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Technical Note

Fuzzy modeling approaches for the prediction of maximum charge per delay in surface mining

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1. Introduction

The increasing development of opencast mines due to the enhanced demand for minerals has led to the use of large amounts of explosives for blasting. Explosives are an efficient source of energy required for breakage and excavation of rocks. When an explosive detonates in a blast hole, instantaneously a huge amount of energy in forms of pressure and temperature is liberated. Only a small proportion of this total energy is utilized for actual breakage and displacement of rock mass and the rest of the energy is spent in undesirable side effects like ground vibrations, air blasts, noises, back breaks, etc. [1].

As the ground vibration is the most important environmental effect of blasting operation some regulations related to structural damages caused by ground vibration have been developed. The regulations are primarily based on the peak particle velocity (*PPV*) resulted from blasting operations. To come out with proper amounts of Maximum Charge per Delay which produces limited ground vibration, several empirical equations are available that can be found in the literature [2–5]. These empirical equations are normally used for estimating *PPV* of ground vibration by blasting.

In most research, distance and maximum charge per delay are considered as the main parameters in estimating of *PPV*. However, it should be noted here that the characteristic of ground vibration is different according to the location and sequence of each blasting and also depends on the propagation path of elastic wave. Rock mass and blasting themselves have their own uncertainties. The simulation of these effects is very difficult and researchers neglect these parameters. *PPV* is the function of distance and maximum charge per delay. According to Rai et al. [6], when the maximum charge per delay is calculated using these predictors, it does not gives the very accurate value of charge and this is because these equations are actually formulated to calculate the *PPV*; for this, Rai et al. have proposed to directly calculate the maximum charge per delay. It seems that there is a great need for case studies in order to evaluate the efficiency and credibility of empirical equations for maximum charge per delay in different investigation cases.

In recent years ANFIS has emerged as a powerful tool for analyzing of engineering problems. In the present investigation, an attempt has been made to predict the maximum charge per delay (kg) with the help of both conventional empirical criteria and ANFIS method using admissible *PPV* and distance from blast face to vibration monitoring point. A comparison of the results for two methods has been demonstrated for Sungun copper mine in Iran.

2. Site description

Sungun copper mine is located in the north-west of Iran, in Azarbayjan-e-Sharqi province. The total ore reserve of the deposit is more than 384 million tonnes. However, probable and possible reserve is 1000 million tonnes, with an average grade of 0.67%. The existing estimation about effected land of Sungun copper mine is 38.2 km^2, of which half will be completely ruined in next 30 years. There are some important industrial structures very close to mine pit limits including industrial site of mine, concentrating plant, belt conveyors, crushing site, etc. [7].

Drilling and blasting technique is the most economical method available for loosening and fragmenting the in situ rock mass in the Sungun mine. But blast induced ground vibration as a consequence of environmental effects of blasting process in the form of repetitive dynamic loading, has unfavorable effects on nearby structures. Blast induced ground vibration was studied in Sungun open pit Copper Mine in order to control vibration intensity.

The geotechnical studies show that the major fault systems of the area have NW-SE, N-S and NE-SW strikes. Also the mine area according

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to geotechnical and statistical studies of intact rocks and discontinuities has been divided into six separate blocks. In the mine area the overall rock mass is extremely broken and fractured due to the action of these faults (at least eighty major faults) and volcanic activities. The RMR and GIS rock mass rating methods that have been used in classifying rock masses and obtaining its parameters, indicate that rock mass quality changes from "Poor" to "Fair" in the mine blocks. The compressive strength tests (point-load, triaxial and uniaxial) of the intact rock show that the strength of intact rock increases directly with siliceous and indirectly with Argillic alterations [7].

