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PREDICTION OF ROCK MASS RATING USING FUZZY LOGIC WITH SPECIAL ATTENTION TO DISCONTINUITIES AND GROUND WATER CONDITIONS

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ABSTRACT: The Rock Mass Rating (RMR) system is a classification based on the six parameters which was defined by Bieniawski. This system may possess some fuzziness in its practical applications. For example, experts mostly relate discontinuities and ground water conditions in linguistic terms with approximation. Descriptive terms vary from one expert to the other, while in the RMR system; values which are related to these terms are probably the same. The other hand, sharp transitions between two classes create uncertainties. So it is proposed to determine weighting intervals for discontinuities and water condition. Two fuzzy models based on the Mamdani algorithm were introduced to evaluate proposed weights, so that the first fuzzy model includes 55 scores using fuzzy model and the remained scores which are related to discontinuities and ground water conditions are obtainable by the RMR system. But the second fuzzy model obtains all scores of the RMR system using fuzzy model. Results of fuzzy models are adapted with actual RMR, but second fuzzy model predicts more acceptable results, because it has the ability to use qualitative terms in fuzzy state. But first fuzzy model uses descriptive terms in classic state. So it seems, proposed weighting intervals can manage fuzzification of discontinuities and water conditions.

INTRODUCTION

Bieniawski developed a Rock Mass Rating (RMR) system based on six parameters: (1) The Uniaxial Compressive Strength of intact rock (UCS), (2) Rock Quality Designation (RQD), (3) Joint or Discontinuity Spacing (JS), (4) Joint Condition (JC), (5) Ground Water Condition (GW) and (6) Joint Orientation (JO). He assigned numerical rating values to all these parameters. Based on the value of the rock mass rating, Bieniawski divides the whole universe of rock mass into five classes, and then assigns stand up time to each class (Hudson and Harrison, 2005).

The arithmetic sum of the rating corresponding to the five main parameters is referred to as "the basic RMR" (Figure 1). But the total RMR is obtained by adjusting the basic RMR for the influence of joint orientation for a specific excavation face (Figure 1) (Aydin, 2004).
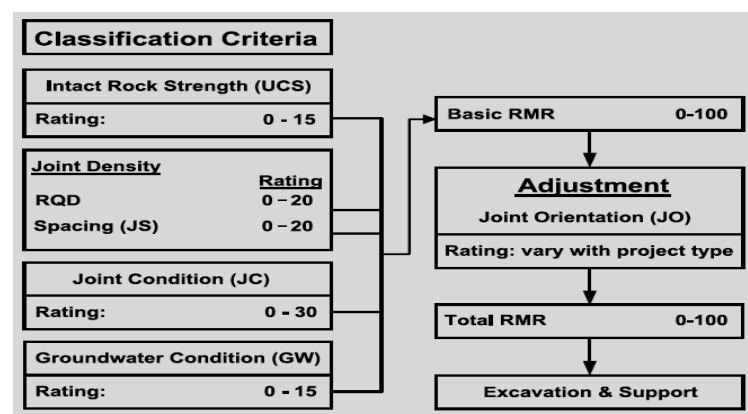

Figure 1 - RMR classification for characterization and design purposes (after Aydin, 2004)

Bieniawski Rock Mass Classification often involves criteria whose values are assigned in linguistic terms and the other hand, sharp class boundaries are a subjective uncertainty in rock mass classification. Fuzzy set theory enables a soft approach to account for these uncertainties. Actually, fuzzy sets make them more objective, particularly through the process of construction of Membership Functions (MFs).

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UCS, RQD and JS are the numerical criteria but JC and GW are expressed mostly in descriptive terms. For fuzzification of descriptive criteria (JC and GW), it is necessary to consider these criteria quantitatively.

In this study, for quantitation of JC and GW, the weights are proposed for each of them. Also for validation of these weights two fuzzy models are introduced, so that, the first fuzzy system obtains basic RMR without descriptive criteria and the second one obtains basic RMR with descriptive criteria.

