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RESEARCH ARTICLE

An Application of Fuzzy Sets to the Blastability Index (BI) Used in Rock Engineering

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Abstract

Rock masses have inherently different resistance to fragmentation by blasting. This property is hereafter referred to as the blastability of a rock mass. Empirical models for the estimation of blastability have been developed. In this study, the Mamdani fuzzy algorithm was used to express the blastability index by fuzzy sets. We use Lilly and Ghose blastability models which are important models of blastability. Parameters of these models were represented by fuzzy sets as the input variables of the fuzzy model. The output of the fuzzy model is a final blastability index rating. Experimental data is obtained from seven mine and one dam sites in Iran. BI values are obtained from both BI fuzzy inference system and conventional BI; Fuzzy sets have more adjustment than conventional model.

Keywords

blastability index, fuzzy inference system, surface blasting

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1 Introduction

Good fragmentation is a subjective matter and depends on the end use of the rock [1]. Mechanical crushing and grinding are particularly expensive operations at a mine and considerable cost and throughput benefits can be obtained by breaking the rock using explosives effectively instead [2–4]. Optimum fragmentation is critical for optimizing a drilling and blasting program that minimizes the overall cost for a mining operation [5, 6]. Rock fragmentation depends on many variables such as rock mass properties, site geology, in situ fracturing and blasting parameters and there is no complete theoretical solution for its prediction [7]. However, some empirical models for the estimation of blastability have been developed. Two different rock masses, when subjected to identical blast geometry and energy input from explosives, will produce quite different degrees of fragmentation. It is because of this fact that the rock masses have inherently different resistance to fragmentation by blasting. That is, the two rock masses have a different ease with which they can be fragmented by blasting. This property is hereafter referred to as the blastability of a rock mass.

In the last two decades, considerable increscent in the applications of soft computing techniques such as fuzzy models, neural networks, etc. to solve many rock mechanics and engineering geological problems has been observed [8–14]. because the fuzzy models can cope with the complexity of complex and ill-defined systems in a flexible and consistent way [15]. In fact, the problems related to rock masses are very complex and determination of the mechanical characteristics of the rock masses involves some uncertainties. Fuzzy set theory introduced by Zadeh is one of the powerful tools to handle uncertainties [16]. This paper is an attempt to provide an approach based on the fuzzy set theory for determining blastability Index. The Mamdani algorithm is perhaps the most appealing fuzzy method to employ in engineering geological problems. In this study, the Mamdani fuzzy algorithm was selected to express the blastability index by fuzzy sets.

2 Blastability index

Although some soft rocks are amenable to digging, at many mines this stage of excavation must be preceded by breakage of the rock through drilling and blasting. The main parameters to be accounted for the design of blasting that will achieve the desired fragmentation safely and economically are rock material and mass properties; type and properties of explosives; blasting geometry and Charge distribution. The rock material and mass properties are fixed, but the other parameters can be changed according to conditions and aims [16]. The influence of intact rock and rock mass properties on blasting operations has long been studied [17–28]. This influence has been mentioned and incorporated in various ways, such as Bond's work index [17, 28], Hino's blastability coefficient [29], rock factor [30] and blastability index [31, 32]. However, only few works has been devoted to develop a quantitative parameter or system to define the ease of fragmentation of rock by blasting. In fact this kind of development was suggested long ago [19] and recently has been reemphasized [26, 33].

Intact rock properties and the discontinuity structure of a rock mass are considered as the most important variables influencing blasting results. This influence is supposed to be a composite intrinsic property of a rock mass and is referred to as the blastability of a rock mass [34]. Two different rock masses, when subjected to identical blast geometry and energy input from explosives, will produce quite different degrees of fragmentation. This is because the rock masses have inherently different resistance to fragmentation by blasting. That is, the two rock masses have a different ease with which they can be fragmented by blasting. This property is hereafter referred to as the blastability of a rock mass.

Many factors affect the blastability of rock masses and it is therefore helpful to consider the blastability of the rock mass to be a composite intrinsic property of the rock mass.

The term 'blastability' is only used in the context of drill and blasting and the consumption of explosives [35]. Quality aspects of blasting and/or control of material fragmentation were not included. One of the most critical parameters in the determination of optimal blasting conditions is the powder factor. Prediction of the appropriate powder factor is an important research objective. Accordingly, many previous researchers have investigated the relationship between powder factor, rock material and mass properties, but although some empirical relations are now in use as a result of these investigations, a final solution could not be found owing to the complexity of the problem. In this article it has been used two important models of blastability, Lilly and Ghose.

