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ORIGINAL PAPER

Application of PCA, SVR, and ANFIS for modeling of rock fragmentation

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Abstract Fragmentation has direct effects not only on the drilling and blasting costs but also on the economy of subsequent operations. In the present study, two soft computing-based models, so called "support vector machines (SVM)" and "adaptive neuro-fuzzy inference system (ANFIS)" were used and compared with Kuz-Ram method. In this regard, six effective parameters including specific charge, stemming length, total delays per number of rows ratio, hole diameter, spacing to burden ratio, and blastability index were considered as input parameters containing a database of 80 variables from the blasting operation of the Chadormalu iron mine of Iran. Principal component analysis (PCA) was performed to clarify the effective parameters on the fragmentation. As statistical indices, root mean square error (RMSE), correlation coefficient (R^2), bias, variance account for (VAF), and mean absolute percentage error (MAPE) were used to evaluate the efficiency of the addressed models between measured and predicted values of rock fragmentation. The results confirmed the ANFIS and SVM as accurate predictive tools for rock fragmentation in open-pit mines. Correlation coefficient, bias, VAF, and MAPE generated by the ANFIS model (respectively 0.89, 0.257, 88.19, and 10.37) were higher than referred values for the SVM model (0.83, 1.87, 75.24, and 16.25, respectively) as well as Kuz-Ram inference.

Keywords Rock fragmentation · Kuz-Ram · SVR · ANFIS · PCA

Introduction

Rock fragmentation, the fragment size distribution of blasted rock, is considered as one of the most significant indices of production blasting due to its direct effects on the costs of drilling and blasting in addition to the economy of the subsequent operations of loading, hauling, and crushing (Jimeno et al. 1995; Aler et al. 1996; Hamdi et al. 2001; Singh et al. 2013a, b; Pradhan et al. 2011). The key objects of production blasting are to achieve optimum rock fragmentation and control the particle size distribution of a muckpile after blasting. Over the past decades, empirical models have been developed for the estimation of size distribution of rock fragments (Rosin and Rammler 1933; Kuznetsov 1973; Cunningham 1983; Lilly 1986; Monjezi et al. 2012). Rock fragmentation depends on many variables such as rock mass properties, site geology, in situ fracturing, and blasting parameters. There is no complete theoretical solution for its prediction. In such situations, a wide range of statistical and machine learning models have been developed and applied to measure the fragmentation distribution (Aler et al. 1996; Mario and Francesco 2006; Monjezi et al. 2009, 2014; Gheibie et al. 2009; Shi et al. 2012; Salimi et al. 2012; Badroddin et al. 2013; Bakhtavar et al. 2014; Enayatollahi et al. 2014). Also, several studies

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have been conducted to improve blast design considering the prediction of fragmentation after blasting (Sontamino and Drebenstedt 2012).

Neuro-fuzzy systems based on artificial neural network (ANN) theory are widely used to determine the properties of fuzzy sets and fuzzy rules by processing data samples. Neuro-fuzzy systems harness two paradigm power: fuzzy logic and ANNs by utilizing the mathematical properties of ANNs in tuning rule-based fuzzy systems that approximate the way man processes information. A specific approach in neuro-fuzzy development is the adaptive neuro-fuzzy inference system (ANFIS), which has shown significant results in modeling nonlinear functions. In ANFIS, the membership function parameters are extracted from a data set that describes the system behavior. The ANFIS learns features in the data set and adjusts the system parameters according to a given error criterion (Jang 1993; Ubeyli and Guler 2005). ANFIS has been purposed by different studies (Nauck and Kruse 1999; Gokceoglu et al. 2004; Cakmakci 2007; Wang and Elhag 2008; Taylan and Karagozoglu 2009; Radulovic and Rankovic 2010; Ata and Kocyigit 2010; Yilmaz and Kaynar 2011; Tayebi Khorami et al. 2011; Alipour and Ashtiani 2011; Iphar 2012; Vafakhah 2013; TienBui et al. 2012; Bazzazi and Esmaeili 2012 ; Sezer et al. 2011; Mohammadi et al. 2011; Oh and Pradhan 2011; Pradhan et al. 2010; Singh et al. 2005, 2012, 2013a, b; Liu et al. 2014). Support vector regression (SVR) is a novel neural network algorithm based on a statistical learning theory and lead to great potential and superior performance in practical applications. This is largely due to the structure risk minimization principles in SVR, which has greater generalization ability and is superior to the empirical risk minimization principle adopted by traditional neural networks. Due to the advantages of the generalization capability in obtaining a unique solution, the SVMs have drawn the attention of researchers and have been applied in many applications (Liu et al. 2004; Yu et al. 2006; Zhao 2010; Khandelwal 2010; Shi et al. 2012; Mohamadnejad et al. 2012; Khandelwal and Kankar 2011; Abbaszadeh et al. 2013 ;Pradhan 2013).

The main novelty of the present study is to apply the principal component analysis (PCA) in order to find the effective parameters on the rock fragmentation in the Chadormalu iron mine of Iran. In this regard, the Kuz-Ram model, support vector regression (SVR), and adaptive neuro-fuzzy inference system (ANFIS) were applied to predict the rock fragmentation. Finally, as statistical indices, root mean square error (RMSE), correlation coefficient (R^2), bias, variance account for (VAF), and mean absolute percentage error (MAPE) were used to evaluate the efficiency of the addressed models between measured and predicted values of rock fragmentation.