3. Blast operations

In blasting operations at the Sungun site, ANFO and Emolan (blasting agent) are used as explosives for dry and wet blast holes, respectively, gelatin dynamite (priming), and Emolan Cartridge (booster). The initiation system is detonating cord, and the delay used between the rows are 13, 20, 50 ms and a combination of these. At this site, the drilling equipments and different types of blasting zones, and the regular blasting parameters that are implemented during blast vibration monitoring according to the contractor's specifications, are listed in Table 1. Explosive weight of each blast hole was measured carefully. The amount of gelatin dynamite and Emolan cartridge used as priming and booster, respectively, has been added to the amount of ANFO depending on their equivalent weight strength. The result of ground vibration measurements of the thirty-seven events performed at the test site, including particle velocity, maximum charge per delay and distance are shown in Table 2 [8].

4. Charge per delay estimation by empirical equations

Empirical equations are versions of the following general form that typically are used by investigators [9,10]:

$$PPV = KR^{a}Q^{b} \tag{1}$$

where $PPV = V$ is the peak particle velocity, Q is maximum charge per delay (kg), R is distance of the measuring transducer form the blasting face (m), and K, a and b are site-specific constants, which can be determined by multiple regression analysis.

The Ambraseys and Hendron [4] and Duvall and Fogelson [5] equations are versions of the following general form of all types demonstrated in Table 3. Also Rai et al. [6] have proposed Q as a predictor for calculation of the maximum charge per delay directly. The equation is the function of *PPV* and distances and therefore can predict the charge precisely:

$$Q = K(VR^{2})^{B} \tag{2}$$

Selected empirical equations (according to Table 3) have been employed in order to analyse the data. Table 4 represents the results of applying the equations to the ground vibration data. As seen in Table 4, the Ambraseys and Hendron equation better fits the data and has a greater coefficient of correlation. It should be noted here that the resulted correlation coefficient is just for the equations in the form of offered one. At the end of this paper the efficiency of the each governed relation in estimation of maximum charge per delay based on *PPV* and distance from blasting face is discussed for the data measured from Sungun copper mine.

5. ANFIS method and algorithm

The adaptive neuro-fuzzy inference system (ANFIS), developed by Jang [11], is a universal approximator and is capable of approximating any real continuous function on a compact set to any degree

Table 2
Results of ground vibration measurements in Sungun copper mine.

No.	Distance (m)	Charge per delay (kg)	Measured PPV (mm/s)
1	917	3313	2.52
2	188	133	2.61
3	334	3313	18.35
4	509.8	644	2.57
5	46	1209	123.5
6	58.5	2418	137
7	613	1152	2.72
8	67.5	943	97.25
9	519	1004	1.07
10	77	101	21.4
11	726	503	1.25
12	425	913	1.27
13	305	503	4.8
14	845	912	1.75
15	132	503	25.4
16	760	913	1.85
17	195	700.5	19
18	331	700.5	10.15
19	40	700.5	122.5
20	70	700.5	111
21	244	645	17.05
22	532	1209	5.73
23	300	843	8.5
24	554	335	3.74
25	436	843	4.72
26	43	335	91.55
27	122	843	49
28	469	334	2.4
29	680	843	2.12
30	262	334	6
31	341	243	2.77
32	1179	2418	1.8
33	601	1152	3.78
34	154	243	17.5
35	1068	2418	1.52
36	504	1152	3.65
37	653	2418	4.22

Table 3
Listed of proposed predictor's equations for calculation of maximum charge per delay.

Equations	Name of Predictor Equation
$PPV = K\left[\frac{R}{\sqrt[2]{Q}}\right]^{-B}$	Duvall and Fogelson, USBM [5]
$PPV = K\left[\frac{R}{\sqrt[3]{Q}}\right]^{-B}$	Ambraseys–Hendron [4]
$Q = K(VR^{2})^{B}$	Rai et al. [6]

Table 1
Surface blast design parameters during the experimental at Sungun mine.

Parameter	Related information	Parameter	Related information
Hole diameter (mm)	90, 127	Stemming (m)	One third of hole length
Hole length (m)	13–15	Specific charge (gr/m^3)	300–800
Bench high (m)	12.5	Blast hole inclination	Vertical
Burden and spacing (m)	2×2, 2×3, 2.5×3.5, 4×5	Charging configuration	Bottom priming, continuous charge

Table 4
Site constant and correlation coefficient from different predictors for Sungun mine.

