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OPTIMIZING ROCK FRAGMENTATION IN OPEN-PIT MINES THROUGH FUZZY INTELLIGENT PREDICTION METHOD

Isa MASOUMI[1]*, Behrooz ZABIHI[2], Shiba MASOUMI[3]

[1] Young Researchers and Elites Club, Science and Research Branch, Islamic Azad University, Tehran, Iran
[2] Department of Mining Engineering, Science and Research Branch, Islamic Azad University, Tehran, Iran
[3] Department of Industrial Management, Babol Branch, Islamic Azad University, Babol, Iran

Abstract: Blasting is one of the most important steps in mining operation and it directly affects final results (extraction ore body and costs). Various parameters such as rock mass and explosive properties, and blast geometry influence blasting results. A number of effective parameters in fragmentation should be taken into account to design a suitable blasting pattern, reduce the secondary costs and minimize the adverse effects such as flyrock, back break and ground vibration. Fuzzy theory is a widely used technique in many engineering subjects in which there exist concepts of quality and uncertainly. In this study, the information obtained from blasting operation in B anomaly Sangan Iron Mines have been used. In this model, the blasting pattern parameters such as burden, spacing, hole depth, stemming, charging length, ratio of (K/B), number of rows, specific charge and charge per delay ratio were considered as the input parameters in fuzzy model. Then, the results of fuzzy model were compared with statistical models. Finally, the results of the two models produced from mine blasting operation were compared and evaluated with real values. The correlation coefficient index for two models were 97.8% and 72.19%, and the RMSE were 2.613 and 9.18, respectively.

Keywords: *rock blasting; rock fragmentation; fuzzy set theory; Sangan Iron Mines; optimization model*

1. INTRODUCTION

Mine production cycle includes five steps: drilling, blasting, loading, haulage and crushing. The purpose behind the first two steps is fragmenting stones to a special size (Oraee and Asi 2006). More specifically, the goal is to achieve a specific fragment size

* Corresponding author: isa_masoumi@yahoo.com (I. Masoumi)

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distribution that eases handling, while minimizing damage to the final pit wall. Fragmentation can affect the productivity and efficiency of downstream operations including digging, crushing, and grinding. To manage downstream effects, blast designs can be optimized through monitoring, analysis and modelling (Bamford et al. 2021). The success index in this process is a suitable fragmentation result which could be considered as the main goal because it decreases many of the expenses such a loading, haulage and rock breaking costs. Because of the high cost and time involved in this operation, it is important for the mine planning engineers to select the best fragmentation design (Paul and Gershon, 1989). Due to the numerous effective factors on excavation and explosion process, they must be well defined and recognized. These factors consist of rock mass properties, explosive properties and characteristics of blasting pattern, which could be divided into two uncontrollable and controllable groups (Hustrulid 1999). So far, many experimental equations have been proposed for blasting pattern design by researchers such as Ash (Jimeno, Jimeno, and Carcedo 1995), Langforse and Khilstorm, Konya and Walter and Olofsson (Dehghani and Monjezi 2008), and Adhikari (1999) while those researches showed that they have been suitable everywhere due to conditions variety or regional situations. Also, a number of experimental models of fragmentation prediction were presented by researchers such as Berta (Berta 1990), Larson, Kuznetsov, Rosin and Rammler, and Cunningham (Sanchidrián and Ouchterlony 2017).

Using new techniques such as artificial intelligence in the field of explosion pattern design and its performance prediction could cause more convenience and efficiency for this method. In this field, researchers such as Oroei and Asi have predicted rock fragmentation in open mines using neural network (Oraee and Asi 2006). Monjezi et al. (2010a) have predicted rock fragmentation and flyrock simultaneously using artificial neural networks. Monjezi et al. applied artificial neural network to predict rock fragmentation in Sarcheshme copper mine (Monjezi, Amiri, Farrokhi, and Goshtasbi 2010b). Bahrami et al. predicted fragmentation resulted from the artificial neural network (Bahrami, Monjezi, Goshtasbi, and Ghazvinian 2011). Besides, Faramarzi et al. have applied rock engineering system (RES) to predict and evaluate rock fragmentation by blasting while the results indicate that this method was not reasonably sufficient (Faramarzi, Mansouri, and Ebrahimi Farsangi 2013). In addition, Ebrahimi et al. applied bee colony algorithm in combination with neural network to anticipate the performance of rock blasting (Ebrahimi, Monjezi, Khalesi, and Armaghani 2016). Bamford et al. (2021) present and evaluate the measurement of rock fragmentation using deep learning strategies. A deep neural network (DNN) architecture was used to predict characteristic sizes of rock fragments from a 2D image of a muckpile. Ding et al. (2023) predict rock fragmentation through cascaded forward neural network (CFNN) and radial basis function neural network (RBFNN) models.