2.1 Lilly blastability index

Lilly [31] defined a blastability index that is obtaining by adding the represented value of five geomechanics parameters. In Table 1, the ratings for Lilly blastability index parameters are described. In summary, the Lilly blastability index comprises:

- Rock Mass Description Rating (RMD) ranging from 10 for a powdery rock mass to 50 for a totally massive rock mass;
- Joint Plane Spacing Rating (JPS) ranging from 10 for spacings less than 0.1 m to 50 for spacings greater than 1.0 m;
- Joint Plane Orientation Rating (JPO) ranging from 10 where the predominant defect orientation is horizontal to 40 where the predominant defect dip is into the free face;
- A rating Specific Gravity Influence (SGI) for the unit weight (D in t/m^3) of the rock mass equal to [25 × D-50] for D > 2, or equal to 1 for D <= 2; SGI rating for rock strength equivalent to [0.05 × UCS] where UCS is given in MPa.
- The Moh's scale of Hardness (HD) is the most common method used to rank rocks and minerals according to hardness.

The BI for a rock mass can be estimated by halving the sum of the five ratings. That is, Eq.(1):

$$BI = 0.5 \times \left(RMD + JPS + JPO + SGI + HD \right) \tag{1}$$

The blastability indices based on ratings suffer from the drawback of assigning weightage to the parameters which is subjective. Nevertheless, this approach makes it possible to determine an index including several geomechanical parameters, which can be used to calculate Powder Factor (PF). The PF (kg$_{\mathrm{Anfo}}$/ton) is equivalent to [0.004 × BI].

Table 1 Discription of Lilly blastability index

Geomechanic parameters	Rating
1. RMD	
1.1 Powdery / Friable	10
1.2 Blocky	20
1.3 Total massive	50
2. JPS	
2.1 Close (m)	10
2.2 Intermediate (0.1 to 1 m)	20
2.3 Wide (m)	50
3. JPO	
3.1 Horizontal	10
3.2 Dip out of face	20
3.3 Strike normal to face	30
3.4 Dip into face	40
4. SGI SGI= 25*D* or SGI = 0.05× UCS	
5. HD	1–10

Example:

Consider highly laminated, soft ferruginous shale which has horizontal to sub-horizontal bedding to which the following values correspond: RMD = 15, JPS = 10, JPO = 10, SGI = 10, H = 1, the total sum is 46 and the blastabiliy index is obtained BI = 23. From the related formula powder factor of 0.092 (kg/t) is obtained.

2.2 Ghose blastability index

Ghose [32] proposed another blastability index using four geomechanical parameters. These parameters with their ratings are given in Table 2. The blastability index is obtained by adding up the ratings of the four parameters. The value obtained is adjusted to take into account the conditions under which the blast is carried out (Table 3): From the experience in 12 surface mines, the correlation between the blastability index and the powder factor is established. In Table 3, Adjustment Factors and in Table 4, suggested powder factor of Ghose model are mentioned. This correlation was obtained using slurry explosives with detonation velocity of 3800 (m/s). However, this blastability index is limited for surface blasting only and is given by Eq. (2):

$$BI = \left(D + DS + PL + JPO + AF1 + AF2\right) \tag{2}$$

Where, BI: Blastability Index, D: Density (kg/m^3), DS: Discontinuity Spacing (m), PL: Point Load Strength Index (MPa), JPO: Joint Plane Orientation, AF1: Adjustment Factor 1 and AF2: Adjustment Factor 2.

Table 2 Discription of Ghose blastability index

Parameters	Range of values				
D (kg/m^3)	1.3–1.6	1.6–2	2.0–2.3	2.3–2.5	
Rating	20	15	12	6	4
DS (m)		0.2–0.4	0.4–0.6	0.6–2.0	
Rating	35	25	20	12	8
PL (MPa)	≤ 1	1–2	2–4	4–6	≥6
Rating	25	20	15	8	5
JPO	Dip into face	Strike at an acute angle to face	Strike normal to face	Dip out of face	Horizontal
Rating	20	15	12	10	6

Table 3 Ghose blastability Index adjustment factors

Adjustment factors	Values
AF1: Degree of Confinement (DC)	
Highly confined	–5
Reasonably	0
AF2: Bench Stiffness (BS)	
Hole dept/burden >2	0
Hole dept/burden <1.5	–5
Hole dept/burden 1.5–2	–2

Table 4 Ghose blastability Index suggested powder factor

Blastability index	Powder factor (kg/m^3)
70–85	0.2–0.3
60–70	0.3–0.5
50–60	0.5–0.6
40–50	0.6–0.7
30–40	0.7–0.8

Example:

Consider a shale rockmass which the following values correspond: D = 4.2, DS = 0.8, PL = 3.2, JPO = Dip out of face, DC = reasonably and BS = 2.1, the blastabiliy index is obtained BI = 41. From Table (4), a powder factor of 0.7 (kg/m^3) is obtained.

3 Fuzzy set

The concept of Fuzzy Logic (FL) was conceived by Lotfi Zadeh, a professor at the University of California at Berkley, in 1965 [16] and presented as a way of processing data by allowing partial set membership and a mathematical way to represent linguistic vagueness. It can be considered as a generalization of classical set theory. In classic mathematics, classes of objects have precisely defined criteria for membership; an object can take only two states – it either belongs or does not belong to the class. That is, the membership of an element is crisp (0, 1). In the real world, more often than not classes of objects do not have precisely defined criteria for membership. For example, consider definitions of classes: “the class of all real numbers much greater than 1”, “the class of beautiful women” or “the class of tall men” [16]. Yet, the fact is that imprecisely defined classes play an important role in human thinking.

