Use of rule-based fuzzy model to estimate the uniaxial compressive strength of some clay bearing rocks from Aegean region of Turkey

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Introduction

The uniaxial compressive strength of rocks is controlled by many factors such as mineralogy, texture, porosity, degree of saturation, weathering etc. For this reason, some researchers (Hoshino, 1974; Shea and Kronenberg, 1993; Ulusay et al, 1994 Gokceoglu et al., 1998; Prikryl, 2001) proposed some empirical relationships between the uniaxial compressive strength and such petrophysical parameters of the rocks. Besides, it is possible to find some correlations between the uniaxial compressive strength and slake durability index (Cargill and Shakoor, 1990; Koncagul and Santi, 1999). However, these researchers considered two-cycle slake durability index as recommended by ISRM (1981) and ASTM (1990). As stated by Koncagul and Santi (1999), Cargill and Shakoor (1990) found a statistically significant correlation between the uniaxial compressive strength and slake durability index. Some researchers (Taylor, 1988; Moon and Beattie, 1995; Ulusay et al., 1995; Bell et al., 1997; Gokceoglu et al. 2000) emphasized that two cycle slake durability testing did not appear to offer an acceptable indication of the durability of clay bearing rocks. For this reason, in this study, the four cycles slake durability index values were considered as proposed by Gokceoglu et al. (2000) when developing the predictive model. In addition, the clay contents of the rock studied were also used as the independent variable of the model. The purpose of the present study proposes a predictive model for estimating the uniaxial compressive strength of the clay-bearing rocks selected from Turkey. When developing the predictive model, the rule-based fuzzy model was taken into consideration.

Test Results and Predictive Model

The X-ray diffraction analyses, slake durability index tests and the uniaxial compressive strength tests were performed on the selected samples. According to the X-ray analyses results, the marl samples are mainly composed of carbonate (aragonite, dolomite and calcite), clay minerals, feldspar, quartz, and mica minerals. The clay minerals in the samples vary between 5 and 43.8%. The other independent variable is four cycles slake durability index values. The four cycle slake durability index values are between 73.4 and 99.3%. In fact, the four cycle slake durability index provides a wider representation in the predictive model than the two cycle slake durability index. The uniaxial compressive strength of the marls employed in the present study is considered as output in the fuzzy inference system. Contrary to the other parameters, the uniaxial compressive strength values were evaluated separately, because the uniaxial compressive strength of the marl samples from Yatagan varies between 2.1 and 7.5 MPa, while those from Soma are between 37.1 and 67.3 MPa. The uniaxial compressive strength values of the marls are quite different from each other. This causes some erroneous results. To overcome this problem, the uniaxial strength values were normalized to the interval of 0 and 1 (Eq. 1).

$$\mu - \mathrm{UCS} = \frac{\mathrm{UCS_x}}{\mathrm{UCS_{max}}} \tag{1}$$

where, μ-UCS: normalized uniaxial compressive strength (0-1); UCS_x : the measured uniaxial strength and UCS_{max}: the maximum uniaxial strength (7.5 MPa for Yatagan and 67.3 MPa for Soma). To provide standardization for the input data, this normalization process was also applied to the inputs such as the four cycles slake durability index data, and the clay content. In this study, the Mamdani fuzzy inference system (Fig.1) was employed to construct a prediction model for the uniaxial compressive strength. The inputs of the fuzzy inference system are the four cycle slake durability index and clay content.

For inference in a rule based fuzzy model the fuzzy propositions need to be represented by an implication function is called a fuzzy if-then rule or fuzzy conditional statement (Alvarez Grima, 2000). A fuzzy set is a collection of paired members which consist of members and degrees of "support" or "confidence" for those members. In a discrete form, the fuzzy set "about 7" might be expressed as (0.1/5, 0.7/6, 1/7, 0.7/8, 0.1/9). In a fuzzy set notation, the set (or appropriate numerical grades in each case), and the values before the slash are the degree of confidence or "membership" of those numbers. The use of fuzzy sets to present linguistic terms enables one to represent more accurately and consistently something which is fuzzy (Juang et al., 1992). A linguistic variable whose values are words, phrases or sentences are labels of fuzzy sets (Zadeh, 1973). In this study, the fuzzy sets of the inputs and output were extracted from the relationships between the inputs (Figs. 2a and b) and output (Fig.2c). The defined fuzzy sets of the inputs and output of the model are listed below:

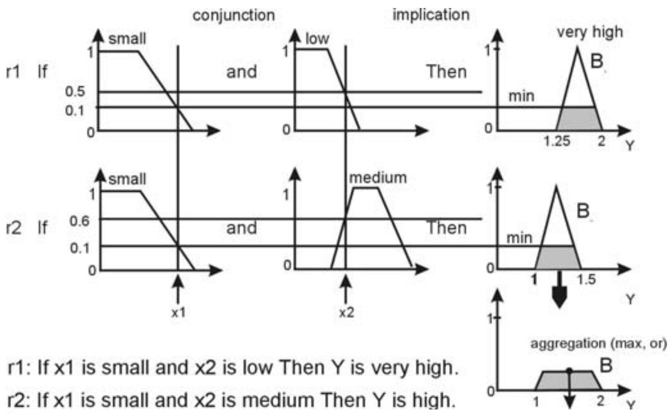

Figure 1. Schematic representation of the fuzzy inference mechanism of two-rule Mamdani model (after Alvarez Grima, 2000).

(a) Clay Content (Input 1)	(b) Four Cycle Slake Durability Index (Input 2)	(c) Uniaxial Compressive Strength (Output)
Very Poor (VP) = {0/0, 0/1, 0.3/0}	Very Low (VL) = {0.675/0, 0.675/1, 0.837/0}	Very Low (VL) = {0/0, 0/1, 0.28/1, 0.512/0}
Poor (P) = {0/0, 0.3/1, 0.5/0}	Low (L) = {0.675/0, 0.837/1, 0.908/0}	Low (L) = {0.28/0, 0.512/1, 0.643/0}
Moderate (M) = {0.3/0, 0.5/1, 0.7/0}	Moderate (M) = {0.837/0, 0.908/1, 0.985/0}	Moderate (M) = {0.512/0, 0.643/1, 0.807/0}
Rich (R) = {0.5/0, 0.7/1, 1/0}	High (H) = {0.908/0, 0.985/1, 1/1}	High (H) = {0.643/0, 0.807/1, 1/1}
Very Rich (VR) = {0.7/0, 1/1, 1/0}	Very High (VH) = {0.985/0, 1/1, 1/0}	Very High (VH) = {0807/0, 0.9/1, 1/1, 1/0}

The general "if-then" structure of the Mamdani algorithm is given in the Eq.2.

$$R_i : \text{if } X_i \text{ is } A_{il} \text{ and ….. then y is } B_i \text{ (for i = 1,2,….k)} \tag{2}$$

where k is the numbers of rules, X_i is the input variable (antecedent variable) and y is the output variable (consequent variable).

The last stage of the construction of fuzzy inference system is to select the defuzzification method. Aggregation of two or more fuzzy output sets gives a new fuzzy set in the basic fuzzy algorithm. In most cases, the result in the form of a fuzzy set is converted in to a crisp result by the defuzzification process (Berkan and Trubatch, 1997). Some defuzzification methods such as centroid (center of gravity, center of weights, center of largest area, center of mass of highest intersected region) and maxima (means of maximums, maximum possibility, left-right maxima) exist in the literature. Continuity, disambiguity, plausibility, computational complexity and weight counting are the main criteria for selecting a defuzzification method (Hellendoorn and Thomas, 1993). However, none of the defuzzification methods commonly used satisfies all these criteria (Alvarez Grima, 2000). Due to its common use in practice and computation simplicity, the center of gravity method for the defuzzification process was selected. Except the input and output fuzzy sets, the other component needed for a fuzzy inference system is the "if-then" rules as explained in the previous paragraphs. In this study, each inputs and output are composed of 5 membership functions. All combinations of two inputs require total 25 rules. However, to increase the accuracy of the model, the weighted rules were considered. The use of the weighted rules causes the increase of the number of rules and finally 42 if-then rules were extracted from the data. An example for the constructed fuzzy inference system is also illustrated in Fig.3.

