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Evaluating the Power Consumption in Carbonate Rock Sawing Process by Using FDAHP and TOPSIS Techniques

Reza Mikaeil[1], Mohammad Ataei[1] and Reza Yousefi[2]
[1]Faculty of Mining, Petroleum & Geophysics, Shahrood University of Technology, Shahrood
[2]School of mechanical engineering, Sharif University of Technology, Tehran
Iran

1. Introduction

The prediction of rock sawability is important in the cost estimation and the planning of the stone plants. An accurate estimation of rock sawability helps to make the planning of the rock sawing projects more efficient. Rock sawability depends on non-controlled parameters related to rock characteristics and controlled parameters related to properties of cutting tools and equipment. In the same working conditions, the sawing process and its results are strongly affected by mineralogical and mechanical properties of rock.

Up to now, many studies have been done on the relations between sawability and rock characteristics in stone processing. Norling (1971) correlated sawability with petrographic properties and concluded that grain size was more relevant to sawability than the quartz content. Burgess (1978) proposed a regression model for sawability, which was based on mineralogical composition, hardness, grain size and abrasion resistance. Vaya and Vikram (1983) found a fairly good correlation between the Brinell hardness test and diamond sawing rates. However, the variables involved were so many that they believed no mathematical solution would be possible. They also considered the Specific Energy (SE) concept, in conjunction with mineralogy, to give a better understanding of the sawing responses of various rock types. Ertingshausen (1985) investigated the power requirements during cutting of Colombo Red granite in up-cutting and down-cutting modes. He found out that the required power was less for the up- cutting mode when the cutting depth was below 20–25 mm. For deeper cuts, however, the power consumption was less for the down-cutting mode. Wright and Cassapi (1985) tried to correlate the petrographic analysis and physical properties with sawing results. The research indicated cutting forces to have the closest correlation. Birle et al. (1986) presented similar work in 1986, but again considered only blade life as the criterion on which a ranking system should be based. Hausberger (1989) concluded that an actual sawing test was the most reliable method for determining the machinability of a rock type. He observed that the higher proportion of minerals with well defined cleavage planes helps the cutting to be easier. Jennings and Wright (1989) gave an overall assessment of the major factors which affect saw blade performance. They found out that hard materials usually require a smaller size diamond than do softer stones because the load per particle is not sufficiently high and greater clearance is required for swarf.

Conversely, if large diamond grits are used on hard materials, the penetration of the diamond is limited, and normally either excessive grit pull-out will occur or large wear flats will appear on the diamond particles. Unver (1996) developed empirical equations for the estimation of specific wear and cutting force in the sawing of granites. He used mean quartz grain size, NCB cone indenter hardness number, and mean plagioclase grain size in his equations. Clausen et al. (1996) carried out a study on the acoustic emission during single diamond scratching of granite and suggested that acoustic emission could be used in sawability classification of natural stones. They also concluded that the cutting process is affected by the properties and frequency of minerals, grain size and degree of interlocking. Tonshoff and Asche (1997) discussed the macroscopic and microscopic methods of investigating saw blade segment wear. Luo (1997) investigated the worn surfaces of diamond segments in circular saws for the sawing of hard and relatively soft granites. He found out that for the sawing of hard granite, the worn particles were mainly of the macro-fractured crystal and/or pull-out hole type. Ceylanoglu and Gorgulu (1997) correlated specific cutting energy and slab production with rock properties and found good correlations between them. Webb and Jackson (1998) showed that a good correlation could be obtained between saw blade wear performance and the ratio of normal to tangential cutting forces during the cutting of granite. Xu (1999) investigated the friction characteristics of the sawing process of granites with diamond segmented saw blade. The results of the experimental studies indicated that most of the sawing energy is expended by friction of sliding between diamonds and granites. Xipeng et al. (2001) found that about 30 percent of the sawing energy might be due to the interaction of the swarf with the applied fluid and bond matrix. Most of the energy for sawing and grinding is attributed to ductile ploughing. Brook (2002) developed a new index test, called Brook hardness, which has been specifically developed for sliding diamond indenters. The consumed energy is predictable from this new index test. Konstanty (2002) presented a theoretical model of natural stone sawing by means of diamond-impregnated tools. In the model, the chip formation and removal process are quantified with the intention of assisting both the toolmaker and the stonemason in optimising the tool composition and sawing process parameters, respectively.

Li et al. (2002) proposed a new machining method applicable to granite materials to achieve improved cost effectiveness. They emphasized the importance of the tribological interactions that occur at the interface between the diamond tool surface and the workpiece. Accordingly, they proposed that the energy expended by friction and mechanical load on the diamond crystal should be balanced to optimize the saw blade performance. Xu et al. (2003) conducted an experimental study on the sawing of two kinds of granites with a diamond segmented saw blade. The results of their study indicated that the wear of diamond grits could also be related to the high temperatures generated at individual cutting points, and the pop-out of diamonds from the matrix could be attributed to the heat conducted to saw blade segments. Ilio and Togna (2003) proposed a theoretical model for the interpretation of saw blade wear process. The model is based on the experimentally determined matrix characteristics and grain characteristics. The model indicates that a suitable matrix material must not only provide the necessary grain support in the segment, but it should also wear at an appropriate rate in order to maintain constant efficiency in cutting. Eyuboglu et al. (2003) investigated the relationship between blade wear and the sawability of andesitic rocks. In their study, a multiple linear regression analysis was carried out to derive a prediction equation of the blade wear rate. They showed that the wear rate of