FUZZY SET THEORY

The fuzzy set was introduced as a mathematical way to represent linguistic vagueness. The fuzzy logic is useful to process the imprecise information by selecting a suitable MF. In a classical set, an element belongs to or does not belong to a set. That is, the membership of an element is crisp, 0 or 1, against; a fuzzy set is a generalization of an ordinary set which assigns the degree of membership for each element to range over the unit interval between 0 and 1 (Iphar and Goktan, 2006). The membership or non membership of an element x in the crisp set A is represented by the characteristic function μ_A of A, defined by (Acaroglu *et al*., 2008)

$$\mu_{(A)}x = \begin{cases} 1 & If \quad x \in A \\ 0 & If \quad x \notin A \end{cases} \qquad (1)$$

Where $\mu_{(A)}x$ is the membership degree of the variable *x*. An MF fulfils fuzzification of input/output variables. The shapes of the MFs normally were considered trapezoidal or triangular. Describing input–output relationship, conditional rules is an important aspect in the fuzzy system. The fuzzy proposition is represented by a functional implication called as fuzzy "if–then" rule (Iphar and Goktan, 2006).

FUZZY INFERENCE SYSTEM

The Fuzzy Inference System (FIS) is a famous computing system which is based on the concepts of fuzzy set theory, fuzzy if–then rules, and fuzzy reasoning (Ross, 1995). Several FIS have been employed in different applications. The most commonly models are the Mamdani fuzzy model, Takagi–Sugeno–Kang (TSK) fuzzy model, Tsukamoto fuzzy model and Singleton fuzzy model (El-Shayeb, *et al.*, 1997), but among the aforesaid models, Mamdani is one of the most common algorithms used in fuzzy systems. The Mamdani fuzzy algorithm takes the following form (Iphar and Goktan, 2006).

$$R_i = \text{If "}x_1\text{" is "}A_{i1}\text{" and "}x_2\text{" is "}A_{i2}\text{" and "}x_r\text{" is "}A_{ir}\text{" then "}y\text{" is "}B_i\text{"} \quad (\text{for } i=1, 2,\dots, k) \quad (2)$$

Where: x_1 and x_2 are input variables, A_{i1}, A_{ir} and B_i are linguistic terms (fuzzy sets), y is output variable and k is the number of rules. Figure 2 is an illustration of a two-rule Mamdani FIS which derives the overall output "z" when subjected to two crisp inputs "x" and "y" (Jang *et al.*, 1997). Inputs in the FIS, "x" and "y", are crisp values. The rule-based system is described by Eq. 2. For a set of disjunctive rules, the aggregated output for the "k" rules is given by

$$\mu_{ck}(z) = \max_k [\min[\mu_{Ak}(input(x)), \mu_{Bk}(input(y))]] \quad (\text{for } k=1,2,\dots,r) \quad (3)$$

Where: μ_{C_k}, μ_{A_k} and μ_{B_k} are the membership function of output "z" for rule "k", input "x" and input "y", respectively. Eq. 3 has a simple graphical interpretation as shown in Figure 2.

In Figure 2 symbols A1 and B1 refer to the first and second fuzzy antecedents of the first rule, respectively. The symbol C1 refers to fuzzy consequent of the first rule, A2 and B2 refer to the first and second fuzzy antecedents of the second rule, respectively, C2 refers to fuzzy consequent of the second rule. The minimum membership value for the antecedents propagates through to the consequent and truncates the MF for the consequent of each rule. Then the truncated MFs for each rule are aggregated. In Figure 2, the rules are disjunctive so the aggregation operation max results in an aggregated MF 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 MF (Ross, 1995). There are several defuzzification methods such as Centroid of Area (COA) or Center of Gravity, Mean of Maximum, Smallest of Maximum, etc (Grima, 2000,

Hellendoorn and Thomas, 1993). In Figure 2, the COA defuzzification method is used for obtaining the numeric value of output.
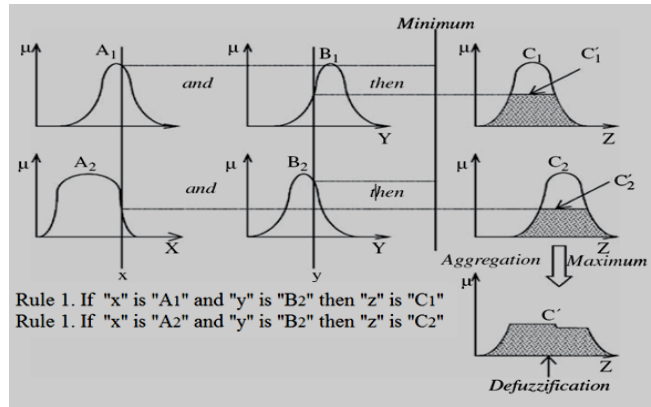

Figure 2 - The Mamdani FIS (after El-Shayeb *et al.*, 1997)

QUANTITATION OF DESCRIPTIVE CRITERIA

Experts mostly relate JC and GW condition in linguistic terms with approximation and possibility. It means expression descriptive terms vary from one expert to the other, while in the RMR system (Bieniawski, 1989), values which are related to these terms are probably the same.