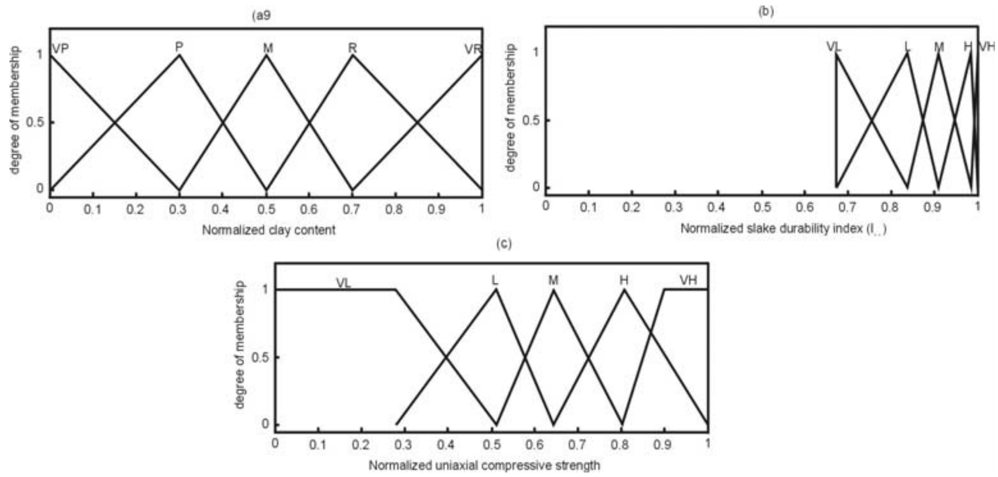

Figure 2. The membership functions of the inputs (a and b) and output (c) for the fuzzy inference system.

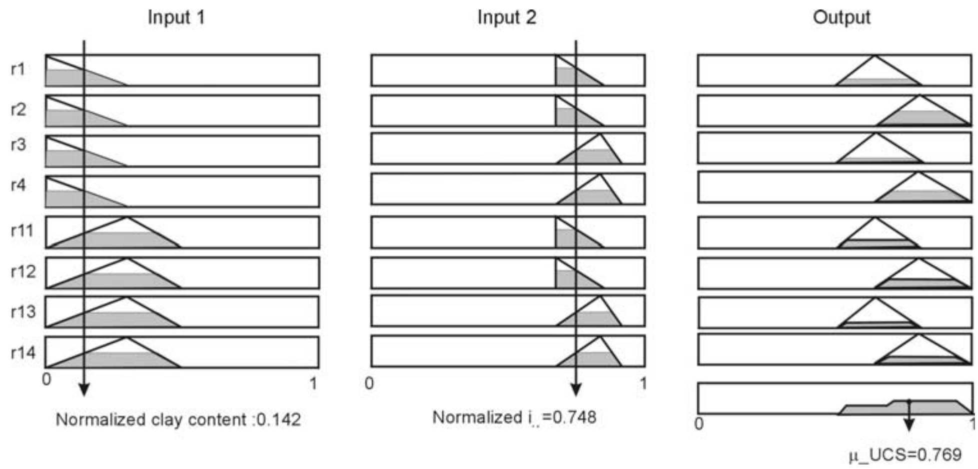

Figure 3. An example of the fuzzy inference system constructed in the study.

Results and Conclusions

The following results and conclusions can be drawn from the present study: **a)** Use of predictive models is very important for the rock mechanics practice. However, the reliability of the prediction models depends on the number and quality of the data. In addition, the technique employed is also very important. Because, some different techniques such as statistical regressions, fuzzy inference systems and neural networks exist in the literature. In this study, fuzzy inference system is considered. **b)** When considered statistical performance indices (VAF=68.3 for trained data and 86.2 for control data; RMSE=0.105 for trained data and 0.068 for control data), the developed fuzzy inference system exhibited a high prediction capacity. **c)** In this study, the weighted rules were considered in the fuzzy inference system. Although, this caused the increase of the number of the rules, accuracy of the model was also increased. Such these types of flexibility provide an advantage to the fuzzy inference system.

As a conclusion, due to the capability of the modeling of complex systems, the fuzzy set theory is a useful tool for the application of rock mechanics and engineering geology.

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