Data processing

Case study

Chadormalu iron ore mine is located at the center of Iran Desert, at 180 km of the north eastern of Yazd province and 300 km of the south of Tabas city (Fig. 1). Chadormalu deposit has some 400 million tons of resource and 320 million tons of reserves split between the northern and southern ore bodies with average Fe and P content of 55.2 and 0.9 %, respectively. Measurement of fragment size of blasted rock is considerably important in order to evaluate the efficiency of the production blasting operation. There are several methods of size distribution measurement and sub-categorized into direct and indirect methods. Although, the sieve analysis is a direct and the most accurate method of measuring size distribution, the high expenses and time-consuming features refuse the practical use of this method in a large scale; hence, indirect tools have been more developed as observational, empirical, and digital methods. With the advances in technology, digital image processing and analysis systems are becoming increasingly popular in fragmentation measurement due to their advantages over photographic methods.

Split system is one of the digital image processing software which has been developed to compute the size distribution of fragmented rock from digital images. In this study, size distributions were analyzed by using Split-Desktop software. This software has five progressive steps for analyzing each image: the first step determines the scale for each image taken in the field, the second step performs the automatic delineation of the fragments in each of the processed image, the third one edits the delineated fragments to ensure accurate results, the fourth step involves the calculation of the size distribution based on the delineated fragments, and finally, the last step graphs various outputs to display the size distribution results. Figure 2 shows the sample of figures that have been used for analyses in the Split-Desktop software.

ANFO has been used as explosive in the blasting operation of the mine. Blasting holes of 165- and 251-mm diameters were used in benches with a 15-m height. The drill-hole pattern (burden×spacing) is 6×7 and 7×8 m based on rock types. The size of outfall entrance gyratory crusher and outfall exit is 90 and 30 cm, respectively. In this study, a database including 80 data sets was collected from blasting operation of the Chadormalu iron mine and six parameters were considered as input parameters for modeling rock fragmentation. Descriptive statistical distribution of input and output parameters and their respective symbols are indicated in Table 1. Furthermore, BI and the dependent parameters are summarized in Table 2. Note that blastability index (BI) is calculated by Eq. 1 (Lilly 1986):

$$\mathrm{BI} = 0.5\,(\mathrm{RMD} + \mathrm{JPS} + \mathrm{JPO} + \mathrm{SGI} + H) \quad (1)$$

Fig. 1 Geographical location of the Chadormalu iron mine

where RMD is rock mass description, JPS is joint plane spacing, JPO is joint plane orientation, SGI is specific gravity influence, and H is hardness. The ratings and evaluation basis of the parameters are summarized in Table 3. In the Table 3, the spacing and orientation of joints can be specified by borehole logging or outcrop survey. Specific gravity and strength can be estimated on site using the point load test and also in the laboratory. Block size can be estimated by various methods summarized by Palmstrom (2001).

Principal component analysis

In order to establish the predictive models among the parameters obtained in this study, principal component analysis (PCA) was performed in the first stage of the analysis. PCA is a classical method that provides a sequence of the best linear approximations to a given high-dimensional observation, and it has received much more attentions in many literatures (Cadima and Jolliffe 1995; Croux and Haesbroeck 2000; Higuchi and Eguchi 2004; Shawe-Taylor and Cristianini 2005; Tao et al. 2007; Zhang et al. 2010). PCA is used abundantly in all forms of analysis (from neuroscience to computer graphics) because it is a simple, nonparametric method of extracting relevant information from confusing data sets. With minimal additional effort, PCA provides a roadmap on how to reduce a complex data set to a lower dimension.

For instance, Fig. 3 represents a two-variable data set which has been measured in the X-Y coordinate system. The principal direction in which the data varies is shown by the U axis and the second most important direction is the V axis orthogonal to it. If we transform each (X, Y) coordinate into its corresponding (U, V) value, the data is de-correlated, meaning that the co-variance between the U and V variables is zero. For

Fig. 2 Sample of image prepared for Split-Desktop software

a given set of data, principal component analysis finds the axis system defined by the principal directions of variance (i.e., the *U*-*V* axis system in Fig. 4). The directions *U* and *V* are called the principal components. In this new reference frame, note that variance is greater along axis *U* than it is on axis *V*. PCA computes new variables which are obtained as linear combinations of the original variables. These variables are found by calculating the covariance (or correlation) matrix of the data patterns (Jolliffe 1986; Engelbrecht 2007).

In this paper, PCA were performed on a set of output and features (input parameters), and the ratio of variance of first component to total variance (variance ratio) were calculated. According to the above paragraph, this ratio can be determined by the similarity among the output and a set of features.

Several analyses with two, three, and four features were performed to obtain the effective parameters on the fragmentation (Fig. 5). As can be seen in Fig. 5, the feature containing three inputs (S/B, BI, and SC) were shown to be effective factors, and fragmentation has been considered as a function of these important inputs; hence, these parameters were selected as input parameters for the predictive models.