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andesite could be predicted from the statistical model by using a number of stone properties. The model indicated the Shore scleroscope hardness as the most important rock property affecting wear rate. Xu et al. (2003) carried out an experimental study to investigate the characteristics of the force ratio in the sawing of granites with a diamond segmented blade. In the experiments, in order to determine the tangential and the normal force components, horizontal and vertical force components and the consumed power were measured. It was found out that the force components and their ratios did not differ much for different granites, in spite of the big differences in sawing difficulty. Gunaydin et al. (2004) investigated the correlations between sawability and different brittleness using regression analysis. They concluded that sawability of carbonate rocks can be predicted from the rock brittleness, which is half the product of compressive strength and tensile strength. Ersoy et al. (2004, 2005) experimentally studied the performance and wear characteristics of circular diamond saws in cutting different types of rocks. They derived a statistical predictive model for the saw blade wear where specific cutting energy, silica content, bending strength, and Schmidt rebound hardness were the input parameters of the model. An experimental study was carried out by Xipeng and Yiging (2005) to evaluate the sawing performance of Ti–Cr coated diamonds. The sawing performances of the specimens were evaluated in terms of their wear performances during the sawing of granite. It was concluded that the wear performance of the specimens with coated diamonds were improved, as compared with uncoated diamonds. Delgado et al. (2005) experimentally studied the relationship between the sawability of granite and its micro-hardness. In their study, sawing rate was chosen as the sawability criterion, and the micro-hardness of granite was calculated from mineral Vickers micro-hardness. Experimental results indicated that the use of Vickers hardness microindentor could provide more precise information in sawability studies. Mikaeil et al. (2008a and 2008b) developed a new statistical model to predicting the production rate of carbonate rocks based on uniaxial compressive strength and equal quartz content. Additional, they investigated the sawability of some important Iranian stone. Yousefi et al. (2010) studied the factors affecting on the sawability of the ornamental stone.

Especially, among the previous studies some researchers have developed a number of classification systems for ranking the sawability of rocks. Wei et al. (2003) evaluated and classified the sawability of granites by means of the fuzzy ranking system. In their study, wear performance of the blade and the cutting force were used as the sawability criteria. They concluded that with the fuzzy ranking system, by using only the tested petrographic and mechanical properties, a convenient selection of a suitable saw blade could be made for a new granite type. Similarly, Tutmez et al. (2007) developed a new fuzzy classification of carbonate rocks based on rock characteristics such as uniaxial compressive strength, tensile strength, Schmidt hammer value, point load strength, impact strength, Los Angeles abrasion loss and P-wave velocity. By this fuzzy approach, marbles used by factories were ranked three linguistic qualitative categories: excellent, good and poor. Kahraman et al. (2007) developed a quality classification of building stones from P-wave velocity and its application to stone cutting with gang saws. They concluded that the quality classification and estimation of slab production efficiency of the building stones can be made by ultrasonic measurements.

The performance of any stone factory is affected by the complex interaction of numerous factors. These factors that affect the production cost can be classified as energy, labour, water, diamond saw and polishing pads, filling material and packing. Among the above

factors, energy is one of the most important factors. In this chapter, it was aimed to develop a new hierarchy model for evaluating and ranking the power consumption of carbonate rock in sawing process. By this model, carbonate rocks were ranked with the respect to its power consumption. This model can be used for cost analysis and project planning as a decision making index. To make a right decision on power consumption of carbonate rock, all known criteria related to the problem should be analyzed. Although an increasing in the number of related criteria makes the problem more complicated and more difficult to reach a solution, this may also increase the correctness of the decision made because of those criteria. Due to the arising complexity in the decision process, many conventional methods are able to consider limited criteria and may be generally deficient. Therefore, it is clearly seen that assessing all of the known criteria connected to the power consumption by combining the decision making process is extremely significant.

The major aim of this chapter is to compare the many different factors in the power consumption of the carbonate rock. The comparison has been performed with the combination of the Analytic Hierarchy Process (AHP) and Fuzzy Delphi method and also the use of TOPSIS method. The analysis is one of the multi-criteria techniques that provide useful support in the choice among several alternatives with different objectives and criteria. FDAHP method has been used in determining the weights of the criteria by decision makers and then ranking the power consumption of the rocks has been determined by TOPSIS method. The study was supported by results that were obtained from a questionnaire carried out to know the opinions of the experts in this subject.

This chapter is organized as follows; in the second section, a brief review is done on concept of the fuzzy sets and fuzzy numbers. In the third section FDAHP method is illustrated. This section is included the methodology of FDAHP method. Fourth section also surveys TOPSIS method. In the fifth section, after explanation of effective parameters on power consumption, the FDAHP method is applied for determination of the weights of the criteria given by experts. Then the ranking the power consumption of carbonate rocks is carried out by TOPSIS method. Eventually, in sixth and seventh sections, results of the application are reviewed. These sections discuses and concludes the paper. According to the authors' knowledge, ranking the power consumption using the FDAHP-TOPSIS is a unique research.

