International Journal of Mining Science and Technology 22 (2012) 459–463

Contents lists available at SciVerse ScienceDirect

International Journal of Mining Science and Technology

journal homepage: www.elsevier.com/locate/ijmst

Sizing of rock fragmentation modeling due to bench blasting using adaptive neuro-fuzzy inference system and radial basis function

Karami Alireza [a,*], Afiuni-Zadeh Somaieh [b]

[a] Department of Civil Engineering, Malayer Branch, Islamic Azad University, Malayer, Iran
[b] Department of Biochemistry, Molecular Biology and Biophysics, University of Minnesota, MN 55455, USA

ARTICLE INFO

Article history:
Received 10 November 2011
Received in revised form 11 December 2011
Accepted 12 January 2012
Available online 10 July 2012

Keywords:
Sizing
Bench blasting
Open pit mine
ANFIS
RBF

ABSTRACT

One of the most important characters of blasting, a basic step of surface mining, is rock fragmentation. It directly effects on the costs of drilling and economics of the subsequent operations of loading, hauling and crushing in mines. Adaptive neuro-fuzzy inference system (ANFIS) and radial basis function (RBF) show potentials for modeling the behavior of complex nonlinear processes such as those involved in fragmentation due to blasting of rocks. In this paper we developed ANFIS and RBF methods for modeling of sizing of rock fragmentation due to bench blasting by estimation of 80% passing size (K_{80}) of Golgohar iron ore mine of Sirjan, Iran. Comparing the results of ANFIS and RBF models shows that although the statistical parameters RBF model is acceptable but the ANFIS proposed model is superior and also simpler because the ANFIS model is constructed using only two input parameters while seven input parameters used for construction of the RBF model.

1. Introduction

Blasting remains the cheapest method of hard rock fragmentation. The process of rock breakage by blasting in open pit mines is a complex phenomenon which is controlled by many variables and parameters. Considering all these parameters in a single analysis is not possible at the present time especially when some of them are not clearly understood yet and the effects of others are difficult to quantify [1]. However, it is necessary to have an accurate means of measuring the sizing of rock fragmentation in the muck pile for validation of blasting-pattern design processes. Mackenzie determined the cost curves based on the mean fragmentation size. He showed that loading, hauling and crushing costs decreased with increasing rock fragmentation [2].

The numerical prediction of rock fragmentation on large scale works is quite difficult and ineffective and cannot be applied because of the technical and economical reasons. It is also difficult to isolate the influence of individual variables on the fragmentation parameters from data obtained from field tests because of the diversity of the experimental conditions [3]. Since such a relationship involves a complex multi-variable system, it cannot be expressed in a straightforward manner by simple regression analyses.

On the other hand, fuzzy logic is a technique that defines and generates responses based on ambiguous, imprecise and complicated information. Fuzzy systems have attracted attention in various fields such as decision-making, pattern recognition and data analysis [4–10]. The adaptive neuro-fuzzy inference system (ANFIS) is a fuzzy inference system implemented within the architecture and learning procedure of adaptive networks like a multilayer neural network (ANN). The adaptive network simulates a fuzzy inference system represented by the fuzzy if–then rules. The hybrid network of ANFIS system is functionally equivalent to Sugeno's inference mechanism [8]. As the fuzzy models can work with complicated and ill-defined systems in a flexible and consistent way, an increase in their applications to solve various problems in the field of mining and geomechanics has been reported [11–13].

In this paper, the ANFIS method was used to simulate the results of the sizing of fragmentation due to bench blasting. A model was obtained based on the initial known input parameters to determine the sizing of fragmentation of rocks. The achieved ANFIS model, was then compared with radial bases function (RBF) neural network based model. The objective of present investigation was to predict K_{80} of the rock mass which can be used in future blast designs.

2. Theoretical routines

2.1. Adaptive neuro-fuzzy inference system

Among various fuzzy inference systems (FIS), Takagi-Sugeno (TS) system has been successfully applied for fuzzy modeling [14,15]. An ANFIS system can be considered to be an implementation of a TS

* Corresponding author. Tel.: +98 851 2228093.
E-mail address: alireza.karamii@gmail.com (A. Karami).

2095-2686/$ - see front matter © 2012 Published by Elsevier B.V. on behalf of China University of Mining & Technology.
http://dx.doi.org/10.1016/j.ijmst.2012.06.001

system in neural-network architecture. In the following, we briefly explain an ANFIS system by using a model with two inputs as an example [16] (Fig. 1). To construct the ANFIS model, five layers are used, as shown in Fig. 1. Each layer has some nodes described by a node function. The circles in the network represent nodes with no variable parameters, while the squares show nodes with adaptive parameters to be determined by network during training.

The nodes in the first layer represent the fuzzy sets in the fuzzy rules. It has parameters that control the shape and the location of the center of each fuzzy set which are called premise parameters. In the second layer, every node computes the product of its inputs. In Layer 3, normalization of the firing strength of the rules occurs by calculating the ratio of the *i*th rule's firing strength to the sum of all rules firing strengths. Nodes in forth layer are adaptive, where each node function represents a first-order model with consequent parameters. Layer 5 is called the output layer where each node is fixed. It computes the overall output as the summation of all the inputs from the previous layer. Optimizing the values of the adaptive parameters is the most important step for the performance of the adaptive system. Specially, the supposed parameters in Layer 1 and the consequent parameters in Layer 4 need to be determined. Jang proposed a hybrid-learning algorithm for determining the parameters of an ANFIS model [17]. A hybrid learning algorithm uses the gradient descent and least-square techniques for optimizing the network parameters. The least-squares estimation can be used to determine consequent parameters, assuming that the Layer 1 parameters are fixed. Then, the Layer 4 parameters can be fixed, and a back propagation approach is used to fit the premise parameters in Layer 1. Iterating between the Layer 1 parameters and the Layer 4 parameters optimization, the optimal values for all free parameters are computed.