Therefore it is proposed to determine weighting intervals for descriptive classes in RMR system (Bieniawski, 1989) (JC and GW). Table 1 shows the proposed weights for qualitative criteria. As can be seen in table.1 JC and GW criteria are weighted in intervals [0, 1] and [0, 0.8], respectively.

Table 1 - Proposed weights for JC and GW

Descriptive of JC	Smooth soft filling separation <5	Smooth to slightly rough, soft filling mud- weather	Slightly rough, highly-weathered Separation <1mm	Slightly rough Slightly weathered separation <1mm	Very rough unweathered separation <0.1mm
RMR score	0	10	20	25	30
Proposed weighting	0-0.1	0.1-0.45	0.45-0.65	0.65-0.8	0.8-1
Descriptive of GW	Flowing	Dripping	Wet	Damp	Completely rry
RMR score	0	4	7	10	15
Proposed weighting	0-0.1	0.1-0.25	0.25-0.4	0.4-0.6	0.6-0.8

CONSTRUCTION OF TWO MAMDANI FIS FOR RMR PREDICTION

Two fuzzy models based on the Mamdani algorithm are introduced and applied for basic RMR prediction. In both models, the COA defuzzification method is used for obtaining the numeric value of output and also "min" and "max" are employed as "and" and "or", respectively. The crisp value adopting the COA defuzzification method was obtained by (Grima, 2000)

$$Z_{COA}^* = \frac{\int \mu_A(z).Z\,dz}{\int \mu_A(z)\,dz}$$ (4)

Where: is the crisp value for the "z" output and,
         (*z*) is the aggregated output MF.

As can be seen in Figure 3, the first fuzzy model (FIS A) constructed with three inputs and one output and the second fuzzy model (FIS B) constructed with five inputs and one output. To estimate RMR; UCS, RQD and JS are used as input parameters for FIS A and three aforesaid inputs mid JC and GW are used as input parameters for FIS B.
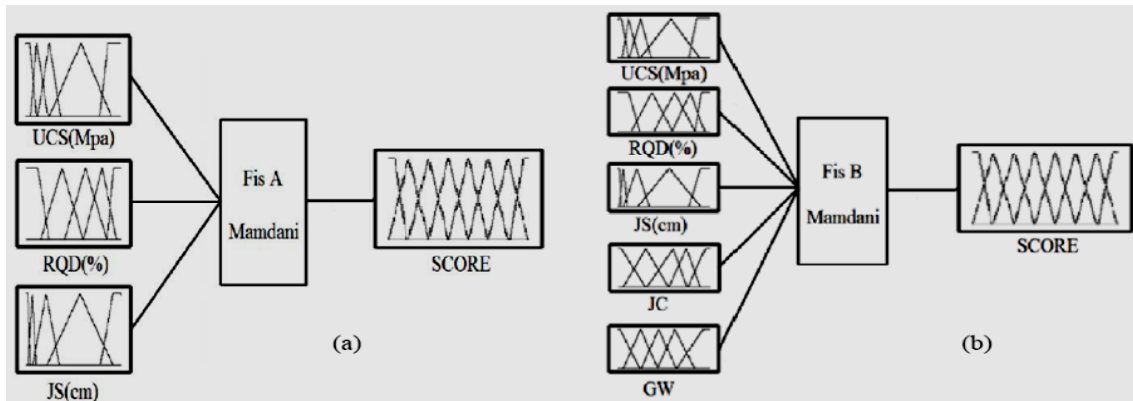