Although there have been several researches which have been implemented in this field based on artificial intelligent, the ability of fuzzy set theory has not been completely considered as a reliable tool for fragmentation prediction. In other words, using suitable parameters as prediction criteria for the most optimum as well as regional circumstances have inevitable effects on prediction of fragmentation. In this study, to predict fragmentation resulted from blasting, a fuzzy set theory has been used in B mass of Sangan Iron mines, and modelled with the studies resulted from the mine explosions. Fuzzy logic and multivariable regression models have been compared in order to measure the prediction of fragmentation, and results of these two models have been studied with real values.

2. METHODOLOGY

2.1. FUZZY THEORY

Fuzzy theory was first introduced by Zadeh in an article titled "fuzzy set" in information and control journal (Zadeh 1965). Zadeh believed in using a method with no classic theoretical limitation because it extremely emphasized on accuracy and had no efficiency on complex systems. By reasoning via fuzzy sets and rules, the fuzzy set can express transitional boundaries or qualitative knowledge, and then make a comprehensive fuzzy judgment that is similar to the human thought process (Zhang, Sun, Shao, and Yang 2016). In classic theory, any elements can either belonged to a set or not. In fuzzy sets, inexplicit methods are used based on uncertainty in which the employed elements were not numerical but in the form of qualitative (linguistic) variables (Azimi, Osanloo, Shirazi, and Bazzazi 2010). Fuzzy sets are defined by means of a function in [0, 1] interval and for any member of which a degree of membership is allocated and one member could belong to more than one collection by a different membership degree.

Suppose that U is the global set includes all possible elements and members in these discussed applications. It is recalled that a classic A set or set A in the global space U could be introduced by membership method with double amount [0, 1] belonging to the function for A and presented by $\mu(x)$ (Ross 2010).

$$\mu_A(x) = \begin{cases} 1 & \text{if} \quad x \in A \\ 0 & \text{if} \quad x \notin A \end{cases}. \tag{1}$$

Set A in mathematics equals $\mu_A(x)$ membership function, therefore by knowing $\mu_A(x)$ set A will be known. In fuzzy sets, the degree of a member belonging to a fuzzy set, expressed by means of membership amount [0, 1] that is called membership function in a fuzzy set theory. If X is a global set and its elements expressed by x, then the set A in X will be shown with ordered pairs as follows (Ross 2010):

$$A = \{x, \mu_A(x) \colon x \in X\}\,, \tag{2}$$

where x is the membership function in A.

Membership functions have different types and could imply triangular linear, trapezoid membership function and bell-shaped membership function. In general, triangular and trapezoid membership functions are the most usual membership functions used in conditional (if–then) fuzzy models (Kim, Lee, and Lee 2017).

2.2. FUZZY RULES (IF-THEN)

In fuzzy systems, human knowledge are shown in fuzzy principles (if–then). *A* rule (if–then) will be a conditional interpretation as follows (Azimi, Osanloo, Shirazi, and Bazzazi 2010):

If (fuzzy interpretation) then (fuzzy interpretation).

2.3. FUZZY SYSTEMS

Fuzzy systems are expert systems based on principles which predict the output with methods based on fuzzy logic principles from special inputs. A fuzzy system has fuzzy inputs and a collection of principles (if-then) to determine fuzzy output. The user enters numerical values that must be converted to fuzzy variables to be processed with fuzzy rules (inference step). The results are fuzzy values and then converted to numbers by using unfuzzified methods. Usually three types of fuzzy systems are applied (Alavala 2008).

(1) Net fuzzy systems;
(2) Takagi–Sugeno–Kang (TSK) fuzzy systems;
(3) Fuzzifying and defuzzifying systems.

The main structure of a net fuzzy system consists of fuzzy rules (if–hen), fuzzy inference engine, and fuzzy sets in input space and fuzzy sets in output space. The main problem with the net fuzzy systems is that its inputs and outputs are fuzzy collections. However, in engineering systems the inputs and outputs are variables with real values. In order to solve this problem, Takagi–Sugeno–Kang have introduced another type of fuzzy system in which the inputs and outputs are variables with real values (Takagi and Sugeno 1985; Sugeno and Kang 1988). In this system “then” part of the fuzzy rule from descriptive phrase with linguistic values is converted to a simple mathematic relation. In fact, TSK fuzzy system is a weighting average of “then” part of a mathematical formula. Therefore, it does not provide a framework for human knowledge. This system did not make us free from different fuzzy logic principles and as a result, there is no flexible fuzzy system in this structure. In order to solve this problem usually the third type of fuzzy system means fuzzy systems with fuzzifiers or defuzzifiers were used and obtained by adding a fuzzifier in the input and defuzzifier in net a fuzzy system output and removed net fuzzy system and TSK system errors. Figure 1 shows the main structure of fuzzy systems with fuzzifier and defuzzifier (Wang and Zuo 2012).