Name of predictor equation	Equation	R
Duvall and Fogelson, USBM [5]	$PPV = 302.07\left[\frac{R}{\sqrt[2]{Q}}\right]^{-1.56}$	0.948
Ambraseys–Hendron [4]	$PPV = 1810.06\left[\frac{R}{\sqrt[3]{Q}}\right]^{-1.58}$	0.958
Rai et al. [6]	$Q = 0.0598(VR^2)^{0.71}$	0.710

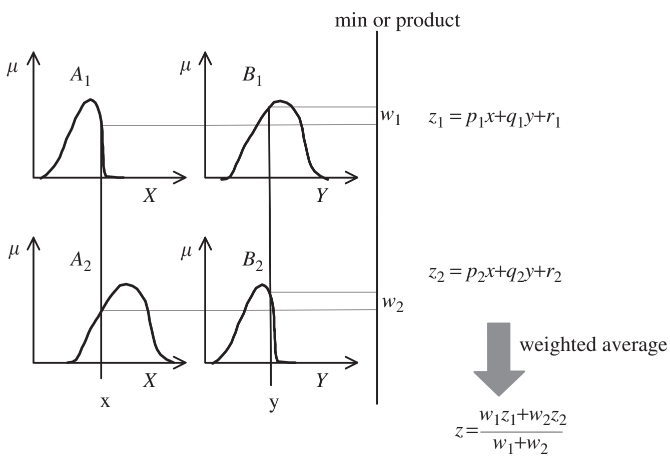

Fig. 1. Sugeno fuzzy model for two rules.

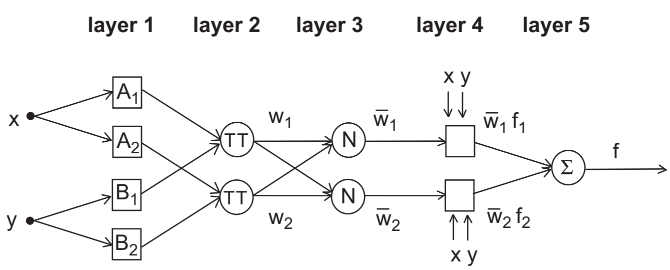

Fig. 2. ANFIS architecture for the Sugeno model.

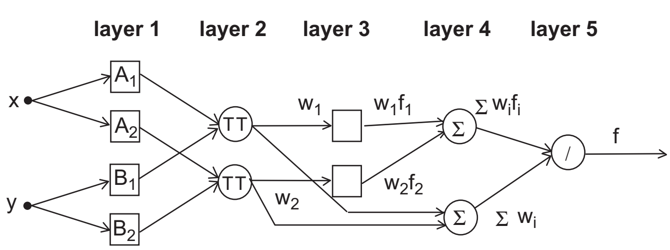

Fig. 3. ANFIS architecture for the two-input two-rule Sugeno fuzzy model.

of accuracy [12]. ANFIS is a soft computing technique, which incorporates the concept of fuzzy logic into the neural networks, and has been widely used in many applications of engineering science as well as the earth sciences [13–15]. ANFIS can simulate and analyze the mapping relation between the input and output data through a hybrid learning to determine the optimal distribution of membership function. It is mainly based on the fuzzy "if-then" rules from the Takagi and Sugeno fuzzy model [12] as shown in Fig. 1. The equivalent ANFIS architecture is shown in Fig. 2. Another ANFIS architecture for two inputs is shown in Fig. 3. It comprises five layers in this inference system and each layer involves several nodes, which are described by the node function.