Figure 3 - Main structure of fuzzy models: (a) FIS A; (b) FIS B

In Figure 4 the MFs of input parameters were abbreviated and indicated. As can be seen in Figure 4, triangular and trapezoidal MFs were considered appropriate for the proposed fuzzy models. For example "VB" is used for "very bad", "B" for "bad", "M" for "medium", "G" for "good" and "E" for "excellent".
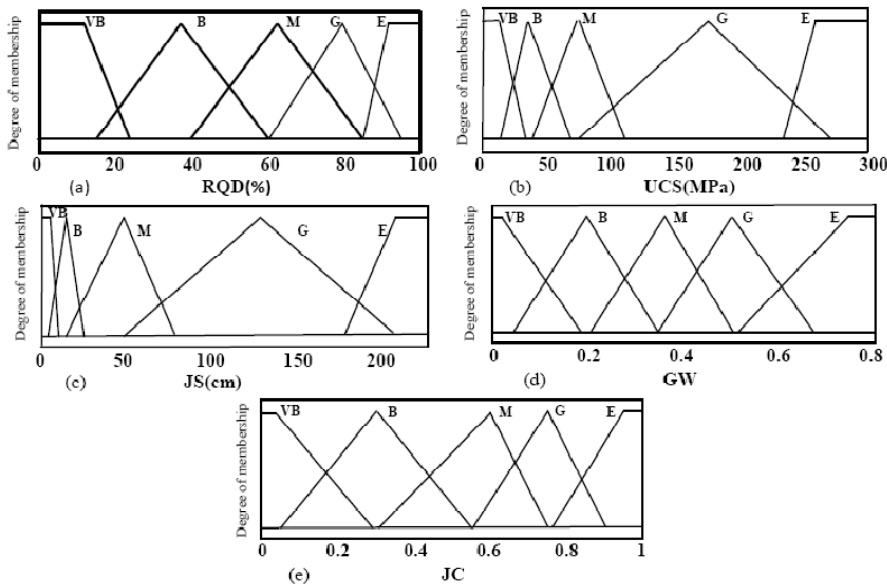

Figure 4 - Fuzzy input parameters: (a) MFs of RQD; (b) MFs of UCS; (c) MFs of JS; (d) MFs of GW; (e) MFs of JC

In both models, the output MFs consists of eight fuzzy sets (Figure 5) in terms "Very Very Bad", "Very Bad", "Bad", "Medium", "Good", "Very Good", "Very Very Good" and "Excellent". Also triangular and trapezoidal MFs were considered for the fuzzy model outputs. The range of rating FIS A output is interval [0, 55], but FIS B output is interval [0,100]. A total of 125 rules for FIS A and 375 rules for FIS B were utilized and a decision was made out of the combined input(premise part) and output(consequent part) membership functions based on expert experience and the applied database. An example of the if-then rules in FIS A and FIS B is as follows:

Rule of FIS A: If (UCS is G) and (RQD is M) and (JS is E) then (SCORE is VVG)   (5)

Rule of FIS B: If (UCS is E) and (RQD is G) and (JS is B) and (JC is B) and (GW is B) then (SCORE is G)   (6)
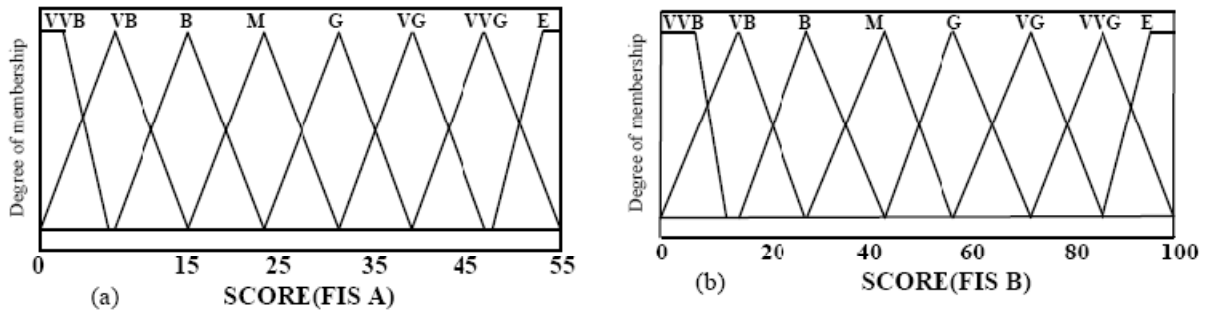
Figure 5 - Fuzzy output parameters: (a) MFs of FIS A output; (b) MFs of FIS B output