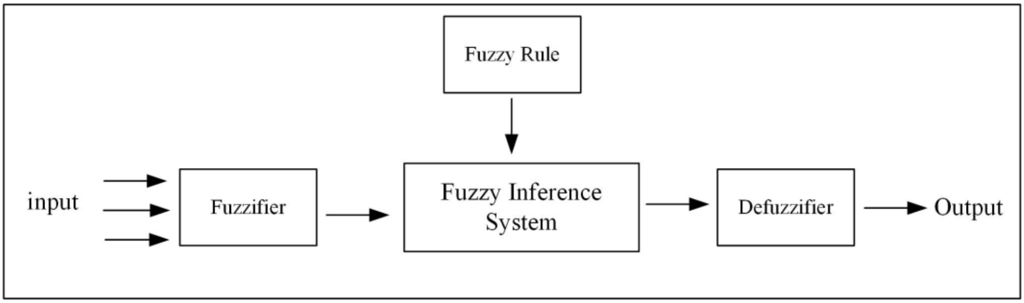

Fig. 1. Main structure of fuzzy systems with fuzzifier and defuzzifier

2.3. FUZZY SYSTEMS DESIGN

Fuzzy system configuration method which is conducted by means of a conditional interpretation (if-then) consists of four general steps:

- Fuzzifiying input (explicit) numerical values;
- Fuzzy rule base (stating system rules);
- Fuzzy inference engine;
- Defuzzifier output fuzzy values.

Since fuzzy rules system are used with qualitative values, input crisp values must be converted to qualitative values. The act of converting measured real values to qualitative values or descriptive phrases is called fuzzifying. In a fuzzy model, the system behaviour is described by (if–then) rules. A fuzzy rule base formulated by fuzzy (if–then) set rules. A fuzzy rule base consists of following fuzzy rules (Niittymäki 2001):

$$\text{If } X_1, A_1, ..., X_n, A_n \text{ then } Y \textit{ is } B, \tag{3}$$

where A and B are fuzzy sets and X, Y are respectively fuzzy system output and input variables which are descriptively qualitative. Fuzzy models are different based on their usage. The most common inference engines include Mamdani fuzzy model, TSK fuzzy model, Tsucamoto fuzzy model and Singleton fuzzy model (Iphar and Goktan 2006). The difference in inference engine with the others is in its rules result, gathering method and defuzzyfiying. Because Mamdani method analysis and interpretation is simpler in comparison to other methods, Mamdani model has been explained in this study and has been used for blasting modelling (Yagiz and Gokceoglu 2010; Grima 2000). Mamdani algorithm is the most commonly used algorithm in fuzzy systems. This method has the following structure (Sonmez, Tuncay, and Gokceoglu 2004; Grima 2000):

$$\text{If } X_1 \textit{ is } A_{iI} \text{ ... and } X_r \textit{ is } A_{ir} \text{ then } Y \text{ is } B_i \text{ for } I = 1, 2, 3 ... K, \tag{4}$$

in which:

- X_r and X_I: input variables;
- B_i and A_{ir} and A_{iI}: linguistic expressions (fuzzy sets);
- Y: output variable;
- K: number of rules.

Although many methods such as minimum–maximum, maximum–maximum, minimum–minimum and maximum–average, etc., existed for fuzzy relations combination, the most common one is maximum-minimum method or Mamdani minimum method (Ross 2010). Figure 2 shows how we can inference in Mamdani minimum method.