2.2. Radial basis function method

The radial basis function (RBF) method is one of the most popular artificial neural networks. The RBF network consists of two layers: a hidden radial basis layer which uses Gaussian function as activation function and an output linear layer [18]. Each node of the hidden layer has a parameter vector called center. This center is used to compare with the network input vector to produce a radically symmetrical response. Response of the hidden layer are scaled by the connection weights of the output layer and then combined to produce the network output. The presupposition of *j*th hidden node to input data vector x_i is given by Eq. (1):

$$\varphi_{ij} = \exp(-\alpha||x_i - c_i||^2) \quad (1)$$

where c_j is an *M*-dimensional center; and α a positive constant which determines the width of the symmetrical response of the hidden node. The network input is the vector distance between its weight vector and the input vector. The network output is defined as Eq. (2):

$$\widehat{\gamma} = \sum_{j=1}^{k} \varphi_{ij} h_j \quad (2)$$

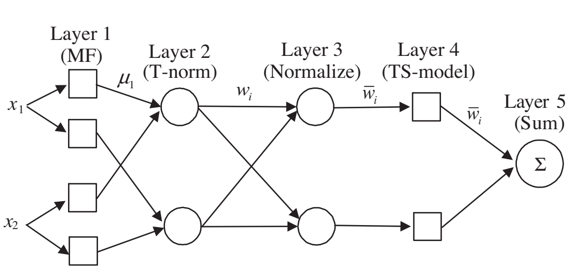

Fig. 1. ANFIS architecture.

where h_j are the network connection weights; and *k* the number of hidden nodes. The output of RBF neural network is defined as the linear combination of radial basis function layer [19].

2.3. Performance measurement

One of the most common methods for validation and consistency assessment of a model is measurement of the root mean square error (RMSE) which is a degree of distribution of the data. The RMSE can be calculated by Eq. (3) and relative error $\widetilde{Y}$ is also calculated by Eq. (4).

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N_{\mathrm{tst}}}\left(y_i^{\mathrm{pred}} - y_i^{\mathrm{obs}}\right)^2} \quad (3)$$

$$\widetilde{Y} = \frac{1}{N}\sum_{i=1}^{N}\frac{\left|y_i^{\mathrm{obs}} - y_i^{\mathrm{pred}}\right|}{y_i^{\mathrm{obs}}} \times 100 \quad (4)$$

where *N* denotes the total number of objects in the entire testing set; y_i^{pred} the predicted output for *i*th pattern data; and y_i^{obs} is its experimental output data.

The predictive ability of the models was also revealed by predictive Q^2_{LOO} and $Q^2_{F_3}$ for internal validation method (Leave one out cross validation) and external validation (randomized method) respectively. $Q^2_{F_3}$ is suggested by Consonni et al. as a new formula for calculating the predictive squared correlation coefficients which is based on the mean squares of the training set in order to be independent of external test objects distribution [20]. The Q^2_{LOO} and $Q^2_{F_3}$ value should be at least 0.3–0.4 in order to assess that the model has statistically significant prediction ability. In this study, the Q^2_{LOO} value is calculated by Eq. (5).

$$O^2_{\mathrm{LOO}} = 1 - \frac{\left[\sum_{i=1}^{N}\left(y_i^{\mathrm{pred}} - y_i^{\mathrm{obs}}\right)^2\right]}{\left[\sum_{i=1}^{N}\left(y_i^{\mathrm{obs}} - y_i^{\mathrm{mean}}\right)^2\right]} \quad (5)$$

where *N* is the total number of objects in the testing set; y^i_{pred} the predicted output for *i*th pattern test data, y^i_{obs} its experimental output data; and y^i_{mean} the average value for experimental output data. The $Q^2_{F_3}$ value also calculated by Eq. (6).

$$O^2_{F_3} = 1 - \frac{\left[\sum_{i=1}^{N_{\mathrm{tst}}}\left(y_i^{\mathrm{pred}} - y_i^{\mathrm{obs}}\right)^2\right]/N_{\mathrm{tst}}}{\left[\sum_{i=1}^{N_{\mathrm{trn}}}\left(y_i^{\mathrm{obs}} - y_{\mathrm{trn}}^{\mathrm{mean}}\right)^2\right]/N_{\mathrm{trn}}} \quad (6)$$

where the summation in the numerator runs over the external test set while in the denominator over the training set; the number N_{trn} of training set objects and the number N_{tst} of external objects are usually different.

3. Model construction and evaluation

3.1. Case study

The study was conducted at Golgohar iron ore mine in Sirjan, south-west of Kerman, Iran. It is one of the biggest iron ore producing company that a total reservoir of 250 million tons with an average grade of 56% iron is estimated. The iron ore field has density 4.1–4.3 (ton/m^3).

The type of over burden rocks in this area is mostly medium to coarse-grained sandstone and the blast hole diameter is $9_{7/8}$ in. (251 mm). Blasting patterns are 5.0 m × 6.0 m and 5.5 m × 7.5 m and depth of the blast hole is 17 m (with the bench height of 15 m). Anfo for dry condition and Slurry and Emulan for wet condition are being used to supply a production of over 20,000 tons/day. The size of outfall entrance gyratory crusher is 100 cm and