An ‘‘A’’ crisp set of real objects are described by a unique membership function such as X_A in Fig. 1a. Contrary, a fuzzy set is a generalization of an ordinary set which assign the degree of membership for each element to range over the unit interval between 0 and 1 Fig. 1b. That is, the transition from ‘‘belong to a set’’ to ‘‘not belong to a set’’ is gradual, and this smooth transition is characterized by the membership function that give fuzzy sets. Exibility in modeling commonly used linguistic expressions such as ‘‘the uniaxial compressive strength is high’’ or ‘‘highly weathered rock’’.

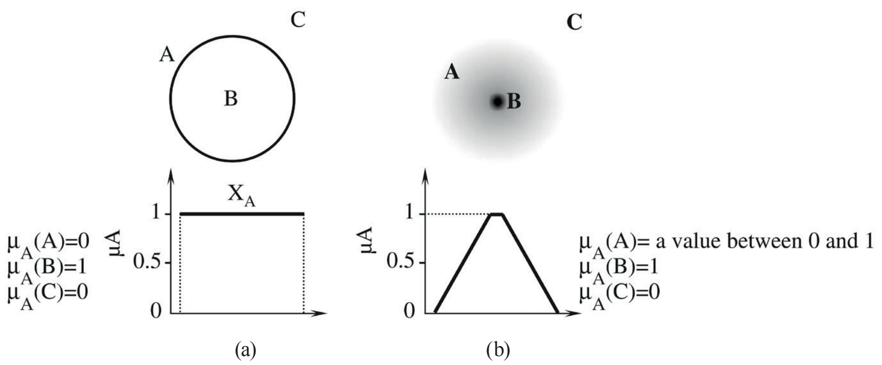

Fig. 1 (a) Crisp set and (b) fuzzy set [14]

In addition, fuzzy set theory can be used for developing rule-based models which combine physical insights, expert knowledge and numerical data in a transparent way that closely resembles the real world. Fuzzy set theory provides a systematic calculus to deal with linguistic information, and it performs numerical computation by using linguistic labels stipulated by membership functions. Moreover, fuzzy ''if–then'' rules form the key component of a Fuzzy Inference System (FIS) that can effectively model human expertise in a specific application.

3.1 Fuzzy if–then rules

To inference in a rule based fuzzy model, the fuzzy proposition need to be represented by an implication function. The implication function is called fuzzy "if–then" rule. A fuzzy if–then rule, also known as the fuzzy rule, assumes the form ''if x is A then y is B" where, A and B are linguistic values defined by fuzzy sets on Universes of discourse X and Y, respectively. Often "x is A" is called the antecedent or premise, while "y is B" is called the consequence or conclusion. Examples of fuzzy if–then rules are widespread in daily linguistic expressions such as "If pressure is high, then volume is small" [36].

Each rule in a fuzzy model is a relation such as $R_i = (X \times Y) \rightarrow [0,1]$ which is calculated by using the Eq. (3).

$$\mu_{R_i}(x,y) = I(\mu_{A_i}(x), \mu_{B_i}(y)) \tag{3}$$

Where $\mu_{Ri}(x,y)$ is the R relation's membership degree of rule i according to "x" and "y" inputs; $\mu_{Ai}(x)$ and $\mu_{Bi}(y)$ are the membership degrees of "x" and "y" inputs, respectively; and "I" denotes the "and" or "or" operator.

Most rule-based systems involve more than one rule. The process of obtaining the overall consequent (conclusion) from the individual consequents contributed by each rule in the rule base is known as aggregation of rules. In determining an aggregation strategy two simple extreme cases exist, namely; conjunctive system of rules and disjunctive system of rules [37].

3.1.1 Conjunctive system of rules

In the case of system of rules that must be jointly satisfied, the rules are connected by "and" connectives. In this case aggregated output, y, is found by the fuzzy intersection of all individual rule consequents, y^i, where $i = 1, 2, \dots r$ as $y = y^1$ and y^2 and … and y^r or $y = y^1 \cap y^2 \cap \dots \cap y^r$ which is defined by the membership function, Eq. (4) [37].

$$\mu_y(y) = \min(\mu_y^1(y), \mu_y^2, ..., \mu_y^r(y)) \;\; for\; y \in Y. \tag{4}$$

3.1.2 Disjunctive system of rules

For the case of a disjunctive system of rules where the satisfaction of at least one rule is required, the rules are connected by "or" connectives. In this case, aggregated output is found by the fuzzy union of all individual rule contributions, as $y = y^1$ or y^2 or … or y^r or $y = y^1 \cup y^2 \cup \dots \cup y^r$ which is defined by the membership function, Eq. (5) [37].

$$\mu_y(y) = \max(\mu_y^1(y), \mu_y^2, ..., \mu_y^r(y)) \;\; for\; y \in Y. \tag{5}$$

3.2 Fuzzy inference system

The Fuzzy Inference System (FIS) is a popular computing framework based on the concepts of fuzzy set theory, fuzzy if–then rules, and fuzzy reasoning. FISs have been successfully applied in fields such as automatic control, data classification, decision analyses, expert systems, and computer vision. Because of its multidisciplinary nature, FISs are associated with a number of names such as fuzzy rulebased systems, fuzzy expert systems, fuzzy modeling, fuzzy associative memory, fuzzy logic controllers and simply fuzzy models [15, 36, 38].