Table 2 BI and the dependent parameters in the Chadormalu mine

Block no.	RMD	JPS	JPO	SGI	H	BI
1	16	20	20	65	3	62
2	12.6	20	40	17.5	4	47.05
3	12.5	10	30	65	5	61.25
4	14.5	20	30	50	5	59.75
5	12.2	20	30	40	5	53.6
6	12.8	20	30	65	6	66.9
7	12.9	20	40	25	4	50.95
8	14.4	20	30	65	6	67.7
9	19.7	50	30	40	5	72.35
10	13.8	20	40	65	5	71.9

RMD rock mass description, *JPS* joint plane spacing, *JPO* joint plane orientation, *SGI* specific gravity influence, *H* hardness, *BI* blastability index

Modeling

The Kuz-Ram model

Kuznetsov's investigation in 1973 correlated the mean fragmentation size with the powder factor of TNT as well as geological structure (Kuznetsov 1973). He also proved the relationship between average fragmentation size and the amount of explosive used in a particular rock type. The original Kuznetsov equation is given as

$$\overline{X} = A\left|\frac{V_0}{Q}\right|^{0.8} Q^{0.167} \tag{2}$$

where $\overline{X}$ is the mean fragment size (cm), A is rock factor (7 for medium rocks, 10 for hard and highly fissured rocks, and 13 for hard and weakly fissured rocks), V_0 is the rock volume

Table 1 Descriptive statistical of input and output parameters for this study

Variables	Symbol	Minimum	Maximum	Mean	Standard deviation
Ratio of total delays per number of rows	DR	21.7	62.5	48.816	9.94
Specific charge (kg/m^3)	SC	0.38	1.2	0.772	0.211
Stemming length (m)	ST	3.4	7.5	5.811	1.313
Hole diameter (mm)	HD	165	251	204.77	43.149
Blastability index	BI	42	73.25	59.226	8.809
Spacing to burden ratio	S/B	1.123	1.42	1.215	0.062
Fragmentation (cm)	F	8	42.5	21.709	7.897

Table 3 Parameters of the blastability index (Shim et al. 2009)

Parameter	Ratings	Formula
RMD=(rock mass description)	–	RMD=10+10X_i X_i=block size of in situ rock mass
JPS=(joint plan spacing)	10=Joint spacing <0.1 m 20=0.1 m<Joint spacing<oversize (m) 50=Oversize (m)<joint spacing	–
JPO=(joint plan orientation)	10=Joint dip<10^0 20=│Joint dip direction-dip direction of bench│<30^0 30=60^0<│joint dip direction-dip direction of bench│ 40=30^0<│joint dip direction-dip direction of bench│<60^0	–
SGI=(specific gravity influence)	–	SGI=25(SG−2)
H=(hardness)	–	*H*=UCS/5 *if Y*<50 Gpa *H*=*E*/3 *if Y*>50 GPa

SG Specific gravity of rock, *UCS* uniaxial compressive strength (MPa), *E* elastic modulus (GPa)

broken per blasthole (m^3) (burden×spacing×bench height), and Q is the mass of TNT which is equivalent in energy to that of the explosive charge in each blasthole (kg). Cunningham, in South Africa, realized that the Rosin-Rammler curve had been generally recognized as a reasonable description of the fragmentation for both crushed and blasted rock (Cunningham 1983). The Rosin-Rammler equation is used to characterize the partial-sized distribution of a material in a variety of applications (Rosin and Rammler 1933). The equation is

$$R = e^{-\left|\frac{X}{X_C}\right|^n} \tag{3}$$

where R is the proportion of the material retained on screen, X is screen size, X_c is empirical constant, and n is index of uniformity. What was needed to properly define the Rosin-Rammler curve was the exponent "n" in the Eq. 3. To obtain this value, Cunningham used field data and regression analysis of the field parameters that were previously studied. The combination of the algorithms thus developed along with the Kuznetsov equation became known as the "Kuz-Ram model." The present form of the algorithm used is

$$n = \left|2.2{-}1.4\frac{B}{D}\right| \cdot \left|1{-}\frac{W}{B}\right| \cdot \left|\frac{1+{}^{S}/_{B}}{2}\right|^{0.5} \cdot \left|\frac{L}{H}\right| \tag{4}$$

where B is the burden (m), S is the spacing (m), D is the hole diameter (mm), W is the standard deviation of drilling accuracy (m), L is the total charge length (m), and H is the bench height (m). A further development which enabled the use of different explosives other than TNT was incorporated into the Kuznetsov equation (Kuznetsov 1973) by Cunningham. The final equation to determine average fragmentation size is shown below:

$$\overline{X} = A\left|\frac{V_0}{Q}\right|^{0.8} Q^{0.17}\left|\frac{E}{115}\right|^{-0.63} \tag{5}$$

E is a relative weight strength term of the actual explosive (where ANFO=100), while the relative weight strength of TNT is 115 (Konya and Walter 1991).

