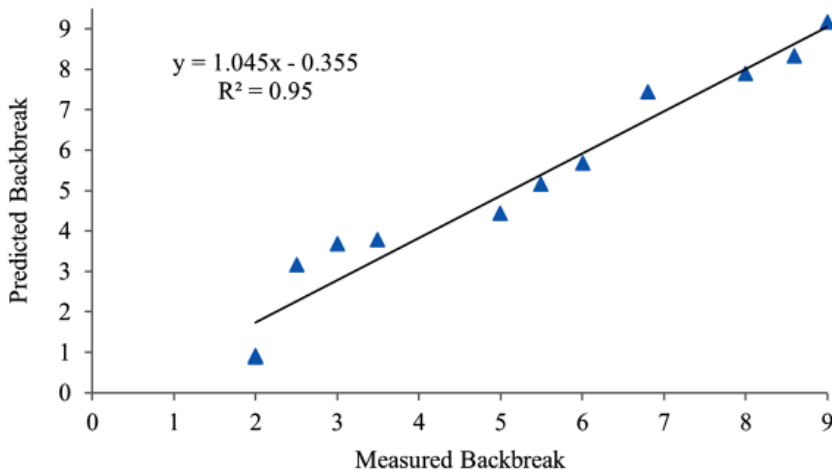


Fig. 5. Correlation between measured and predicted backbreak

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## 5.  Conclusions

In this study, backbreak was predicted using adaptive neuro-fuzzy inference system. For modeling backbreak ten effective parameters were considered as input parameters and 42 data sets were collected from Sangan iron mine. Then, sensitivity analysis was performed by cosine amplitude method and the most effective parameters on the backbreak were obtained: charge last delay, number of rows, stemming length and specific charge, respectively. These effective parameters were selected as input parameters of ANFIS model for prediction of backbreak. In this work, the available data sets were divided into two subsets randomly: 30 data sets for training and 12 data sets for testing. Subtractive clustering was used to generate fuzzy inference system (FIS) structure automatically. The ANFIS model proposed for prediction of backbreak has four membership functions for each input parameter and four linguistic rules. The VAF, RMSE, $R^2$ indices were calculated 0.94, 0.6 and 0.95 for ANFIS model. These results show that the ANFIS model is a suitable tool for prediction of backbreak causing by blasting operation in Sangan iron mine.

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