2. Fuzzy sets and fuzzy numbers

To deal with vagueness of human thought, Zadeh (1965) first introduced the fuzzy set theory, which was oriented to the rationality of uncertainty due to imprecision or vagueness. A major contribution of fuzzy set theory is its capability of representing vague data. The theory also allows mathematical operators and programming to apply to the fuzzy domain. A fuzzy set is a class of objects with a continuum of grades of membership. Such a set is characterized by a membership (characteristic) function, which assigns to each object a grade of membership ranging between zero and one. With different daily decision making problems of diverse intensity, the results can be misleading if the fuzziness of human decision making is not taken into account (Tsaur et al., 2002) Fuzzy sets theory providing a more widely frame than classic sets theory, has been contributing to capability of reflecting real world (Ertugrul & Tus, 2007).

Fuzzy sets and fuzzy logic are powerful mathematical tools for modeling: uncertain systems in industry, nature and humanity; and facilitators for common-sense reasoning in decision making in the absence of complete and precise information. Their role is significant when

applied to complex phenomena not easily described by traditional mathematical methods, especially when the goal is to find a good approximate solution (Bojadziev & Bojadziev, 1998). Fuzzy set theory is a better means for modeling imprecision arising from mental phenomena which are neither random nor stochastic. Human beings are heavily involved in the process of decision analysis. A rational approach toward decision making should take into account human subjectivity, rather than employing only objective probability measures. This attitude, towards imprecision of human behavior led to study of a new decision analysis filed fuzzy decision making (Lai & Hwang, 1996). A tilde '~' will be placed above a symbol if the symbol represents a fuzzy set. A triangular fuzzy number (TFN), $\tilde{M}$ is shown in Fig. 1. A TFN is denoted simply as $(l|m, m|u)$ or (l, m, u). The parameters l, m and u, respectively, denote the smallest possible value, the most promising value, and the largest possible value that describe a fuzzy event.
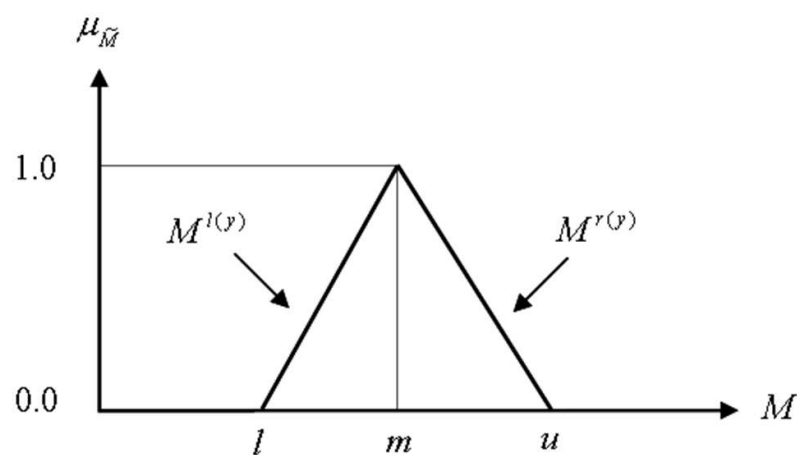

Fig. 1. A triangular fuzzy number, $\tilde{M}$

Each TFN has linear representations on its left and right side such that its membership function can be defined as

$$\mu(x | \tilde{M}) = \begin{cases} 0, & x < l, \\ (x-l)/(m-l), & l \le x \le m, \\ (u-x)/(u-m), & m \le x \le u, \\ 0, & x > u. \end{cases} \tag{1}$$

A fuzzy number can always be given by its corresponding left and right representation of each degree of membership:

$$\tilde{M} = (M^{l(y)}, M^{r(y)}) = (l + (m-l)y, u + (m-u)y), \qquad y \in [0,1], \tag{2}$$

Where $l(y)$ and $r(y)$ denote the left side representation and the right side representation of a fuzzy number, respectively. Many ranking methods for fuzzy numbers have been developed in the literature. These methods may give different ranking results and most methods are tedious in graphic manipulation requiring complex mathematical calculation. The algebraic operations with fuzzy numbers have been explained by Kahraman (2001) and Kahraman et al. (2002).

3. Fuzzy Delphi Analytic Hierarchy Process

The Analytic Hierarchy Process (AHP) is an approach that is suitable for dealing with complex systems related to making a choice from among several alternatives and which provides a comparison of the considered options, firstly proposed by Saaty (1980). The AHP is based on the subdivision of the problem in a hierarchical form. In fact, the AHP helps organize the rational analysis of the problem by dividing it into its single parts; the analysis then supplies an aid to the decision makers who, making several pair-wise comparisons, can appreciate the influence of the considered elements in the hierarchical structure; the AHP can also give a preference list of the considered alternative solutions (Bentivegna et al., 1994; Roscelli, 1990; Saaty, 1980; Saaty & Vargas, 1990).