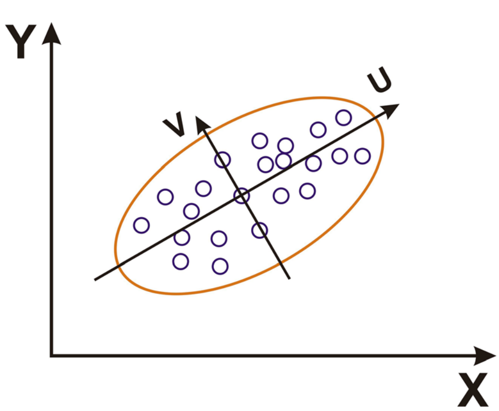


Fig. 3 Principal components for data representation

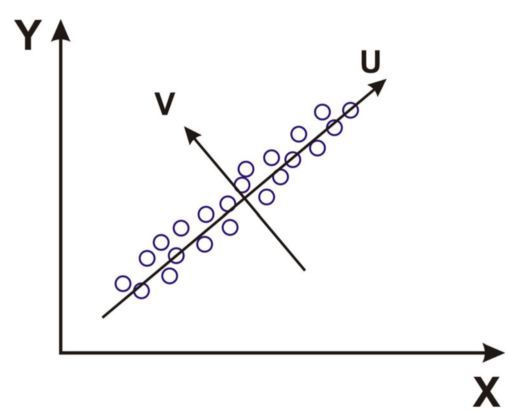


Fig. 4 Principal components for dimension reduction

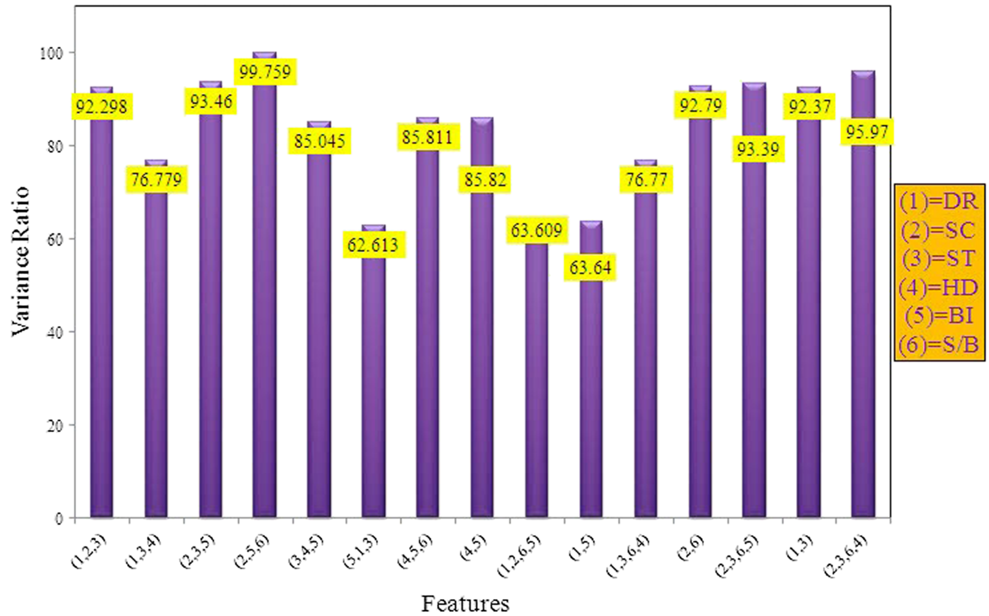


Fig. 5 Principal components analysis for some features in this study

A graphic comparison between measured fragmentation using Split-Desktop software and predicted fragmentation by Kuz-Ram equation is shown in Fig. 6. As it is depicted in Fig. 6, a weak conformity exists between these two sorts of fragmentation.

Support vector regression

Support vector regression (SVR) estimates a continuous-valued function that encodes the fundamental interrelation between a given input and its corresponding output in the training data. This function then can be used to predict outputs for given inputs that were not included in the training set. This is similar to a neural network. However, a neural network's solution is based on empirical risk minimization. In contrast, SVR introduces structural risk minimization into the regression and thereby achieves a global optimization, while a neural network achieves only a local minimum (Eubank 1988). There are many papers and books which provide a detailed description of the theory of SVM technique (Vapnik 1998; Cristianini and Shawe-Taylor 2000; Yu et al. 2006); hence, only a brief description of a SVR which has been considered in the paper is given here. A generic cost estimation model can be written as

$$y = f(X) = W^T X + b \tag{6}$$

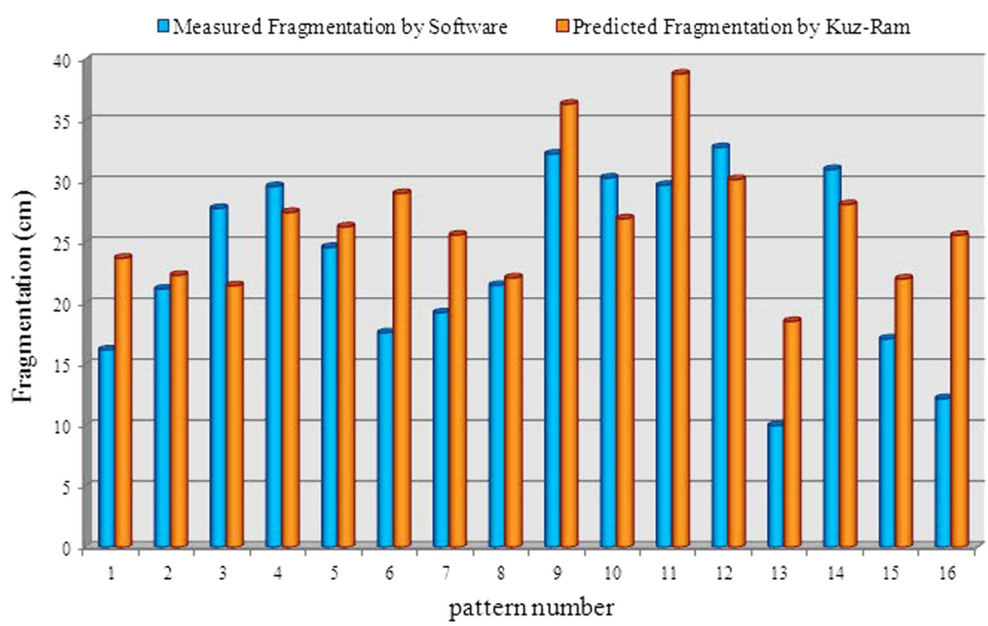


Fig. 6 Comparison of measured and predicted fragmentation by Kuz-Ram equation

Table 4 Admissible kernel functions

Name	Definition	Parameter
Linear	$K(X_i,X_j)=(X_i)^T X_j$	–
Polynomial	$K(X_i,X_j)=[(X_i)^T X_j+1]^d$	d
Radial basis function (RBF)	$K(X_i,X_j)=e^{-\gamma\lVert x_i-x_j\rVert^2}$	γ
Sigmoid[a]	$K(X_i,X_j)=\tanh[(X_i)^T X_j+r]$	r