In FIS A, the range of rating output belongs to the interval [0,55], and to achieve a basic RMR, it is necessary to add FIS A output to the sum of scores obtained from JC and GW. It should be noted that scores of JC and GW, which are achieved from the RMR system, were used as the reference classification structure. But FIS B output is equal to the basic RMR. The shape and range of FIS A inputs MFs are equal to the first three FIS B inputs MFs; in addition to this, the shapes of output MFs for both models are the same. But the range of output MFs in the FIS A model belongs to the interval [0, 55] and the range of output MFs in the FIS B model belongs to the interval [0,100]. So the range of JC and GW MFs in FIS B are modified upon proposed weights in Table 1. In fact, the purpose of expression of two fuzzy models (FIS A and FIS B) in this study is evaluation of proposed weights for the JC and GW. In other word, FIS A and FIS B are compared to show the importance of fuzzification JC and GW parameters in the classification system. FIS A obtains 55 scores with the use of fuzzy model and the rest of scores, which consist of descriptive terms obtained by the RMR system, but FIS B obtains the total scores of the RMR system (Bieniawski, 1989) from fuzzy model.

SIMULATION RESULTS

To validate and compare the acquired results between the FIS A and FIS B models, correlation R^2 and Root Mean Square Error (RMSE) can be used . Here R^2 is used to validate the predictive models based on the comparing predicted and measured (real) values, whereas, RMSE is used to compare the result of FIS A and FIS B models. RMSE is calculated by the following equation:

$$RMSE(A) = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(A_{imeas} - A_{ipred})^2} \qquad (7)$$

Where: A_{imeas} is the ith measured element,

   A_{ipred} is the ith predicted element and

   n is the number of dataset.

Evaluating the performance of proposed models has been done using database from the TABAS Coal Mine (Daws, 1992). The data testing has about 20 datasets. Table 2 show the results of the FIS A and FIS B models. RMSE are 5.37 and 3.32 for FIS A and FIS B, respectively. As can be seen in Figure 6, correlation coefficients are 0.922 and 0.959 for FIS A and FIS B, respectively, which shows a very good agreement.
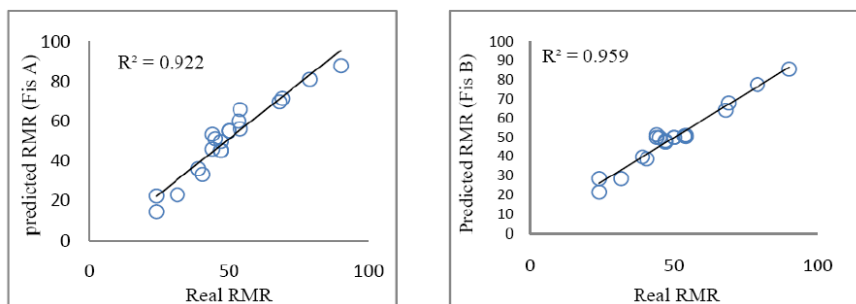

Figure 6- Comparison between real and predicted RMR for fuzzy models: (a) FIS A; (b) FIS B

Table 2- Results of FIS A and FIS B

Data NO.	Real RMR	Fis A RMR	Fis B RMR
1	79	81.00	77.60
2	90	87.82	85.70
3	69	71.34	68.02
4	47	45.00	47.69
5	47	45.00	47.58
6	50	55.00	50.00
7	47	49.62	48.28
8	50	55.00	50.00
9	45	51.00	50.00
10	31.5	22.74	28.57
11	24	14.18	28.57
12	54	55.99	50.43
13	44	53.27	50.00
14	39	35.86	39.84
15	44	45.73	51.41
16	54	65.78	51.15
17	40.5	33.00	38.83
18	68	69.59	64.27
19	53.5	59.92	50.75
20	24	22.17	21.44

CONCLUSIONS

- In this study the fuzzy set theory is applied to one of the conventional RMR system (Bieniawski, 1989) by two fuzzy models. RMSE was obtained equalled 3.32 and 5.37 for FIS B and FIS A respectively. Moreover, R^2 was 0.959 and 0.922 for FIS B and FIS A respectively.

- The results of fuzzy models were in good agreement with actual RMR. However, FIS B predicts more valuable results, which is due to the application of qualitative terms in the fuzzy model, while, FIS A uses descriptive terms in the classic method.

- It seems, weighting intervals which were proposed for JC and GW, can manage fuzzification of JC and GW, because these proposed weights solve problem of sharp transitions between two adjacent excavation classes and the subjective uncertainties on data that are close to the range boundaries of rock classes.

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