The AHP is a tool that can be used for analyzing different kinds of social, political, economic and technological problems, and it uses both qualitative and quantitative variables. The fundamental principle of the analysis is the possibility of connecting information, based on knowledge, to make decisions or previsions; the knowledge can be taken from experience or derived from the application of other tools. Among the different contexts in which the AHP can be applied, mention can be made of the creation of a list of priorities, the choice of the best policy, the optimal allocation of resources, the prevision of results and temporal dependencies, the assessment of risks and planning (Saaty & Vargas, 1990). Although the AHP is to capture the expert's knowledge, the traditional AHP still cannot really reflect the human thinking style (Kahraman et al., 2003).

The traditional AHP method is problematic in that it uses an exact value to express the decision maker's opinion in a comparison of alternatives (Wang & Chen, 2007). And AHP method is often criticized due to its use of unbalanced scale of judgments and its inability to adequately handle the inherent uncertainty and imprecision in the pair-wise comparison process (Deng, 1999). To overcome all these shortcomings, FDAHP was developed for solving the hierarchical problems. Decision makers usually find that it is more confident to give interval judgments than fixed value judgments. This is because usually he/she is unable to explicit his/her preference to explicit about the fuzzy nature of the comparison process.

Delphi method is a technique for structuring an effective group communication process by providing feedback of contributions of information and assessment of group judgments to enable individuals to re-evaluate their judgments. Since its development in the 1960s at Rand Corporation, Delphi method has been widely used in various fields (Liu and Chen, 2007a, Liu and Chen, 2007b, Hoseinie et al. 2009, Cheng and Tang, 2009, Cheng et al. 2009). On the other hand, Delphi Method use crisp number and mean to become the evaluation criteria, these shortcomings might distort the experts' opinion. In order to deal with the fuzziness of human participants' judgments in traditional Delphi method, Ishikawa et al. (Ishikawa et al. 1993) posited fuzzy set theory proposed by Zadeh (Zadeh, 1965) into the Delphi method to improve time-consuming problems such as the convergence of experts' options presented by Hwang and Lin (Hwang and Lin, 1987). The FDM is a methodology in which subjective data of experts are transformed into quasi-objective data using the statistical analysis and fuzzy operations. The main advantages of FDM (Kaufmann and Gupta, 1988) are that it can reduce the numbers of surveys to save time and cost and it also includes the individual attributes of all experts. This paper proposes the use of FDAHP for determining the weights of the main criteria.

3.1 Methodology of FDAHP

Calculate the relative fuzzy weights of the decision elements using the following three steps based on the FDM and aggregate the relative fuzzy weights to obtain scores for the decision alternation.

(1) Compute the triangular fuzzy numbers (TFNs) $\tilde{a}_{ij}$ as defined in Eq. (3). In this work, the TFNs (shown as Fig. 2) that represent the pessimistic, moderate and optimistic estimate are used to represent the opinions of experts for each activity time.
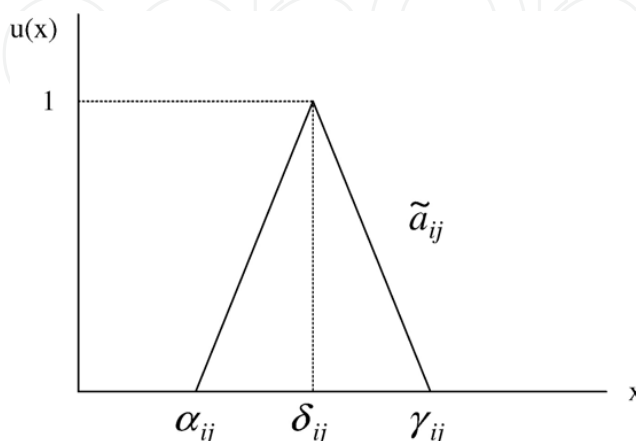

Fig. 2. The membership function of the Fuzzy Delphi Method.

$$\tilde{a}_{ij} = (\alpha_{ij}, \delta_{ij}, \gamma_{ij}) \tag{3}$$

$$\alpha_{ij} = Min(\beta_{ijk}), k = 1, ..., n \tag{4}$$

$$\delta_{ij} = (\prod_{k=1}^{n} \beta_{ijk})^{1/n}, k = 1, ..., n \tag{5}$$

$$\gamma_{ij} = Max(\beta_{ijk}), k = 1, ..., n \tag{6}$$

Where, $\alpha_{ij} \leq \delta_{ij} \leq \gamma_{ij}$, $\alpha_{ij}, \delta_{ij}, \gamma_{ij} \in [1/9,1] \cup [1,9]$ and $\alpha_{ij}, \delta_{ij}, \gamma_{ij}$ are obtained from Eq. (4) to Eq. (6). α_{ij} indicates the lower bound and γ_{ij} indicates the upper bound. β_{ijk} indicates the relative intensity of importance of expert k between activities i and j. n is the number of experts in consisting of a group.