[a] For some r values, the kernel function is invalid

where W is the weight vector corresponding to X and b is the bias. The generalization performance of such linear function $f(X)$ is fairly limited and unable to reflect the true regression procedure. In order to overcome such weakness, a standard mathematical solution is the introduction of kernel function $\varphi(X)$, which is a nonlinear mapping function from the input space to a higher dimensional feature space. By using $\varphi(X)$, we can reach infinite dimensions for a more expressive f. Commonly used kernel functions are listed in Table 4. With the help of $\varphi(X)$, linear regression function Eq. 6 is extended to nonlinear function Eq. 7:

$$y=f(X)=W^T\varphi(X)+b \tag{7}$$

where W is the weight vector corresponding to $\varphi(X)$. Our goal is to estimate the coefficients (W and b) following two rules at the same time. First, to achieve the best performance, $f(X_i)$ should be as close as possible to the truth y_i for all training samples. Second, to prevent over-fitting, $f(X)$ should be as flat as possible. These are equivalent to the following programming problem, namely primal problem of SVR:

$$\min \frac{1}{2}W^T W+C\frac{1}{l}\sum_{i=1}^{l}\left(\zeta_i+\zeta_i^*\right)\ s.t.\begin{cases} W^T\varphi(X_i)+b\Big)-y_i\leq\varepsilon+\zeta_i,\\ y_i-\left(W^T\varphi(X_i)+b\right)\leq\varepsilon+\zeta_i^*\\ \zeta_i,\zeta_i^*\geq 0, i=1,\ldots,l.\end{cases} \tag{8}$$

In the above formulation, slack variables of ζ_i and ζ_i^* are included to cope with otherwise infeasible constraint of the optimization problem, and constant $C>0$ determines the tradeoff between the parameter norm (used to measure the "flatness": smaller norm means smoother function) and deviations from target greater than ε (Fig. 7). This problem is usually solved by introducing using Lagrange multipliers, leading to the minimization of

$$\begin{aligned}L_P=&\frac{1}{2}\lVert W\rVert-\sum_{i=1}^{n}\alpha_i\left(\varepsilon+\xi_i-y_i+W^T\phi(X_i)+b\right)\\&-\sum_{i=1}^{n}\mu_i\xi_i-\sum_{i=1}^{n}\alpha_i^*\left(\varepsilon+\xi_i^*+y_i-W^T\phi(X_i)-b\right)\\&-\sum_{i=1}^{n}\mu_i^*\xi_i^*+C\sum_{i=1}^{n}\xi_i+\xi_i^*\end{aligned} \tag{9}$$

considering W, b, ξ_i, and ξ_i^* and its maximization with respect to the Lagrange multipliers, α_i, α_i^*, μ_i, and μ_i^*. In order to solve this problems, one needs to compute the Karush-Kunh-Tucker conditions (Fletcher 1987) that state some conditions over the variables in Eq. 9, and

$$\frac{\partial L_P}{\partial W}=W-\sum_{i=1}^{n}\left(\alpha_i-\alpha_i^*\right)y_i\phi(X_i)=0 \tag{10}$$

$$\frac{\partial L_P}{\partial b}=\sum_{i=1}^{n}\alpha_i-\alpha_i^*=0 \tag{11}$$

$$\frac{\partial L_P}{\partial \xi_i}=C-\alpha_i-\mu_i=0 \tag{12}$$

$$\frac{\partial L_P}{\partial \xi_i^*}=C-\alpha_i^*-\mu_i^*=0 \tag{13}$$

$$\alpha_i,\alpha_i^*,\mu_i,\mu_i^*\geq 0 \tag{14}$$

$$\alpha_i\left\{\varepsilon+\xi_i-y_i+W^T\phi(X_i)+b\right\}=0 \tag{15}$$

$$\alpha_i^*\left\{\varepsilon+\xi_i^*-W^T\phi(X_i)-b+y_i\right\}=0 \tag{16}$$

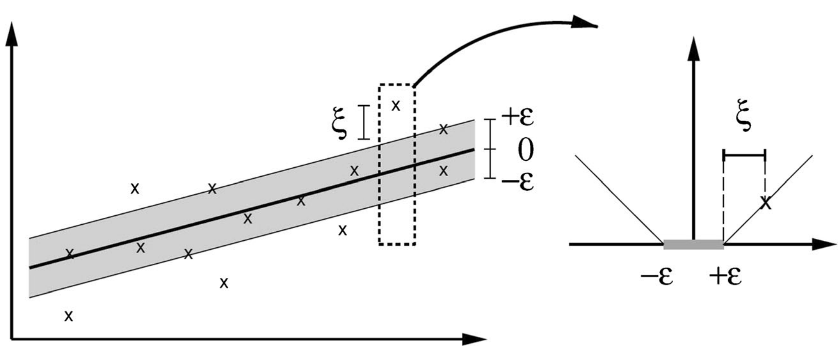


Fig. 7 Prespecified accuracy ε and slack variable ζ in SVR

Table 5 Parameters of the SVR model

Parameter	Value
Type	ε-SVR
Kernel	Radial basis function
Degree	2
Γ	1
Tolerance of stopping criterion	0.001
ε	0.1