The output signals from nodes in the previous layers will be accepted as the input signals in the present layer. After manipulation by the node function in the present layer, the output will be served as input signals for the next layer. Here, square nodes, named adaptive nodes, are adopted to demonstrate that the parameter sets in these nodes are adjustable. Whereas, circle nodes, named fixed nodes, are adopted to demonstrate that the parameter sets are fixed in the system. To explain the procedure of the ANFIS simply, two inputs x and y and one output f are considered in the fuzzy inference system. Every input variable is described by fuzzy sets: A1 and A2 for the X variable, B1 and B2 for the Y variable, respectively. Hence, the rule base will contain two fuzzy "if-then" rules as follows:

$$\begin{aligned} &\textit{Rule 1}: && \text{if } x \text{ is } A_1 \text{ and } y \text{ is } B_1, \\ & && \text{then } f_1 = p_1x+q_1y+r_1, \\ &\textit{Rule 2}: && \text{if } x \text{ is } A_2 \text{ and } y \text{ is } B_2, \\ & && \text{then } f_2 = p_2x+q_2y+r_2. \end{aligned} \tag{3}$$

The mathematical model:

Layer 1: every node i in this layer is an adaptive node with a note output defined by

$$\begin{aligned} &Q_{1,i} = \mu_{A_i}(x), \quad i=1,2, \\ &\textit{or} \\ &Q_{1,i} = \mu_{A_i}(y), \quad i=3,4 \end{aligned} \tag{4}$$

where x (or y) is the input to the node and a_i (or Bi-2) is the fuzzy set associated with this node, and

$$\mu_{A_i}(x) = \frac{1}{1+[(x-c_i)/a_i]^{2b_i}} \tag{5}$$

where{ a_i, b_i, c_i } is the parameter set—premise parameters.

Layer 2: Every node in this layer is a fixed node labeled Π, which multiplies the incoming signals and outputs that T-norm operator result, e.g.

$$O_{2,i} = w_i = \mu_{A_i}(x)\mu_{B_i}(y), \quad i=1,2 \tag{6}$$

The output each node represents the firing strength of a rule.

Layer 3: Every node in this layer is a fixed node labeled N

$$O_{3,i} = \overline{w}_i = \frac{w_i}{w_1+w_2}, \quad i=1,2 \tag{7}$$

Outputs is called normalized firing strengths.

Layer 4: Every node i in this layer is an adaptive node with a node function of:

$$O_{4,i} = \overline{w}_i f_i = \overline{w}_i(p_ix+q_iy+r_i) \tag{8}$$

where $\overline{w}_i$ is the output of layer 3 and{ p_i, q_i, r_i } are the parameter set.

Layer 5: The single node in this layer is labeled Σ, which computes the overall output as the summation of incoming signals:

$$O_{5,i} = \textit{overall output} = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f}{\sum_i w_i} \tag{9}$$

We can perform weight normalization in the last layer.

ANFIS architecture is designed based on Mamdani and Tsukamoto fuzzy models. Explicitly, this layer is summing the outputs of previous layers' nodes to be the output of the whole network. The basic learning rule of ANFIS is the back-propagation gradient descent, which calculates error signals (defined as the derivative of the squared error with respect to each node's output) recursively from the output layer backward to the input nodes. This learning rule is exactly the same as the back-propagation learning rule used in the common feed-forward neural-networks. From the ANFIS architecture illustrated in Fig. 2 and 3, it is observed that by determination of the values of premise parameters, the overall output f can be expressed as a linear combination of the consequent parameters. It can be said that, ANFIS algorithm uses a hybrid-learning rule to learn the fuzzy model, employing differentiable functions, and therefore makes it easy to use of conventional learning algorithms derived from the neural net theory. ANFIS combines the classical back-propagation method to learn the parameters of the membership functions and the conventional least-squares estimator to learn the parameter of the first-order polynomial of the Takagi–Sugeno–Kang fuzzy model [12]. There are two passes in the hybrid learning procedure for ANFIS. In the forward pass of the hybrid-learning algorithm, functional signals go forward till layer 4 and the consequent parameters are identified by the least-squares estimate. In the backward pass, the error rates propagate backward and the premise parameters are updated by the gradient descent. When the values of the premise parameters are fixed, the overall output can be expressed as a linear combination of the consequent parameters:

$$\begin{aligned} f &= \frac{w_1}{w_1+w_2} f_1 + \frac{w_2}{w_1+w_2} f_2 = \overline{w}_1 f_1 + \overline{w}_2 f_2 \\ &= (\overline{w}_1 x) p_1 + (\overline{w}_1 y) q_1 + (\overline{w}_1) r_1 + (\overline{w}_2 x) p_2 + (\overline{w}_1 y) q_2 + (\overline{w}_1) r_2 \end{aligned} \tag{10}$$

which is linear in the consequent parameters p_1, q_1, r_1, p_2, q_2 and r_2.