The basic structure of a FIS consists of three conceptual components; a rule base, which contains the selection of rules; a database, which defines the membership functions used in the fuzzy rules; and a reasoning mechanism, which performs the inference procedure upon the rules and given facts to derive a reasonable output or conclusion. Basic FIS can take either fuzzy

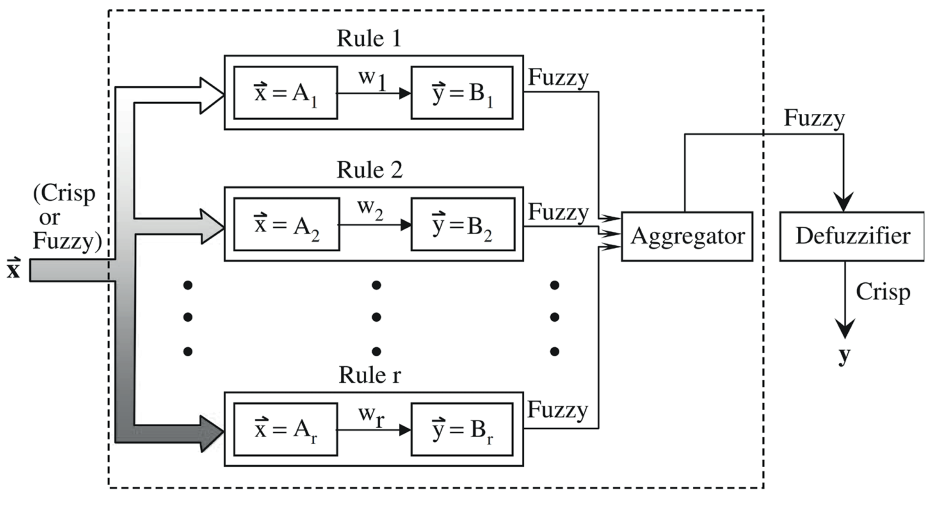

Fig. 2 Block diagram for FIS [36]

inputs or crisp inputs, but the outputs it produces are almost always fuzzy sets. In cases where a crisp value is needed, defuzzification method should be carried out. A FIS with a crisp output is shown in Fig. 2, where the dashed line indicates a basic FIS with fuzzy output and the defuzzification block serving for transforming an output fuzzy set into a crisp single value.

There are several FISs that have been employed in various applications. The most commonly used include:

- Mamdani fuzzy model;
- Takagi–Sugeno–Kang fuzzy (TSK) model;
- Tsukamoto fuzzy model;
- Singleton fuzzy model.

The differences between these FISs lie in the consequents of their fuzzy rules, and thus their aggregation and defuzzification procedures differ accordingly. In this paper, the Mamdani fuzzy model is widely used since this model is easier to interpret and analyze when compared with the others [15, 39–42].

3.2.1 The Mamdani fuzzy model

The Mamdani FIS was first proposed as an attempt to control a steam engine and boiler combination by a set of linguistic control rules obtained from experienced human operators [43]. This fuzzy approach proved to be a very effective way to cope with the non-linearity and the dynamic behavior of the plant.

The Mamdani method is perhaps the most appealing fuzzy method to be employed in engineering geological problems. For example, geological processes or phenomena are described with simple vague predicates such as ‘‘the weathering degree of the rock mass is high’’ [15]. In the Mamdani fuzzy model, the “if–then” rules take place of the usual set of equations used to characterize a system. The general “if–then” rule structure of the Mamdani algorithm is given in the Eq. (6):

$$R_i = If\,"x_1"is"A_{i1}"and"x_2"is"A_{i2}"and..."x_r"is"A_{ir}" \\ then"y"is"b_i"\left(for\; i=1,2,\ldots,k\right) \tag{6}$$

where "x_i" (r = 1, 2, …, R) are the input variables (antecedent variables), "A_{ir}" and "b_i" are linguistic terms or fuzzy sets which are defined by the membership functions "A_{ir} (x_r)" and "b_i", "y" is the output variable (consequent variable), and "k" is the number of rules. Although many methods of composition of fuzzy relations (e.g. min–max, max–max, min–min, max–mean, etc.) exist in the literature, max–min and max–product compositions are the two most commonly used techniques [37]. Fig. 3 is an illustration of a two-rule Mamdani FIS which derives the overall output "z" when subjected to two crisp inputs and "y" [36].