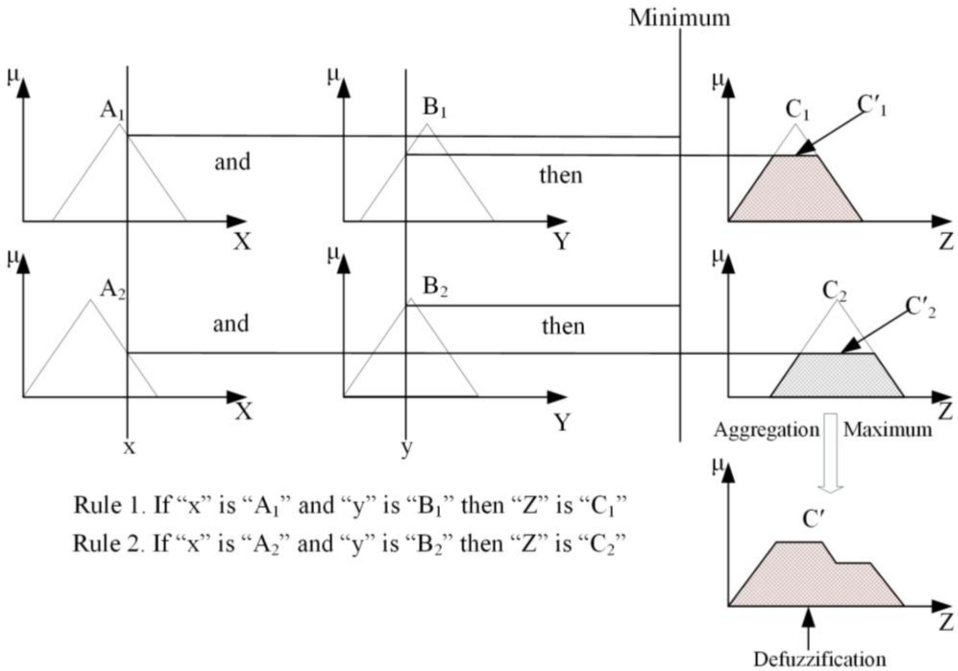

Fig. 2. How to inference in Mamdani minimum method

Finally, in fuzzy inference operation and calculation, the product will be in descriptive form. In using the results, we must convert it to numerical values. This function is called defuzzifier which is diverse. For example, it could imply centroid of area defuzzifier, center of gravity defuzzifier and maximum defuzzifier (Grima 2000; Lee, Jeon, and Kim 2003; Aydin 2004). The centroid of area defuzzifier is the most common one used in fuzzy systems and fuzzy controls. Centroid of area defuzzifier, in general, is described in following mathematical form (Yagiz and Gokceoglu 2010):

$$\bar{y} = \frac{\int y\mu(y)dy}{\int \mu(y)dy}\,. \tag{5}$$

3. CASE STUDY DESCRIPTION

The Sangan mining district, with a proven reserve of 1 Gt of 35 to 60% iron, is a world-class iron ore district in Iran, and located in the far eastern part of the Cenozoic Alborz Magmatic Arc (Mehrabi et al. 2021). Sangan Iron mine located 300 km of eastern south of Mashhad, about 58 km away from southern part of Tayabad and 16 km from the eastern north Sangan city in a region by latitude N 34°24′ longitude E 60°16′. Sangan Iron ore deposit region is totally rectangular-shape with the length of 26 km and width of 8 km consisting of 3 parts including western (anomalies A, B, C northern and C southern), central (Baghak and Dardoy anomalies) and eastern. Sangan Iron mines with the geological 1.2 billion-tone reserves are quantitatively the second biggest Iron mine in Iran. The highest amount of Iron ore belongs to the western region, the total ratio of western mine geological reserves is 585 million tones and the proven reserves are 375 million tonnes. Annual production of B and C northern blocks are 4.8 million tonnes.

4. BLASTING DATA COLLECTION

The first step in fragmentation modelling is the correct selection of effective factors and parameters on fragmentation to present an accurate and comprehensive model. There are a number of parameters that influence the outcome of any blasting exercise. Some of them are parameters which can be controlled in designing process. Some of the most important parameters are burden, spacing, hole depth, stemming length, specific charge, etc., which were commonly used in every blasting design (Jimeno, Jimeno, and Carcedo 1995; Hustrulid 1999; Hustrulid, Kuchta, and Martin 2013; Andrievsky and Akhpashev 2017; Akbari, Lashkaripour, Bafghi, and Ghafoori 2015; Nefis and Korichi 2016). These parameters directly influence the blasting procedure and consequently the fragmentation results (Jeon, Kim, and You 2015). By studying these conditions and existing limitations in Sangan Iron mines B mass, 9 parameters have been used as input ones. These parameters are burden (m), spacing (m), hole–depth (m), stemming (m), charging length (m), ratio of (K/B), number of rows, specific charge (kg/m^3), and ratio of charge per delay (kg/ms), respectively.

Based on these parameters, 40 data series from *B* mass explosion were collected in a five-month period. In order to analyze the fragmentation of any blasting, 20 to 30 pictures of fragmented iron mass have been recorded after explosion. Then, these pictures were studied by GOLD SIZE software. It must be mentioned that all analysis in this software is based on D_{80} which equals 30 cm. The related parameters and symbols have been shown in Table 1. Figure 3 represents the level of working face fragmentation.

Table 1. Input parameters to fuzzy model

Input parameter	Symbol	Minimum	Maximum
Burden	*B*	1.7	2.5
Spacing	*S*	2.2	3
Hole depth	*H*	2.5	6.5
Stemming length	*T*	0.72	1.95
Charging length	*L*	1.68	4.55
Ratio of (*K*/*B*)	*K*/*B*	1	2.88
Number of rows	*N*	1	8
Specific charge	Sc	0.548	1.4
Ratio charge per delay	Cpd	11.4	151.2

Fig. 3. Level of working face fragmentation

5. RESULTS AND DISCUSSION

5.1. STATISTICAL ANALYSIS

The statistical method could be used to predict the outputs and obtain the relationship between input and output parameters. Multi variable regression is a statistical method which is applied to analyze the relationship between dependent and independent variables as well as data analysis and modelling (Green et al. 2006; Pao and Pao 2008).

In this study, regarding the obtained results from the performed explosion in mass B, and based on the mentioned parameters in Table 1, multivariable regression method was applied to predict fragmentation. The relationship between input parameters and fragmentation based on statistical method has been done by SPSS 17 software and the result is as follows:

$$F = 77.38 + 32.1B - 69.01S - 0.011H + 10.74L - 5.75K/B$$
$$+ 1.18N + 43.59Sc + 0.161Cpd, \qquad (6)$$

where F is the fragmentation obtained from multivariable regression. The relationship between fragmentations, which have been resulted from multivariable regression, with real values is shown in Fig. 4.