Performance of the developed models was tested with the help of coefficient of correlation (R) or coefficient of determination (R^2) [16], by computing mean square error (MSE) using:

$$MSE = \frac{1}{Q} \sum_{1}^{Q} (y-x)^2 \tag{11}$$

and by computing mean absolute error (MAE) using:

$$MAE = \frac{1}{Q} \sum_{1}^{Q} |y-x| \tag{12}$$

where x is target, y is output and Q is number of test patterns.

6. Maximum charge per delay estimation by ANFIS

The fuzzy modeling algorithms that is employed in this work included the parametric-based fuzzy model (Sugeno algorithm). The Sugeno model is used real field data instead of expert knowledge learned from past experiences. The principal components of the fuzzy model were fuzzy inference, fuzzy sets for input/output variables, and fuzzy if-then rules. The architecture of the fuzzy modeling presented in Fig. 4 has fuzzy rules representing a non-linear mapping between inputs and outputs.

Distance and PPV are used as input variables, and the output variable was Q. Fig. 5 shows input and output variables in the MATLAB [17] environment. When supplied with adequate

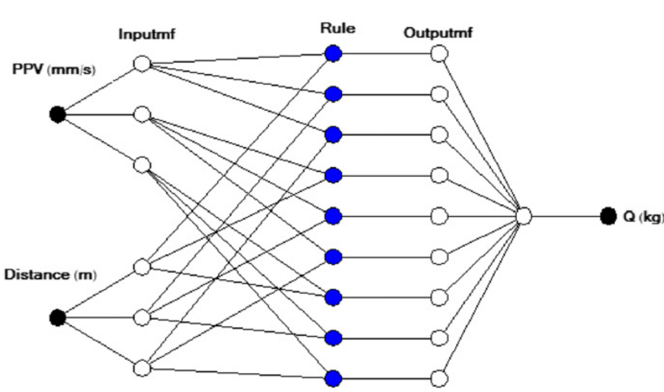

Fig. 4. ANFIS model structure.

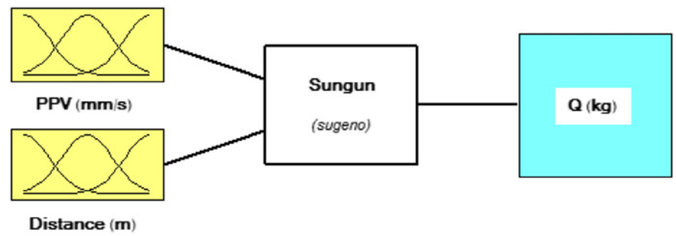

Fig. 5. Input variables and output of Sugeno model.

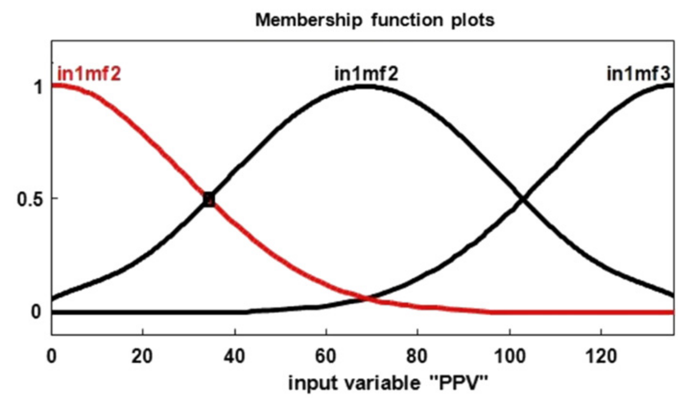

Fig. 6. Membership function of *PPV*.