(2) Following outlined above, we obtained a fuzzy positive reciprocal matrix $\tilde{A}$

$$\tilde{A} = [\tilde{a}_{ij}], \tilde{a}_{ij} \times \tilde{a}_{ji} \approx 1, \forall i, j = 1, 2, ..., n$$

Or

$$\tilde{A} = \begin{bmatrix} (1,1,1) & (\alpha_{12}, \delta_{12}, \gamma_{12}) & (\alpha_{13}, \delta_{13}, \gamma_{13}) \\ (1/\gamma_{12}, 1/\delta_{12}, 1/\alpha_{12}) & (1,1,1) & (\alpha_{23}, \delta_{23}, \gamma_{23}) \\ (1/\gamma_{13}, 1/\delta_{13}, 1/\alpha_{13}) & (1/\gamma_{23}, 1/\delta_{23}, 1/\alpha_{23}) & (1,1,1) \end{bmatrix} \tag{7}$$

(3) Calculate the relative fuzzy weights of the evaluation factors.

$$\tilde{Z}_i = [\tilde{a}_{ij} \otimes ... \otimes \tilde{a}_{in}]^{1/n}, \tilde{W}_i = \tilde{Z}_i \otimes (\tilde{Z}_i \oplus ... \oplus \tilde{Z}_n)^{-1} \tag{8}$$

Where $\tilde{a}_1 \otimes \tilde{a}_2 \cong (\alpha_1 \times \alpha_2, \delta_1 \times \delta_2, \gamma_1 \times \gamma_2)$; the symbol $\otimes$ here denotes the multiplication of fuzzy numbers and the symbol $\oplus$ here denotes the addition of fuzzy numbers. $\tilde{W}_i$ is a row vector in consist of a fuzzy weight of the ith factor. $\tilde{W}_i = (\omega_1, \omega_2, ..., \omega_n)$ i=1, 2,…n, and W_i is a fuzzy weight of the ith factor.

4. TOPSIS method

TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) is one of the useful MADM techniques to manage real-world problems (Yoon & Hwang, 1985). TOPSIS method was firstly proposed by Hwang & Yoon (1981). According to this technique, the best alternative would be the one that is nearest to the positive ideal solution and farthest from the negative ideal solution (Benitez, et al., 2007). The positive ideal solution is a solution that maximizes the benefit criteria and minimizes the cost criteria, whereas the negative ideal solution maximizes the cost criteria and minimizes the benefit criteria (Wang & Elhag, 2006). In short, the positive ideal solution is composed of all best values attainable of criteria, whereas the negative ideal solution consists of all worst values attainable of criteria (Wang, 2008). In this paper TOPSIS method is used for determining the final ranking of the sawability of rocks. TOPSIS method is performed in the following steps:

Step 1. Decision matrix is normalized via Eq. (9):

$$r_{ij} = \frac{w_{ij}}{\sqrt{\sum\limits_{i=1}^{J} w_{ij}^2}} \quad j = 1,2,3,...,J \quad i = 1,2,3,...,n \tag{9}$$

Step 2. Weighted normalized decision matrix is formed:

$$v_{ij} = w_i \times r_{ij}, \quad j = 1,2,3,...,J \quad i = 1,2,3,...,n \tag{10}$$

Step 3. Positive ideal solution (PIS) and negative ideal solution (NIS) are determined:

$$A^* = \left\{ v_1^*, v_2^*, ..., v_i^*, ..., v_n^* \right\} \text{ Maximum Values} \tag{11}$$

$$A^- = \left\{ v_1^-, v_2^-, ..., v_i^-, ..., v_n^- \right\} \text{ Minimum Values} \tag{12}$$

Step 4. The distance of each alternative from PIS and NIS are calculated:

$$d_j^* = \sqrt{\sum_{i=1}^{n} \left(v_{ij} - v_j^* \right)^2} \tag{13}$$

$$d_j^- = \sqrt{\sum_{i=1}^{n} \left(v_{ij} - v_j^- \right)^2} \tag{14}$$

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Step 5. The closeness coefficient of each alternative is calculated:

$$CC_j = \frac{d_j^-}{d_j^* + d_j^-} \tag{15}$$

Step 6. By comparing CCj values, the ranking of alternatives are determined.