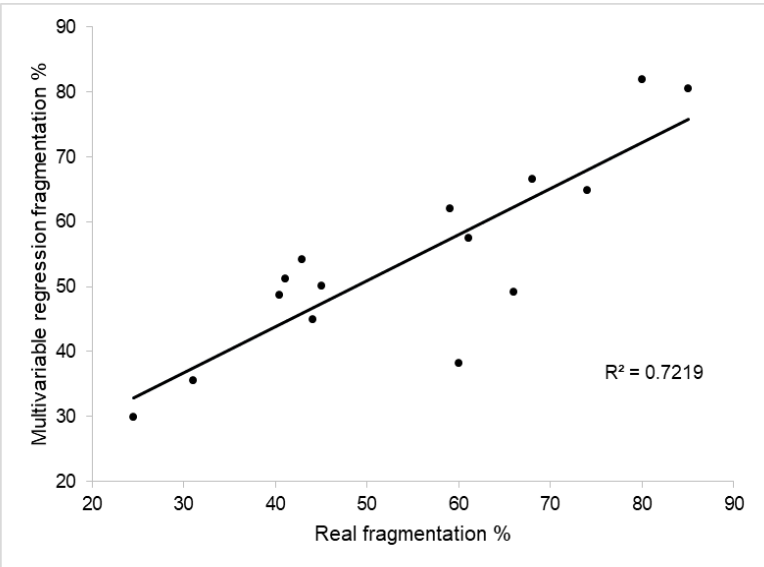

Fig. 4. The relationship between fragmentations resulted from multivariable regression with real values

5.2. PREDICTION USING FUZZY MODEL

In order to build a fuzzy model, at first, fuzzy system is designed and then the model application is evaluated. The presented model has been designed based on triangular and trapezoid membership functions, Mamdani minimum inference engine and centroid of area defuzzifer in which the data are obtained from performed explosions in mass B. Fuzzy system structure and input parameters used for predicting fragmentation are shown in Fig. 5. Since triangular and trapezoid functions are the most common membership functions in conditional fuzzy models, they have been used to fuzzify input and output variables (Azimi, Osanloo, Shirazi, and Bazzazi 2010; Monjezi, Rezaei, and Yazdian 2010c). Input membership functions are considered as high, low and middle ones. For example, HV membership function implies very high and VVL implies very very low and output membership function is considered as good, poor and medium. For example, VVG is very very good fragmentation sign and VVP is very very poor fragmentation sign.

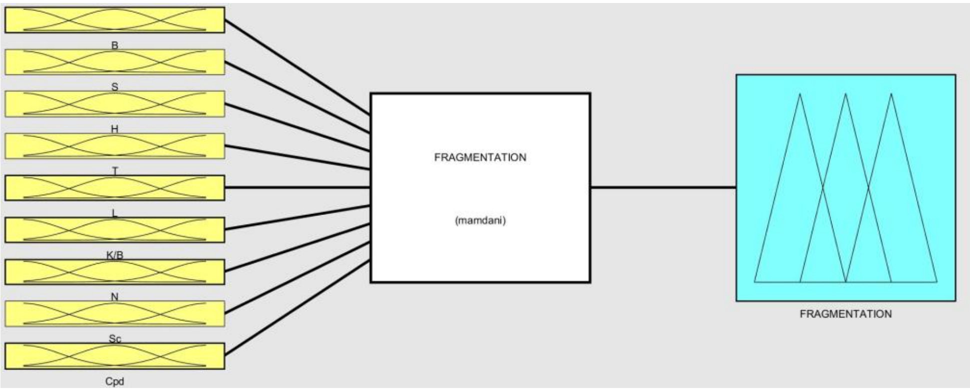

Fig. 5. Fuzzy system structure and input parameters

Input and output parameters membership functions are shown in Fig. 6. In designing a fuzzy model, rules applied as the main functions for the model which have special importance. For this reason, rules should be efficient and more accurate. Hence, investigation of influence of effective parameters and their range have been studied during this period of explosions data collection in Sangan mines B mass to generate an efficient rules base. In this study, 492 rules (if–then) have been considered for fuzzy model rules base. Some rules of this base inserting in fuzzy model have been shown in Table 2.

For instance, from Table 2 in rule number 1 it implies that if burden is middle and spacing is low-middle and hole depth is high and stemming length is middle high and charging length is high and ratio of K/B is middle and number of rows is middle high and specific charge is low middle and ratio charge per delay is high, then fragmentation will be very very good. In order to have crisp values from fuzzy results of inference stage, the most common defuzzifier in fuzzy systems has been used which is centroid area method. After finishing this stage, by performing this model and entering any value of input variables, this model is capable to predict fragmentation.