Inputs in the FIS, "x" and "y", are crisp values. The rule-based system is described by Eq. (6). Based on the Mamdani implication method (Eq. (4)) and for a set of disjunctive rules, the aggregated output for the "k" rules is given by Eq. (7)

$$\mu_{C_k}(z) = \max_k[\min[\mu_{A_k}(input(x)), \mu_{B_k}(input(y))]] \\ k = 1,2,...,r. \tag{7}$$

Where μ_{Ck} , μ_{Ak} and μ_{Bk} are the membership functions of output "z" for rule "k", input "x"and input "y", respectively. Eq. (7) has the simple graphical interpretation as shown in Fig. 3. Fig. 3 illustrates the graphical analyses of the two rules, where symbols A_1 and B_1 refer to the first and second fuzzy antecedents of the first rule, respectively. The symbol C_1 refers to fuzzy consequent of the first rule; A_2 and B_2 refer to the first and second fuzzy antecedents of the second rule, respectively, C_2 refers to fuzzy consequent of the second rule. The minimum function in Eq. (7) arises because the antecedent pairs given in the general rule structure for this system are connected by a logical ‘‘and’’ connective as seen in Eq. (6). The minimum membership value for the antecedents propagates through to the consequent and truncates the membership function for the consequent of each rule. This graphical inference is done for each rule. Then the truncated membership functions for each

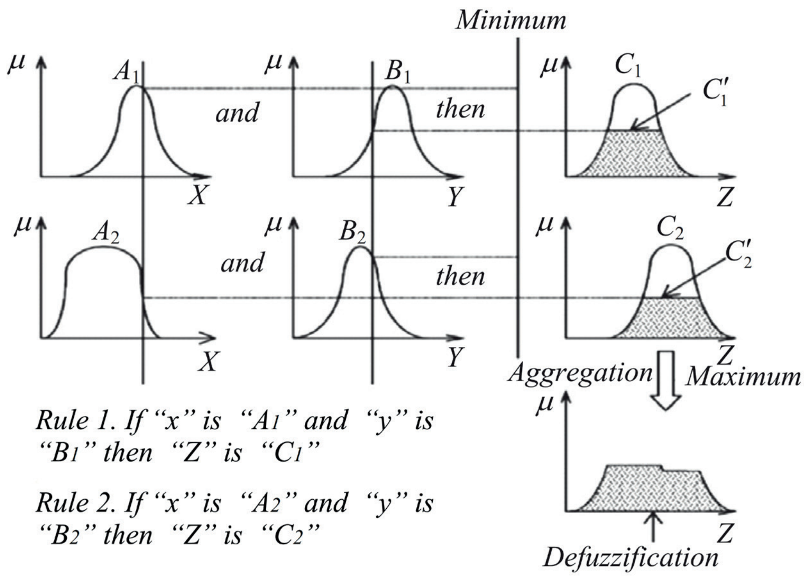

Fig. 3 The Mamdani FIS [36]

rule are aggregated using Eq. (4) for conjunctive rules or Eq. (5) for disjunctive rules. In Fig. 3, the rules are disjunctive so the aggregation operation max results in an aggregated membership function comprised of the outer envelope of the individual truncated membership forms from each rule. If a crisp value is needed for the aggregated output, some appropriate defuzzification technique should be employed to the aggregated membership function [37].

3.3 Defuzzification methods

Defuzzification refers to the way a crisp value is extracted from a fuzzy set as a representative value. Although there are a number of defuzzification methods in the literature such as Centroid of Area (COA) or center of gravity, mean of maximum, smallest of maximum, etc., the most widely adopted defuzzification method is COA method [15, 44-46]. In this study, the crisp value adopting the COA defuzzification method was obtained Eq. (8).

$$z^*_{COA} = \frac{\int_z \mu_A(z) z dz}{\int \mu_A(z) dz}, \tag{8}$$

Where z^*_{COA} is the crisp value for the "z" output and μ_A is the aggregated output membership function.

4 Input–output sets and rule consequents

The main elements of a fuzzy algorithm are the input–output sets and ''if–then'' rules. In this study, the input variables of the fuzzy model were based on Lilliy's description were: the Rock mass RMD, JPS, JPO, SGI and H (Table 1) And for the fuzzy model based on Ghose description were: D, DS, PL, JPO, DC and BS (Table 2 and 3).

These parameters were then represented by fuzzy sets as the input variables of the fuzzy model. In the present fuzzy model, triangular and trapezoidal membership functions were developed as they are the most common type of membership functions used in rule-based fuzzy modeling [9, 14, 15, 41, 47, 48].

The output of the fuzzy model is a final index rating, indicating the value of blastability. The final stage of the model is the construction of the ''if–then'' rules. The ''if–then'' rules were introduced to the fuzzy model by considering the rating probabilities which could be obtained from the adopted blastability index rating method. As the rating system has some parameters and each parameter has some subclasses, the number of ''if–then'' rules is multiplication of number of subclasses. However; some rules that are not likely to come true due to the nature of rock mass could be eliminated from the model.