$$\mu_i \xi_i = 0 \quad \text{and} \quad \mu_i^* \xi_i^* = 0 \tag{17}$$

The usual procedure to solve the SVR is introducing Eqs. 10–13 into Eq. 8, leading to the maximization of

$$L_d = \varepsilon \sum_{i=1}^{n} \left(\alpha_i + \alpha_i^*\right) - \sum_{i=1}^{n} \sum_{j=1}^{n} \left(\alpha_i - \alpha_i^*\right)\left(\alpha_j - \alpha_j^*\right) \phi^T(X_i)\phi(X_j) \tag{18}$$

subject to Eq. 11 and $0 \leq \alpha_i, \alpha_i^* \leq C$. This procedure can be solved using QP and iterative re-weighted least squares (IRWLS) procedures. Support vector regression was trained by using the input variables selected by the PCA model and the fragmentation as the output of the model. The available data sets were divided into two subsets randomly, i.e., 80 % data sets for training and 20 % data sets for testing. The details of the topology selected for the SVR model are listed in Table 5. In order to obtain the parameters of the topology that are listed in Table 5, several configurations were tested with different kernel types (radial basis function, polynomial, and hyperbolic tangent) and parameter values. These tests were performed in the same way as the methodology proposed by Sánchez Lasheras et al. (2010). The problem was solved by using the popular suite of machine learning software written in Java called Weka and developed at the University of Waikato (Witten et al. 2011). The correlation coefficient between measured and predicted fragmentation by SVR is shown in Fig. 8. According to Fig. 8, correlation coefficient between measured and predicted fragmentation is 0. 83. This R^2 showed a good correlation between these two sorts of fragmentation.

Adaptive neuro-fuzzy inference system

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. Subsequently, we briefly explain an ANFIS system by using a model with two inputs as an example (Fig. 9). To construct the ANFIS model, five layers were used, as demonstrated in Fig. 9. Each layer has some nodes described by a node function. The circles in the network represent nodes with no variable parameters, while the squares indicate nodes with adaptive parameters 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

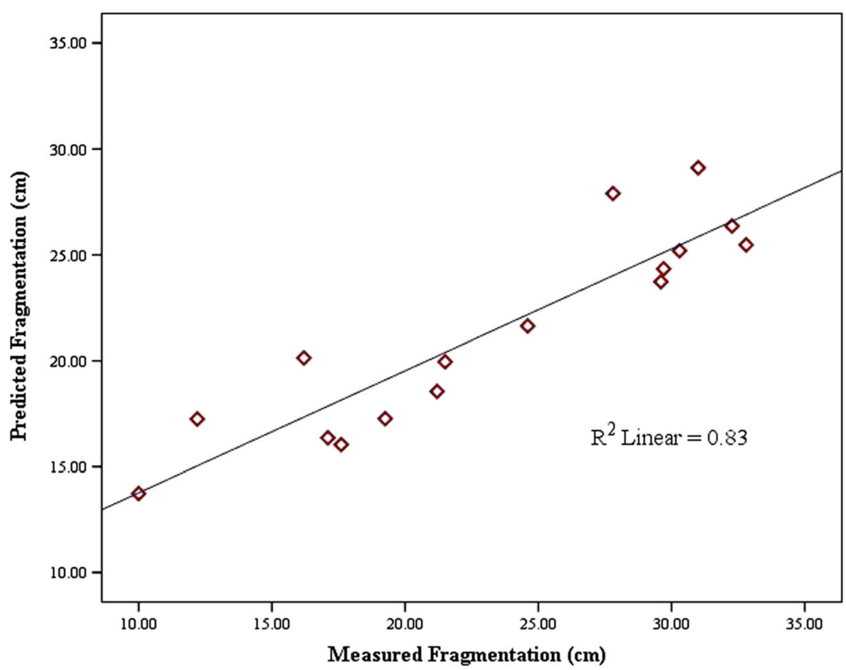
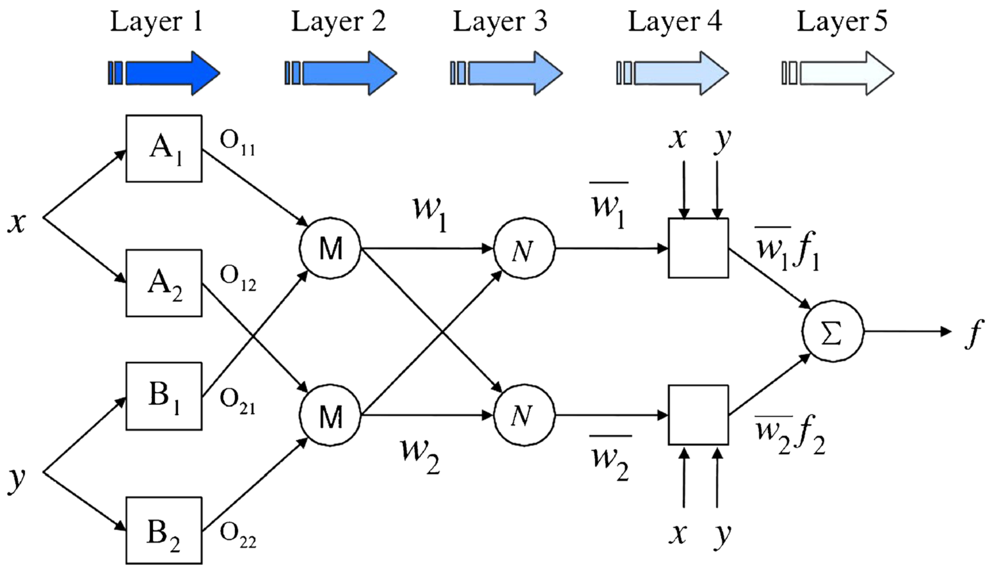