Table 2. Some rules of presented fuzzy model

Rule no.
1. If (B is M)and (S is LM) and (H is H) and (T is MH) and (L is H) and (K/B is M) and (N is MH) and (Sc is LM) and (Cpd is H) then (F is VVG)
2. If (B is M) and (S is LM) and (H is H) and (T is H) and (L is H) and (K/B is M) and (N is H) and (Sc is M) and (Cpd isVH) then (F is VVVG)
3. If (B is L) and (S is L) and (H is MH) and (T is MH) and (L is MH) and (K/B is M) and (N is LM) and (Sc is L) and (Cpd isVL) then (F is M)
4. If (B is H) and (S is MH) and (H is MH) and (T is H) and (L is H) and (K/B is LM) and (N is M) and (Sc is L) and (Cpd is MH) then (F is PM)
5. If (B is M) and (S is MH) and (H is H) and (T is MH) and (L is H) and (K/B is M) and (N is MH) and (Sc is LM) and (Cpd is H) then (F is VVG)
6. If (B is M) and (S is M) and (H is H) and (T is H) and (L is MH) and (K/B is M) and (N is MH) and (Sc is LM) and (Cpd is H) then (F is MG)
7. If (B is L) and (S is LM) and (H is L) and (T is L) and (L is L) and (K/B is VL) and (N is LM) and (Sc is M) and (Cpd is VL) then (F is PM)
8. If (B is MH) and (S is LM) and (H is H) and (T is H) and (L is H) and (K/B is M) and (N is H) and (Sc is M) and (Cpd is VH) then (F is VVVG)
9. If (B is LM) and (S is LM) and (H is MH) and (T is MH) and (L is MH) and (K/B is VH) and (N is L) and (Sc is M) and (Cpd is VL) then (F is M)

In order to have crisp values from fuzzy results of inference stage, the most common defuzzifier in fuzzy systems has been used by centroid area method. After finishing this stage, because of performing this model and entering any value of input variables, this model was capable to predict fragmentation. By entering input parameters, this model is capable of predicting fragmentation. For example, when input parameters are according to Table 3, fragmentation equals 85.3%. In this case, it can be seen that when the burden is assumed to be 2.2, it means that it belongs to middle high fuzzy number by its membership function around 0.4 and also belongs to middle fuzzy number by its membership function around 0.6 which are comprehensible from Fig. 6.

Figure 7 shows the fuzzy inference procedure for predicting fragmentation. In this figure all the inputs are as same as Table 3. As it can be seen, the outcome, which is fragmentation, is equal to 85.3%.