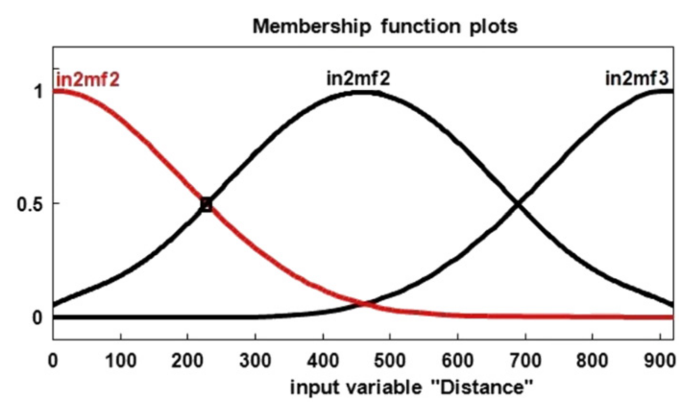

Fig. 7. Membership function of distance.

vibration data ANFIS is capable of drawing a relationship between Q from one hand and distance and PPV from the other hand.

Adaptive Nero Fuzzy Inference System (ANFIS) Editor was used to establish input variables and output. Both input and output variables were fuzzified with membership function (MF) and graphically designed. The Fuzzy Membership Function (MF) is defined as how each point in the input space was mapped to a membership value (or degree of membership) between 0 and 1 the fuzzy inference mechanism. Figs. 6 and 7 show the membership function of input1 (*PPV*) and input2 (Distance), which is also known as fuzzy reasoning that is the core of a fuzzy model. Its main function is to emulate human thinking and reasoning in an approximate fashion.

As there are 2 input and each input has 3 membership function the number of rules is 9(3 × 3). Fig. 8 presents a fuzzy if-then rule editor, and Fig. 9 shows a rule viewer to construct fuzzy if-then rule statements.

An optimized model of ANFIS built after several executions in MATLAB environment and tabulated as Table 5. The values of

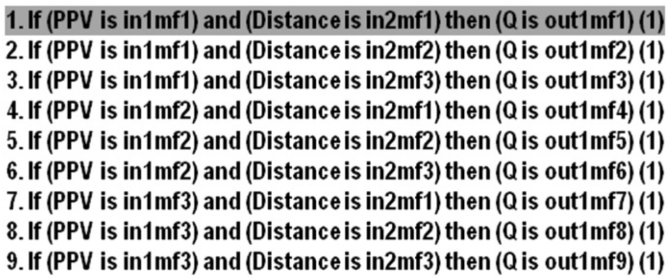
1. If (PPV is in1mf1) and (Distance is in2mf1) then (Q is out1mf1) (1)
2. If (PPV is in1mf1) and (Distance is in2mf2) then (Q is out1mf2) (1)
3. If (PPV is in1mf1) and (Distance is in2mf3) then (Q is out1mf3) (1)
4. If (PPV is in1mf2) and (Distance is in2mf1) then (Q is out1mf4) (1)
5. If (PPV is in1mf2) and (Distance is in2mf2) then (Q is out1mf5) (1)
6. If (PPV is in1mf2) and (Distance is in2mf3) then (Q is out1mf6) (1)
7. If (PPV is in1mf3) and (Distance is in2mf1) then (Q is out1mf7) (1)
8. If (PPV is in1mf3) and (Distance is in2mf2) then (Q is out1mf8) (1)
9. If (PPV is in1mf3) and (Distance is in2mf3) then (Q is out1mf9) (1)

Fig. 8. Fuzzy If-Then rule editor for the Sugeno model.