5 Estimation of the BI based upon fuzzy set theory

Upon assigning a suggested rating for each input parameter from Table 1 and 2 Deficiency of the conventional classification schemes is the existence of sharp transitions between two adjacent classes. The above mentioned uncertainties or fuzziness encountered in the practical application of conventional rock excavation classification systems can be processed by using fuzzy set theory which enables a soft approach to handle such uncertainties. In our fuzzy model for blastability index for Lilly and Ghose that were mentioned above it written 80 rules for Ghose model and 135 rules for Lilly using the specific ranges as mentioned in Table 2 and 3 then some data has been analyzed by fuzzy model to obtain the outputs that were based on defining of our inputs and rules. The results of analyses are shown in Table 5 and 6. As it has been shown if the inputs to be as Table 5 the output from fuzzy model will be 30 for both rock masses that are chosen, as it is clear their parameter are same except JPS, that is 0.95 m for the rockmass1 and 1.05 m for rock mass 2. From an experienced field engineer view there is no significant difference between these rock masses. However conventional classification shows a great difference about 5 points (according to Lilly model). This problem can be solved by fuzzy method. The same experimented is used for Ghose model too. The result of this analysis is shown in Table 5 and 6.

Table 5 Comparison between the two different rock masses in terms of Lilly blastability

Classification parameter	Rock mass properties			
	Rock mass 1	Rating	Rock mass 2	Rating
RMD	Blocky	20	Blocky	20
JPS	0.95	10	1.05	20
JPO	Horizontal	10	Horizontal	10
SGI	2.5	12.5	2.5	12.5
H	5	5	5	5
Final BI		28.75		33.75
Fuzzy model		30		30

Table 6 Comparison between the two different rock masses in terms of Ghose blastability

Classification parameter	Rock mass properties			
	Rock mass 1	Rating	Rock mass 2	Rating
D	1.60	20	1.65	15
DS	0.2	35	0.25	25
PL	1	25	1.1	20
JPO	Dip into face	20	Dip into face	20
DC	Highly confined	-5	Highly confined	-5
BS	1.55	-5	1.65	-2
Final BI		90		73
Fuzzy model		83.2		82.4

6 Application of the method to case studies

This part has been assigned to comparison the result from fuzzy model and conventional classification when using Iranian mine and dam sites, include Chadormalu iron mine [49], Maydook copper mine [50, 51] , Sechahun iron mine [52], Choghart iron mine [53], Pirbakran limestone mine [54],

Table 7 Field data results according to Lilly BI

Site	District	Zone	RMD	JPS	JPO	SGI (t/m3)	HD	Total	Fuzzy
1	Chadormalu iron mine	M1	Total massive	Intermediate	Dip out of face	4.2	6	75.5	75
2	Chadormalu iron mine	W1	Total massive	Intermediate	Dip out of face	4	5	72.5	75
3	Chadormalu iron mine	M2	Blocky	Intermediate	Dip into face	4.2	6	70.5	70
4	Chadormalu iron mine	W2	Blocky	Intermediate	Dip into face	4	5	67.5	65
5	Chadormalu iron mine	M3	Blocky	Intermediate	Strike normal to face	4	6	63	65
6	Chadormalu iron mine	W3	Blocky	Intermediate	Strike normal to face	3.6	5	57.5	52
7	Maydook copper mine	EM	Blocky	Intermediate	Dip out of face	2.5	5	38.5	45
8	Maydook copper mine	EW	Blocky	Wide	Dip out of face	2.6	5	55	56
9	Maydook copper mine	WM	Blocky	Intermediate	Dip into face	2.51	5	48.5	50.1
10	Maydook copper mine	WW	Blocky	Wide	Dip into face	2.6	5	65	65
11	Sechahun iron mine	MHHG	Blocky	Close	Dip out of face	4.2	5.5	67.75	65
12	Sechahun iron mine	MSHG	Blocky	Intermediate	Dip out of face	4.2	5.5	72.75	60
13	Sechahun iron mine	MHLG	Blocky	Close	Dip out of face	3.2	6	43	40
14	Sechahun iron mine	WSHG	Blocky	Close	Dip out of face	2.77	5.8	37.52	40
15	Sechahun iron mine	W	Blocky	Intermediate	Dip out of face	2.87	5.9	43.82	40.5
16	Choghart iron mine	MBIII	Blocky	Intermediate	Dip out of face	4.3	6	61.5	60
17	Choghart iron mine	MBII	Blocky	Intermediate	Strike normal to face	3.5	5	56	53
18	Choghart iron mine	MBII	Blocky	Intermediate	Strike normal to face	3.5	5	56	50
19	Choghart iron mine	MBI	Blocky	Intermediate	Dip out of face	4.3	6	61.5	60
20	Choghart iron mine	MBI	Blocky	Intermediate	Dip into face	4.3	6	71.5	70
21	Choghart iron mine	WBIII	Blocky	Intermediate	Dip out of face	3.5	5.5	46.25	52
22	Choghart iron mine	WBII	Blocky	Intermediate	Strike normal to face	2.7	4	45.5	51
23	Choghart iron mine	WBII	Blocky	Intermediate	Strike normal to face	2.7	4	45.5	50
24	Choghart iron mine	WBI	Blocky	Intermediate	Dip out of face	3.5	5.5	46.25	52
25	Pirbakran limestone mine	I	Blocky	Intermediate	Strike normal to face	2.6	4	44.5	45
26	Pirbakran limestone mine	B	Powdery	Intermediate	Strike normal to face	2.4	4.5	37.25	35
27	Pirbakran limestone mine	SI	Blocky	Intermediate	Strike normal to face	2.4	4	42	40
28	Gotvand dam	R1	Blocky	Intermediate	Strike normal to face	2.55	4.5	44.125	40.7
29	Gotvand dam	R2	Blocky	Intermediate	Strike normal to face	2.65	4.5	45.37	42.1
30	Gotvand dam	U	Powdery	Close	Dip into face	2.15	4.5	39.25	40
31	Golegohar iron mine	MN	Total massive	Wide	Dip out of face	4.2	6	90.5	88.3
32	Golegohar iron mine	WM	Blocky	Intermediate	Dip out of face	2.6	4.5	39.75	45
33	Golegohar iron mine	MS	Powdery	Intermediate	Dip into face	4.2	6	65.5	65
34	Golegohar iron mine	WS	Powdery	Intermediate	Dip into face	2.6	4.5	44.75	45
35	Golegohar iron mine	ME	Total massive	Wide	Dip out of face	4.2	6	90.5	88.3
36	Golegohar iron mine	WE	Blocky	Intermediate	Dip out of face	2.6	4.5	39.75	45
37	Golegohar iron mine	MW	Total massive	Wide	Dip into face	4.2	6	100	93.3
38	Golegohar iron mine	MW	Blocky	Intermediate	Dip into face	2.6	4.5	49.75	51.4
39	Angouran Zinc mine	MNW	Blocky	Intermediate	Dip out of face	3.6	5	52.5	54.4
40	Angouran Zinc mine	MNW	Blocky	Intermediate	Dip out of face	3.6	5	52.5	54.4
41	Angouran Zinc mine	MNW	Powdery	Intermediate	Dip out of face	2.9	4.5	38.5	35
42	Angouran Zinc mine	WNW	Blocky	Intermediate	Dip out of face	2.8	4.5	42.25	45
43	Angouran Zinc mine	WNW	Blocky	Intermediate	Dip out of face	2.6	4.5	39.75	44