5. Application of FDAHP-TOPSIS method to multi-criteria comparison of sawability

The purpose of this paper was to ranking the power consumption of rock in sawing process, with the help of effective factors. Firstly, a comprehensive questionnaire including main criteria of effective factor is designed to understand and quantify the affecting factors in the process. Then, five decision makers from different areas evaluated the importance of these factors with the help of the mentioned questionnaire. FDAHP is utilized for determining the weights of main criteria and finally, TOPSIS approach is employed for ranking. By this way, the ranking of carbonate sawability according to their overall efficiency is obtained. Carbonate rock sawability depends on non-controlled parameters related to rock characteristics and controlled parameters related to properties of cutting tools and equipment. In the same working conditions, the sawing process and its results are strongly affected by mineralogical and mechanical properties of rock. The mineralogical and mechanical properties of rock which related to rock sawability are shown in Fig. 3.
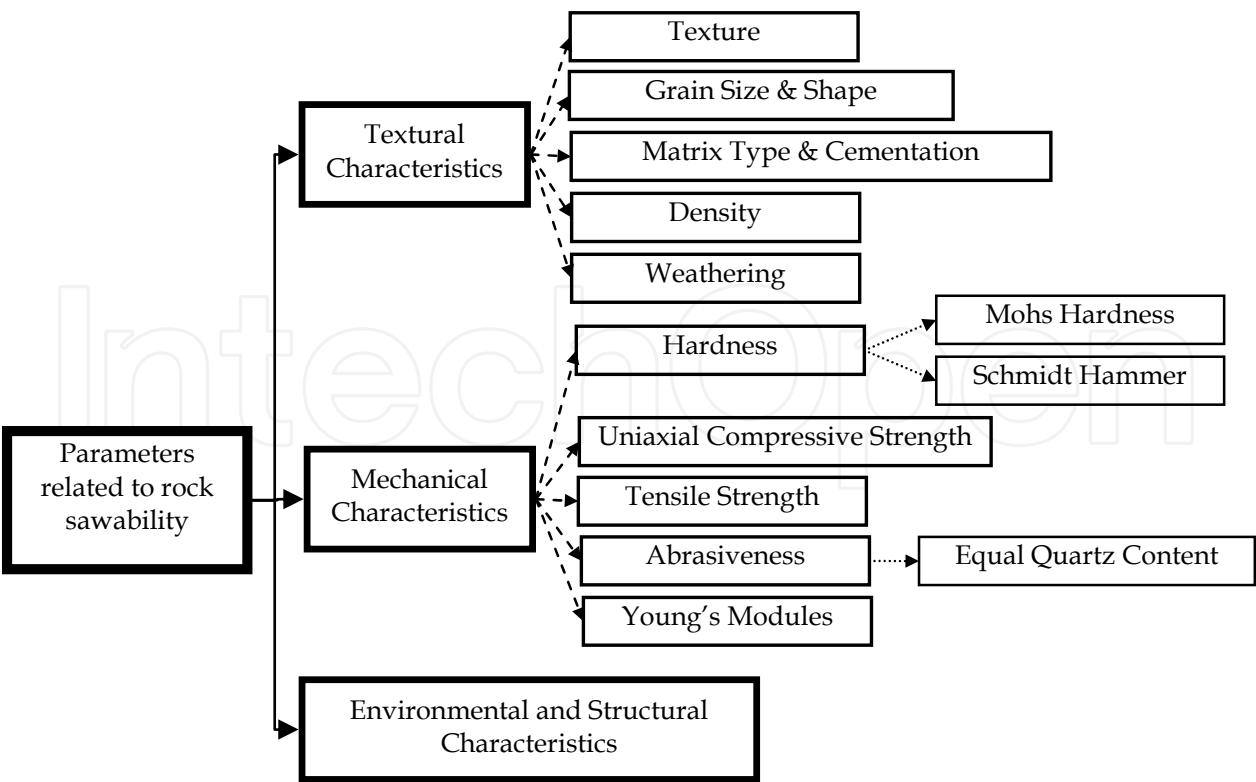

Fig. 3. Important characteristics influencing the rock sawability

5.1 Determination of criteria's weights

Because different groups have varying objectives and expectations, they judge on rock sawability from different perspectives. So, affecting criteria have different level of significance for different users. For this reason, five decision makers are selected from different areas and these decision makers evaluate the criteria. FDAHP is proposed to take the decision makers subjective judgments into consideration and to reduce the uncertainty and vagueness in the decision process.

Decision makers from different backgrounds may define different weight vectors. They usually cause not only the imprecise evaluation but also serious persecution during decision process. For this reason, we proposed a group decision based on FDAHP to improve pair-wise comparison. Firstly each decision maker (Di), individually carry out pair-wise comparison by using Saaty's (1980) 1–9 scale (Table 2).

Comparison index	score
Extremely Preferred	9
Very strongly Preferred	7
Strongly Preferred	5
Moderately Preferred	3
Equal	1
Intermediate values between the two adjacent judgments	2,4,6,8

Table 2. Pair-wise comparison scale (Saaty, 1980)

One of these pair-wise comparisons is shown here as example:

$$D_1 = \begin{matrix} & c_1 & c_2 & c_3 & c_4 & c_5 & c_6 & c_7 & c_8 & c_9 & c_{10} & c_{11} & c_{12} \\ c_1 \\ c_2 \\ c_3 \\ c_4 \\ c_5 \\ c_6 \\ c_7 \\ c_8 \\ c_9 \\ c_{10} \\ c_{11} \\ c_{12} \end{matrix} \begin{bmatrix} 1 & 3 & 5 & 1 & 1 & 1 & 5 & 5 & 3 & 1/3 & 1 & 3 \\ 1/3 & 1 & 3 & 1/3 & 1/3 & 1/3 & 3 & 3 & 1 & 1/5 & 1/3 & 1 \\ 1/5 & 1/3 & 1 & 1/5 & 1/5 & 1/5 & 1 & 1 & 1/3 & 1/9 & 1/5 & 1/3 \\ 1 & 3 & 5 & 1 & 1 & 1 & 5 & 5 & 3 & 1/3 & 1 & 3 \\ 1 & 3 & 5 & 1 & 1 & 1 & 5 & 5 & 3 & 1/3 & 1 & 3 \\ 1 & 3 & 5 & 1 & 1 & 1 & 5 & 5 & 3 & 1/3 & 1 & 3 \\ 1/5 & 1/3 & 1 & 1/5 & 1/5 & 1/5 & 1 & 1 & 1/3 & 1/9 & 1/5 & 1/3 \\ 1/5 & 1/3 & 1 & 1/5 & 1/5 & 1/5 & 1 & 1 & 1/3 & 1/9 & 1/5 & 1/3 \\ 1/3 & 1 & 3 & 1/3 & 1/3 & 1/3 & 3 & 3 & 1 & 1/5 & 1/3 & 1 \\ 3 & 7 & 9 & 3 & 3 & 3 & 9 & 9 & 5 & 1 & 3 & 5 \\ 1 & 3 & 5 & 1 & 1 & 1 & 5 & 5 & 3 & 1/3 & 1 & 3 \\ 1/3 & 1 & 3 & 1/3 & 1/3 & 1/3 & 3 & 3 & 1 & 1/5 & 1/3 & 1 \end{bmatrix}$$

The weighting factors for each criterion were presented in the following steps:
1. Compute the triangular fuzzy numbers (TFNs)

$$\tilde{a}_{ij} = (\alpha_{ij}, \delta_{ij}, \gamma_{ij})$$

According Eq. (4)- Eq. (6)

$$\alpha_{ij} = Min(\beta_{ijk}), k = 1,...,n$$

2. Fuzzy pair-wise comparison matrix $\tilde{A}$

By this way, decision makers' pair-wise comparison values are transformed into triangular fuzzy numbers as in Table 3.

	C_1	C_2	C_3	C_4	C_5	C_6
C_1	(1, 1, 1)	(0.7, 1, 1.4)	(0.7, 1.2, 2.3)	(0.6, 0.7, 1)	(0.6, 0.7, 1)	(0.6, 0.8, 1)
C_2	(0.7, 1, 1.4)	(1, 1, 1)	(0.7, 1.2, 1.7)	(0.7, 0.7, 0.8)	(0.6, 0.7, 1)	(0.7, 0.8, 1)
C_3	(0.4, 08, 1.4)	(0.6 0.8, 1.4)	(1, 1, 1)	(0.4, 0.6, 1)	(0.3, 0.6, 0.8)	(0.4, 0.6, 1)
C_4	(1, 1.4, 1.8)	(1.3, 1.4, 1.4)	(1, 1.7, 2.3)	(1, 1, 1)	(0.8, 1, 1.3)	(1, 1.1, 1.3)
C_5	(1, 1.4, 1.8)	(1, 1.4, 1.8)	(1.3, 1.8, 3)	(0.8, 1.1, 1.3)	(1, 1, 1)	(0.8, 1.1, 1.3)
C_6	(1, 1.3, 1.8)	(1, 1.3, 1.4)	(1, 1.6, 2.3)	(0.8, 1, 1)	(0.8, 0.9, 1.3)	(1, 1, 1)
C_7	(0.4, 0.7, 1.4)	(0.6, 0.7, 1)	(0.4, 0.8, 1)	(0.4, 0.5, 0.8)	(0.3, 0.5, 0.8)	(0.4, 0.5, 1)
C_8	(0.4, 0.7, 1)	(0.6, 0.7, 1)	(0.7, 0.9, 1)	(0.4, 0.5, 0.7)	(0.3, 0.5, 0.7)	(0.4, 0.6, 0.7)
C_9	(0.4, 0.8, 1.4)	(0.4, 0.8, 1.4)	(0.6, 1, 1.7)	(0.3, 0.6, 0.8)	(0.3, 0.6, 0.8)	(0.3, 0.6, 1)
C_{10}	(1.3, 1.5, 1.8)	(1, 1.5, 1.8)	(1, 1.8, 3)	(0.8, 1.1, 1. 3)	(0.8, 1.1, 1.3)	(1, 1.2, 1.3)
C_{11}	(1, 1.1, 1.4)	(0.7, 1.1, 1.4)	(0.7, 1.4, 2.3)	(0.6, 0.9 1)	(0.6, 0.8, 1)	(0.7, 0.9, 1)
C_{12}	(0.7, 1.1, 1.4)	(0.7, 1.1, 1.4)	(1, 1.3, 2.3)	(0.6, 0.8, 1)	(0.7, 0.8, 0.8)	(0.6, 0.8, 1)