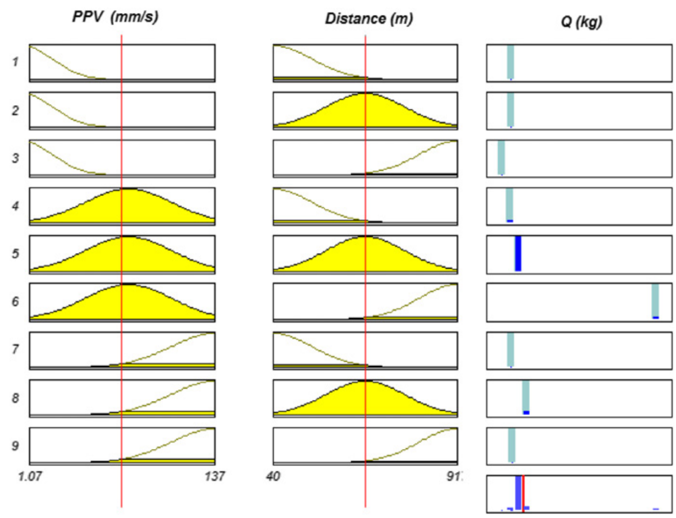

Fig. 9. Fuzzy rule viewer for the Sugeno model.

Table 5
Details of optimized ANFIS model built for Sungun mine.

Parameter	*Related information*
No. of training data	30
No. of testing data	7
Train Optimization algorithm	Hybrid
Membership function	Gaussian
Global error function	MAE
No. of optimum rules	9
No. of optimum epochs	10
MAE for train and test data	222, 235

correlation of coefficient (R) between real and estimated values of Q for training and testing groups are 0.98 and 0.94, respectively.

7. Comparison between applicability of the two methods

In this section, a prediction performance comparison is made between the presently constructed ANFIS Sugeno model and the traditional regression-based model. The results of applying the three empirical equations and ANFIS are compared in Table 6. As seen in this table, the applicability of ANFIS is far better than any of the equations. Correlation coefficient for measured and estimated data obtained from empirical equations and ANFIS has been shown in Fig. 10. The maximum value of correlation coefficient is for ANFIS. In addition the values of estimation error for all methods has been offered in Table 6, according to this table, despite higher correlation coefficient of the Ambraseys and Hendron equation the

Table 6
Comparison of error values in various approaches.

Model	*MAE*	*MSE*	*R*
Duvall and Fogelson USBM [5]	387	286,200	0.75
Ambraseys–Hendron [4]	525	598,896	0.78
Rai et al. [6]	402	359,362	0.73
ANFIS	231	99,104	0.93

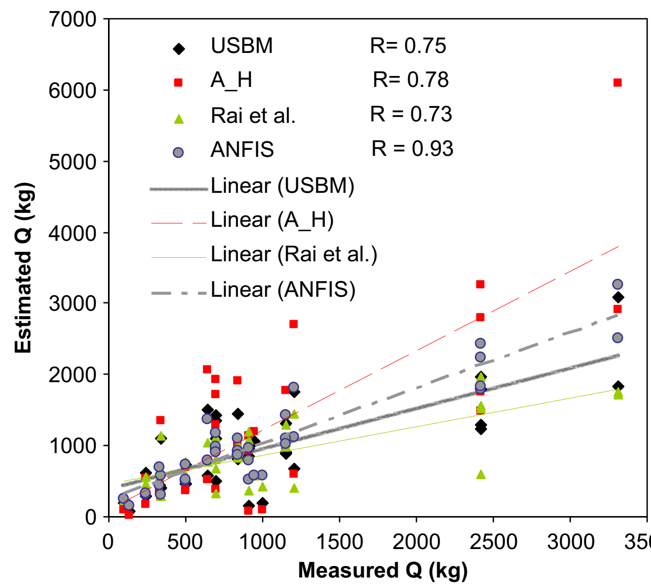

Fig. 10. Linear regression analysis of various approaches.