Fig. 8 Correlation coefficient for SVR model

Fig. 9 Architecture of ANFIS



by calculating the ratio of the *i*th rule's firing strength to the sum of all rules' firing strengths. Nodes in the forth layer are adaptive, where each node function represents the 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 to determine the parameters of an ANFIS model. A hybrid learning algorithm uses the gradient descent and least square techniques to optimize 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. By iterating between the layer 1 parameters and the layer 4 parameter optimization, the optimal values for all free parameters are computed (Jang et al. 1997; Sumathi and Surekha 2010).

In this study, the available data sets were divided into two subsets randomly, i.e., 80 % data sets for training and 20 % data sets for testing (the same as SVR model). Subtractive clustering has an auto-generation capability to determine the number and initial location of the 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 least squares and back propagation gradient, was applied to identify the membership function parameters of a single output, Sugeno-type fuzzy inference systems (FIS). Several models with three input parameters and one output parameter were constructed and trained. To evaluate models with different structures (FIS division) and then to determine the best model, RMSE was calculated for these models. The proposed ANFIS model for predicting fragmentation has three membership functions for each input parameter and three rules. Other parameter types and their values used for the constructed ANFIS model can be seen in Table 6. Figure 10 shows the relationship between measured and predicted values obtained from the ANFIS model in the testing stage.

Discussion

It is absolutely clear that the results of both ANFIS and SVM models in predicting fragmentations are not significantly different to those in reality. Here, the performances of these models were evaluated according to statistical criteria such as correlation coefficient (R^2), root mean square error

Table 6 The ANFIS information used in this study

ANFIS parameter type	Value
MF type	Gaussian
Number of MFs	3
Output function	Linear
Number of nodes	30
Number of linear parameters	12
Number of nonlinear parameters	18
Total number of parameters	30
Training RMSE	3.12

MF membership function, *RMSE* root mean square error

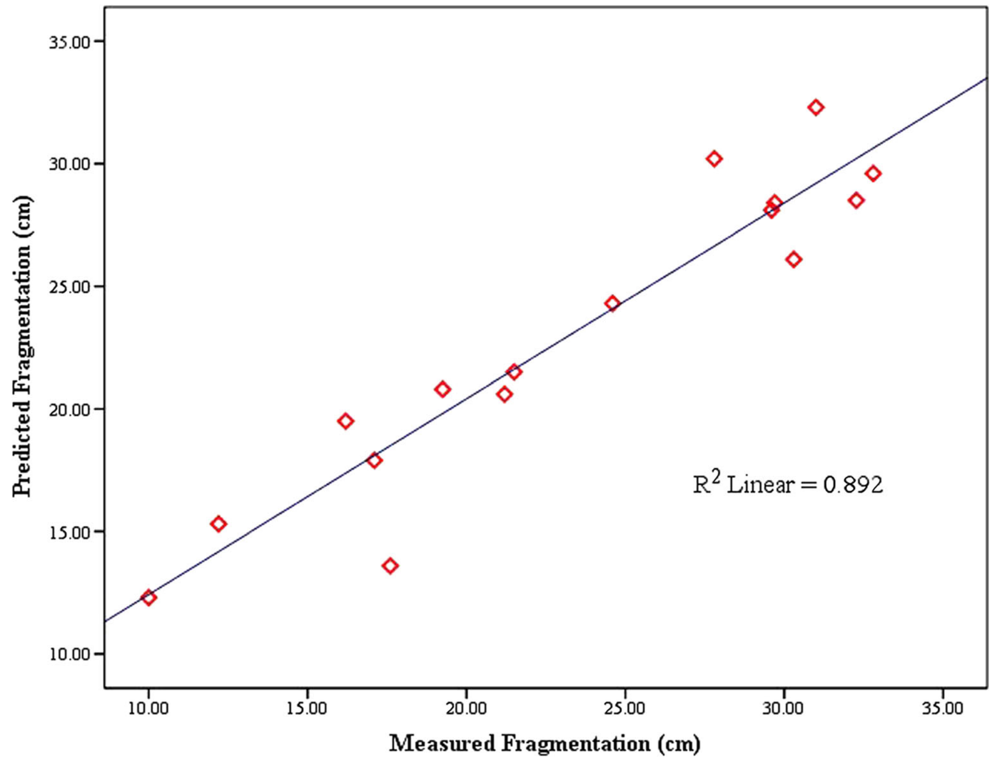


Fig. 10 Correlation coefficient for the ANFIS model

(RMSE), mean absolute percentage error (MAPE), bias, and variance account for (VAF) (Alvarez Grima and Babuska 1999; Kazeminezhad et al. 2005; Tzamos and Sofianos 2006; Yilmaz and Kaynar 2011; Esmaeili et al. 2014). 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.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(A_{i\mathrm{meas}} - A_{i\mathrm{pred}}\right)^2} \tag{19}$$