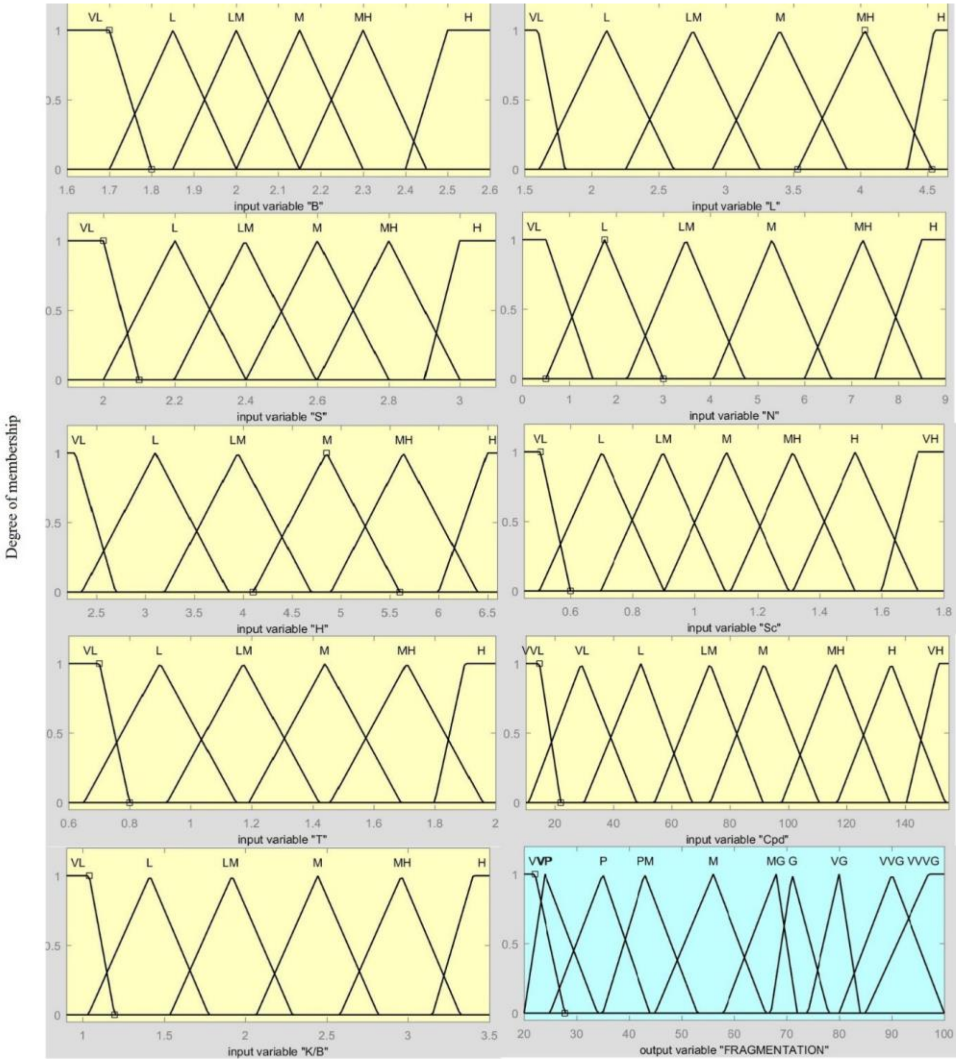

Fig. 6. Membership functions of inputs and output variables

Table 3. Input parameters for testing model

Input parameters	Value	Input parameters	Value
Burden	2.2	Ratio of (K/B)	2.45
Spacing	2.6	Number of rows	8
Hole depth	6.5	Specific charge	0.997
Stemming length	1.95	Ratio charge per delay	151.2
Charging length	4.55		

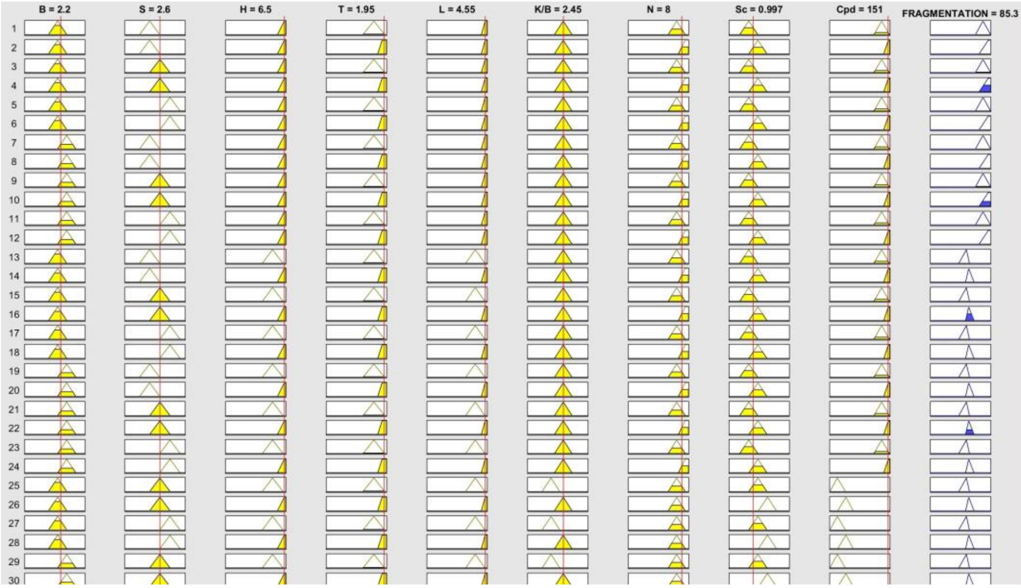

Fig. 7. Fuzzy conclusion equipment for predicting fragmentation

Figure 8 shows the relationship between a fuzzy model and real values of the resulted fragmentation. For evaluation the fuzzy model, it should be compared to real fragmentation outcomes. For this reason, the real fragmentation values have been calculated by the software which has been explained in Section 4.

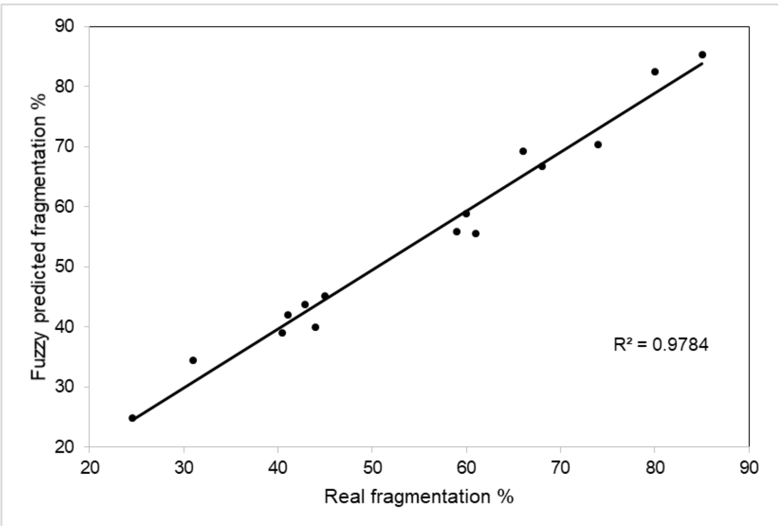

Fig. 8. The relationship between fragmentations resulted from fuzzy model with real values

5.3. EVALUATION OF THE MODELS

Correlation coefficient index (R^2) and root middle square error (RMSE) was used in order to evaluate the fuzzy model and statistical method performance. These two indices are expressed by using the following equations (Lee, Jeon, and Kim 2003; Ozger and Sen 2007).

$$R^2 = 100\left[\frac{\sum_{i=1}^{n}(A_{ipred} - \bar{A}_{pred})(A_{imeas} - \bar{A}_{meas})}{\sum_{i=1}^{n}(A_{ipred} - \bar{A}_{pred})^2 \sum_{i=1}^{n}(A_{imeas} - \bar{A}_{meas})^2}\right]^2, \tag{7}$$

$$RMSE(A) = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(A_{imeas} - A_{ipred})^2}\ , \tag{8}$$

in which A_{imeas} is i-th measured value (Real), A_{ipred} is i-th of predicted value, n number of data series and $\bar{A}_{imeas}$ and $\bar{A}_{pred}$ are average measured values (real) and predicted values, respectively. Fuzzy model and multivariable regression application evaluation are shown in Table 4.