Gotvand dam [55], Golegohar iron mine [56], Angouran Zinc mine [57]. The blastability classes for each site, determined from both the conventional classification BI method and the presently constructed fuzzy model, are given in Table 7 and 8. In the conventional method, the existence of sharp transitions between two adjacent classes, and the uncertainties on data that are close to the range boundaries of rock classes may present some problems in practical applications. The fuzzy model enables the engineer to overcome such uncertainties in decision-making processes.

Table 8 Field data results according to Ghose BI

Site	District	Zone	Density (kg/m^3)	DS (m)	PL (MPa)	JPO	DC	BS	Total	Fuzzy
1	Chadormalu iron mine	M1	4.2	0.8	3.2	Dip out of face	Reasonably	2.1	41	38
2	Chadormalu iron mine	W1	4	0.8	3.9	Dip out of face	Reasonably	1.8	39	42.9
3	Chadormalu iron mine	M2	4.2	0.65	3.1	Dip into face	Reasonably	2.1	51	50
4	Chadormalu iron mine	W2	4	0.55	2.9	Dip into face	Reasonably	1.8	57	54.1
5	Chadormalu iron mine	M3	4	0.65	3	Strike normal to face	Reasonably	1.8	41	42.5
6	Chadormalu iron mine	W3	4.6	0.5	2.6	Strike normal to face	Reasonably	1.6	49	43
7	Maydook copper mine	EM	2.41	0.8	2.6	Dip out of face	Reasonably	2	43	47.1
8	Maydook copper mine	EW	2.6	1	4.7	Dip out of face	Reasonably	2	34	35.1
9	Maydook copper mine	WM	2.45	0.5	2.8	Dip into face	Reasonably	2	61	61
10	Maydook copper mine	WW	2.6	1.2	4.8	Dip into face	Reasonably	2	44	46.3
11	Sechahun iron mine	MHHG	4.2	0.08	3.1	Dip out of face	Reasonably	1.76	62	65.8
12	Sechahun iron mine	MSHG	4.2	0.12	1.54	Dip out of face	Reasonably	2	67	66.1
13	Sechahun iron mine	MHLG	3.2	0.08	3.1	Dip out of face	Reasonably	2	62	65.8
14	Sechahun iron mine	WSHG	2.77	0.09	2.33	Dip out of face	Reasonably	1.6	62	60.3
15	Sechahun iron mine	W	2.87	0.12	2.45	Dip out of face	Reasonably	1.6	62	60.1
16	Choghart iron mine	MBIII	4.3	0.7	2.28	Dip out of face	Reasonably	2	30	48.6
17	Choghart iron mine	MBII	3.5	0.65	3.46	Strike normal to face	Reasonably	1.8	30	43
18	Choghart iron mine	MBII	3.5	0.65	3.46	Strike normal to face	Reasonably	1.8	30	43
19	Choghart iron mine	MBI	4.3	0.3	2.62	Dip out of face	Reasonably	1.6	36	49.5
20	Choghart iron mine	MBI	4.3	0.4	2.62	Dip into face	Reasonably	1.6	46	50
21	Choghart iron mine	WBIII	3.5	0.65	2.29	Dip out of face	Reasonably	1.8	30	48.8
22	Choghart iron mine	WBII	2.7	0.55	3.46	Strike normal to face	Reasonably	1.53	38	42.4
23	Choghart iron mine	WBII	2.7	0.55	3.46	Strike normal to face	Reasonably	1.53	38	42.4
24	Choghart iron mine	WBI	3.5	0.25	2.62	Dip out of face	Reasonably	1.8	41	48.4
25	Pirbakran limestone mine	I	2.6	0.5	2.9	Strike at an acute angle to face	Highly	1.6	52	55
26	Pirbakran limestone mine	B	2.4	0.17	1.65	Strike at an acute angle to face	Reasonably	1	69	60
27	Pirbakran limestone mine	SI	2.4	0.35	1.65	Strike at an acute angle to face	Reasonably	1.25	59	60.9
28	Gotvand dam	R1	2.55	0.65	1.45	Strike normal to face	Reasonably	1.2	43	45
29	Gotvand dam	R2	2.65	0.65	1.55	Strike normal to face	Highly	1.2	38	32.7
30	Gotvand dam	U	2.15	0.05	0.85	Dip into face	Reasonably	1	87	60
31	Golegohar iron mine	MN	4.2	1	3.4	Dip out of face	Reasonably	0.51	41	45
32	Golegohar iron mine	WM	2.6	0.5	2.4	Dip out of face	Reasonably	1.87	47	50
33	Golegohar iron mine	MS	4.2	0.2	3.4	Dip into face	Reasonably	2.15	64	60