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:

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{A_{i\mathrm{meas}} - A_{i\mathrm{pred}}}{A_{i\mathrm{meas}}}\right| \times 100 \tag{20}$$

Bias, the bias or average value of residuals (nonexplained difference) between the measured and predicted values of the dependent variable, represents the mean of all the individual errors and indicates whether the model overestimates or underestimates the dependent variable. It is calculated as

$$\mathrm{Bias} = \frac{1}{n}\sum_{i=1}^{N}\left(A_{i\mathrm{pred}} - A_{i\mathrm{meas}}\right) \tag{21}$$

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

$$\mathrm{VAF} = \left(1 - \frac{\mathrm{var}\left(A_{i\mathrm{meas}} - A_{i\mathrm{pred}}\right)}{\mathrm{var}\left(A_{i\mathrm{meas}}\right)}\right) \times 100 \tag{22}$$

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

The results of applying these models were compared in Table 7. Also, a graphic comparison between measured and estimated data obtained from ANFIS, SVR, and Kuz-Ram models was shown in Fig. 11.

The results confirmed that there is a great congruence in the prediction of rock fragmentation between ANFIS and SVM models to the estimated fragmentation, meanwhile predictions by Kuz-Ram model detected some errors. In contrast to ANFIS and SVM models, Kuz-Ram model was not able to predict the rock fragmentation because of the elimination of some important factors.

Table 7 Performance indices of the models

Models	R^2	RMSE	MAPE	Bias	VAF
ANFIS	0.89	2.48	10.37	0.257	88.19
SVR	0.83	4.04	16.25	1.87	75.24
Kuz-Ram	0.38	6.82	32.4	3.95	38.32

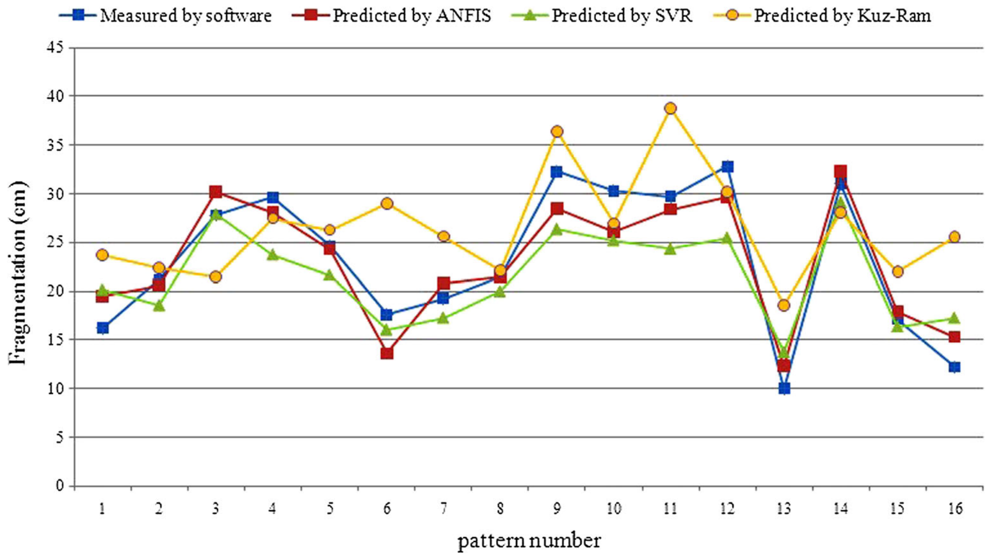


Fig. 11 Comparison of measured and predicted rock fragmentation

Consequently, the validity of ANFIS model to predict rock fragmentation, which is one of the most important processes in a mining operation, is further supported in this study.

Compared to other analysis techniques, the ANFIS results possess a great degree of accuracy, robustness, and more tolerance against errors. Finally, the results of this investigation clearly proved the higher validity of the ANFIS model in order to predict rock fragmentation compared to SVR and Kuz-Ram models.

Conclusions

In this study, Kuz-Ram, SVR, and ANFIS models were conducted to predict the fragmentation caused by blasting. In this regard, six parameters were considered as input parameters, and 80 data sets were collected from the Chadormalu iron mine of Iran.

Principal components analysis (PCA) method concluded that out of six addressed parameters, the spacing to burden ratio, blastability index, and specific charge were the most effective factors on the rock fragmentation in the Chadormalu iron mine. According to the results obtained from this research, the ANFIS is known to be a useful tool to predict rock fragmentation which is one of the most important processes in a mining operation. ANFIS can learn new patterns which had not been previously available in the training datasets, and when the knowledge is updated, the more training datasets can be presented and processed. In this investigation, Gaussian-type membership function with 30 nodes, 12 numbers of linear parameters, and 18 numbers of nonlinear parameters were developed.

Besides that, predictability by support vector regression can be considered as an important tool to solve most scientific problems. Also, the common effects of several parameters on blasting results can be studied by performance of support vector regression. ANFIS has been evaluated and compared with simulation results of the support vector regression. Achieved ANFIS and SVR models are exclusively related to the Chadormalu iron mine, and in other cases, rather than this mine, these results should be modified.

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