Table 4. Performance index of fuzzy and multivariable regression

Fuzzy model	Regression model	Index
97.8%	72.19%	R^2%
2.613	9.18	RMSE

As it can be seen from Table 4, the correlation coefficient for regression model is 72.19% and it is 97.8% for proposed fuzzy model. It remarkably shows a great improvement in prediction the fragmentation of rocks by blasting procedure.

The both models for the executed results (fuzzy, multivariable regression) have been compared in Fig. 9, together with real fragmentation values on fifteen series of data.

Figure 9. demonstrates that using 15 data sets, there are greater deviations between the use of multivariable regression and fuzzy predicted fragmentation. As it can be seen, the cases of blasting pattern numbers 9 and 10 show about 20% differences in the prediction and numbers 3, 11, 13 and 14 have deviation around 10% with the real fragmentation.

In comparison, the predictions' percent of fuzzy predicted fragmentation method are shown the reliable amounts and they are so close to real fragmentations data.

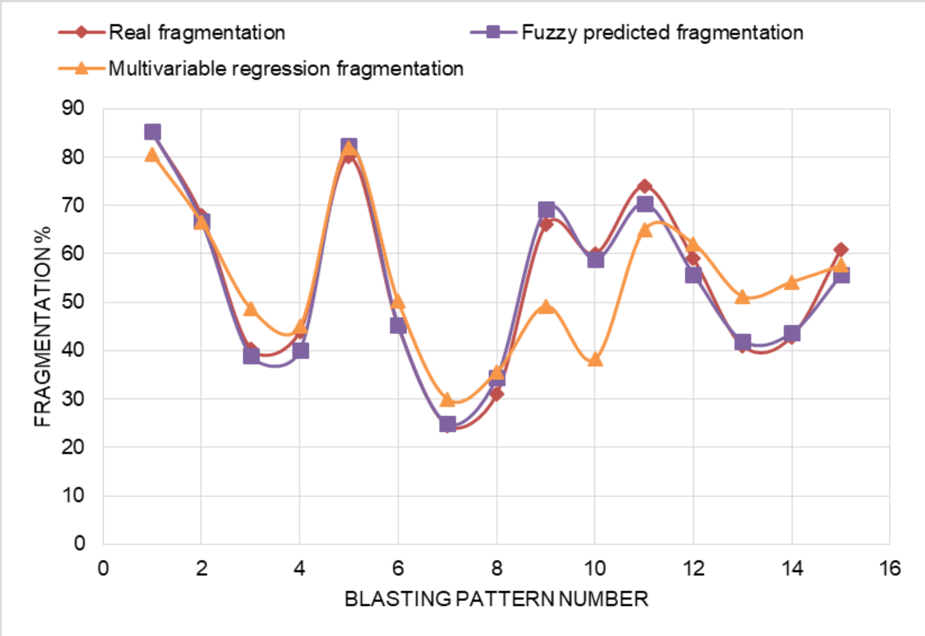

Fig. 9. Comparison of models result (fuzzy, multivariable regression and real fragmentation)

6. CONCLUSION

In mining operations, rock fragmentation affects the productivity and efficiency of downstream operations including digging, hauling, crushing, and grinding. Continuous measurement of rock fragmentation is essential for optimizing blast design. The prediction and achievement of a proper rock fragmentation size is the main challenge of blasting operations in surface mines. This is because an optimum size distribution can optimize the overall mine/plant economics. In this study, the results of fuzzy model were compared with statistical models. Finally, the results of the two models produced from mine blasting operation were compared and evaluated with real values. The following results shows that the fuzzy model is a reliable tool to anticipate rock fragmentation performance and therefore, it will help to increase the efficiency of blasting in surface mining.

1. In performed modelling, to predict the fragmentation in Sangan iron mines B mass (R^2), the correlation coefficient for both fuzzy models and multivariable regressions have been obtained 97.8% and 72.19%, respectively.
2. In a performed modelling for predicting fragmentation of Sangan iron mines B mass, RMSE has been obtained for both fuzzy models and the multivariable regressions which have been 2.613 and 9.18, respectively.

3. According to the obtained results of (R^2), the correlation coefficients and (RMSE) for both models, due to the higher correlation coefficients and less RMSE in a fuzzy model than a statistical model, the fuzzy model had better capability to predict fragmentation.

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