34	Golegohar iron mine	WS	2.6	0.15	2.4	Dip into face	Reasonably	1.5	72	78.4
35	Golegohar iron mine	ME	4.2	1	3.4	Dip out of face	Reasonably	2.5	41	38.2
36	Golegohar iron mine	WE	2.6	0.5	2.4	Dip out of face	Reasonably	1.87	47	50
37	Golegohar iron mine	MW	4.2	1	3.4	Dip into face	Reasonably	2.5	51	50
38	Golegohar iron mine	MW	2.6	0.5	2.4	Dip into face	Reasonably	1.87	57	55
39	Angouran Zinc mine	MNW	3.6	0.5	3	Dip out of face	Reasonably	1.6	57	55
40	Angouran Zinc mine	MNW	3.6	0.2	3.3	Dip out of face	Reasonably	1.6	62	78.4
41	Angouran Zinc mine	MNW	2.6	0.25	2.2	Dip out of face	Reasonably	1.6	62	65.3
42	Angouran Zinc mine	WNW	2.8	0.65	3	Dip out of face	Reasonably	1.2	46	60
43	Angouran Zinc mine	WNW	2.6	0.2	2.9	Dip out of face	Reasonably	1.2	57	78.3

7 Conclusions

Rock mass BI is a measure of the resistance of a rock mass to blasting. Accurate methods of estimating the BI is very important in rock blasting. Various empirical classification systems have been proposed by a number of researchers. BI classification systems assign quantifiable values to selected rock mass characteristics. The resulting ratings are then related to classifying the rock mass behavior in the blasting. Despite their widespread use in hard rock mining, they have some common deficiencies leading to uncertainties in their practical applications. These deficiencies are particularly related with the existing sharp transitions between two adjacent classified classes in geomechanical characters and the subjective uncertainties on data that are close to the range boundaries of these characters.

The present paper has tried to investigate the influence of rock mass quality characteristics on blasting results using fuzzy sets. The basic principles of the fuzzy set theory were described and then the fuzzy set theory was applied to the Lilly BI and Ghose BI conventional classification systems by following the Mamdani fuzzy algorithm.

It was shown that the fuzzy set theory could effectively overcome the uncertainties encountered in the practical applications of conventional BI classification systems, and also provides more information on the obtained final ratings. To be able to check the performance of this approach in practice, hard rock mining data in Iranian mine and dam sites as case studies were used.

The outputs of BI rating method and fuzzy model indicate that there is admissible agreement between ratings obtained from the conventional method and the fuzzy model.

Generally BI values are obtained both from the fuzzy BI and the conventional BI chart; fuzzy sets seem to provide a more practical way for the cases where limited data with some uncertainties are available. The fuzzy model is providing more detailed information about sites which have identical blastability classes. For example, in the conventional Ghose BI method the Blastability conditions for sites 16 and 17 are assigned with a same final rating of 30 (Table 8). However, the fuzzy model indicates BI for sites 16 and 17 are 48.6 and 43, respectively. Therefore, it can be concluded that the blastabilty at Site 17 should relatively be convenient than that of site 16.

The suggested approach takes into account of important rock mass uncertainty in estimation of the BI value which is an input parameter of specific charge estimator model.

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