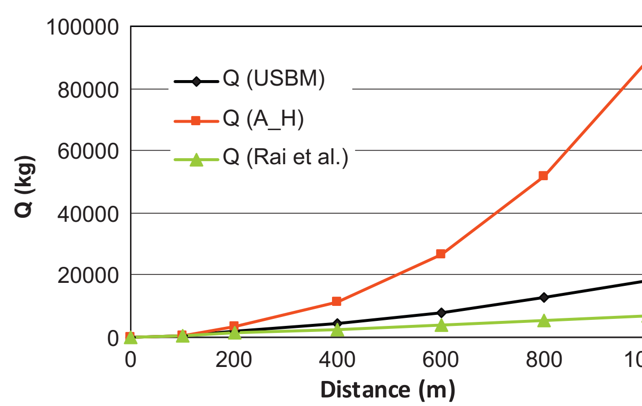

Fig. 11. Variation of maximum charge per delay with distance based on 10 mm/s for Sungun mine blasting.

values of MAE and MSE are also higher than other empirical equations that are undesirable. The reason for this is that, the maximum charge per delay estimation of Ambraseys and Hendron equation increases proportionally with increase in distance in comparison with other empirical equations. The estimated values for maximum charge per delay based on 10 mm/s for empirical equation is illustrated in Fig. 11. It is obvious from Fig. 11 that by increasing the distance from blasting place, the maximum charge per delay value for Ambraseys and Hendron equation has more ascending trend. Considering all criteria's, the result of analysis (see Table 6 and Fig. 12) shows that ANFIS has the best efficiency in comparison with other methods.

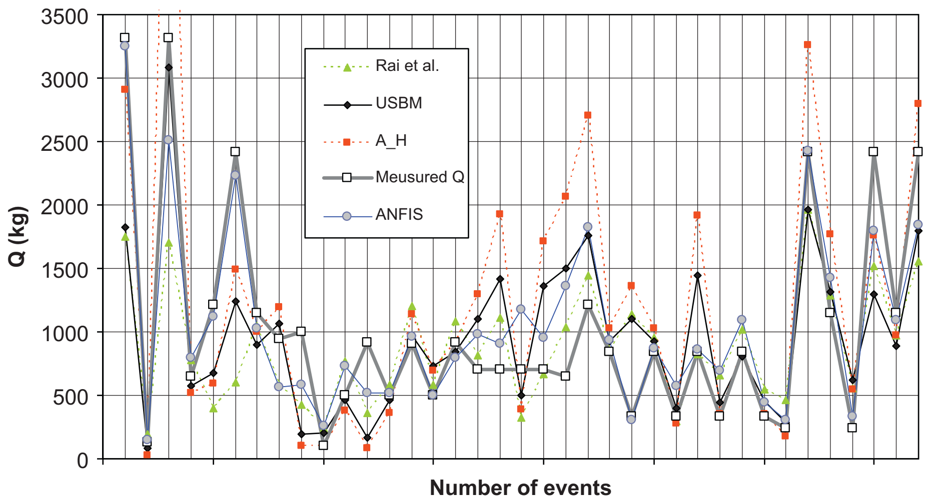

Fig. 12. Scatter diagram of estimated versus measured values for Sungun mine data.

8. Conclusions

A number of researches have been established to formulate the *PPV* and maximum charge per delay in the blast-induced vibrations. Fuzzy logic method has been found application on various engineering areas, particularly where the problem is involved with complexity and uncertainty. In this study the fuzzy logic method has been employed to analyze of the problem. Also the available empirical equations have been investigated. The main aim of this study is to predict maximum charge per delay which is one of the most important factors in blast pattern designing. The model predicts maximum charge per delay value as an output parameter for a given *PPV* and distance from the blast face. The comparison shows that results from model are close to the real ones that are desirable. According to the analysis on Sungun mine vibration data the *MAE* error of estimation in the ANFIS-based model was found to be 231 and in the regression models as 422. These values are 525 and 387 for USBM, Ambraseys–Hendron and Rai et al. models, respectively. The correlation coefficient between predicted and measured *PPV* values (*R*) in the ANFIS based model was equal to 0.93 and for the regression model 75, and finally 78 and 73 for USBM, Ambraseys–Hendron and Rai et al. models, respectively. The comparison indicated that by considering the *MAE*, *MSE*, and *R* the proposed ANFIS-based model outperforms the regression-based models in terms of prediction accuracy.

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