C_7	C_8	C_9	C_{10}	C_{11}	C_{12}
(0.7, 1.5, 2.3)	(1, 1.4, 2.3)	(0.7, 1.2, 2.3)	(0.6, 0.7, 0.8)	(0.7, 0.9, 1)	(0.7, 0.9, 1.4)
(1, 1.5, 1.7)	(1, 1.4, 1.7)	(0.7, 1.2, 2.3)	(0.6, 0.7, 1)	(0.7, 0.9, 1.4)	(0.7, 0.9, 1.4)
(1, 1.2, 2.3)	(1, 1.1, 1.4)	(0.6, 1, 1.7)	(0.3, 0.5, 1)	(0.4, 0.7, 1.4)	(0.4, 0.8, 1)
(1.3, 2, 2.3)	(1.4, 1.9, 2.3)	(1, 1.7, 3)	(0.8, 0.9, 1.3)	(1, 1.2, 1.8)	(1, 1.3, 1.8)
(1.3, 2.1, 3)	(1.4, 2.1, 3)	(1.3, 1.7, 3)	(0.8, 1, 1.3)	(1, 1.2, 1.8)	(1.3, 1.3, 1.4)
(1, 1.9, 2.3)	(1.4, 1.8, 2.3)	(1, 1.6, 3)	(0.8, 0.9, 1)	(1, 1.1, 1.4)	(0.4, 0.6, 1)
(1, 1, 1)	(0.6, 1, 1.4)	(0.4, 0.8, 1.7)	(0.3, 0.5, 1)	(0.4, 0.6, 1.4)	(0.4, 0.6, 1)
(0.7, 1, 1.7)	(1, 1, 1)	(0.6, 0.9, 1.7)	(0.3, 0.5, 0.7)	(0.4, 0.6, 1)	(0.4, 0.7, 1)
(0.6, 1.2, 2.3)	(0.6, 1.1, 1.7)	(1, 1, 1)	(0.3, 0.5, 1)	(0.4, 0.7, 1.4)	(0.4, 0.8, 1)
(1, 2.2, 3)	(1.4, 2.1, 3)	(1, 1.8, 3)	(1, 1, 1)	(1.3, 1.3, 1.4)	(1, 1.4, 1.8)
(0.7, 1.7, 2.3)	(1, 1.6, 2.3)	(0.7, 1.4, 2.3)	(0.7, 0.8, 0.8)	(1, 1, 1)	(0.7, 1.1, 1.4)
(1, 1.6, 2.3)	(1, 1.5, 2.3)	(1, 1.3, 2.3)	(0.6, 0.7, 1)	(0.7, 0.9, 1.4)	(1, 1, 1)

Table 3. Fuzzy pair-wise comparison matrix

3. Calculate the relative fuzzy weights of the evaluation factors.

$$\tilde{Z}_1 = \left[\tilde{a}_{11} \otimes \tilde{a}_{12} \otimes ...\tilde{a}_{112}\right]^{1/12} = [0.6948, 0.968, 1.3738]$$

$$\tilde{Z}_2 = \left[\tilde{a}_{21} \otimes \tilde{a}_{22} \otimes ...\tilde{a}_{212}\right]^{1/12} = [0.7451, 0.968, 1.2989]$$

$$\tilde{Z}_3 = \left[\tilde{a}_{31} \otimes \tilde{a}_{32} \otimes ...\tilde{a}_{312}\right]^{1/12} = [0.5373, 0.7861, 1.2268]$$

$$\tilde{Z}_4 = \left[\tilde{a}_{41} \otimes \tilde{a}_{42} \otimes ... \tilde{a}_{412}\right]^{1/12} = [1.0284, 1.3098, 1.7181]$$

$$\tilde{Z}_5 = \left[\tilde{a}_{51} \otimes \tilde{a}_{52} \otimes ... \tilde{a}_{512}\right]^{1/12} = [1.0502, 1.3773, 1.8295]$$

$$\tilde{Z}_6 = \left[\tilde{a}_{61} \otimes \tilde{a}_{62} \otimes ... \tilde{a}_{612}\right]^{1/12} = [0.9, 1.1823, 1.5363]$$

$$\tilde{Z}_7 = \left[\tilde{a}_{71} \otimes \tilde{a}_{72} \otimes ... \tilde{a}_{712}\right]^{1/12} = [0.4665, 0.6661, 1.0885]$$

$$\tilde{Z}_8 = \left[\tilde{a}_{81} \otimes \tilde{a}_{82} \otimes ... \tilde{a}_{812}\right]^{1/12} = [0.508, 0.6897, 0.9733]$$

$$\tilde{Z}_9 = \left[\tilde{a}_{91} \otimes \tilde{a}_{92} \otimes ... \tilde{a}_{912}\right]^{1/12} = [0.4601, 0.7858, 1.2189]$$

$$\tilde{Z}_{10} = \left[\tilde{a}_{101} \otimes \tilde{a}_{102} \otimes ... \tilde{a}_{1012}\right]^{1/12} = [1.0284, 1.4483, 1.8295]$$

$$\tilde{Z}_{11} = \left[\tilde{a}_{111} \otimes \tilde{a}_{112} \otimes ... \tilde{a}_{1112}\right]^{1/12} = [0.7451, 1.1074, 1.4128]$$

$$\tilde{Z}_{12} = \left[\tilde{a}_{121} \otimes \tilde{a}_{122} \otimes ... \tilde{a}_{1212}\right]^{1/12} = [0.7717, 1.0353, 1.4128]$$

$$\sum \tilde{Z}_i = [8.9356, 12.327, 16.919]$$

$$\tilde{W}_1 = \tilde{Z}_1 \otimes (\tilde{Z}_1 \oplus \tilde{Z}_2 \oplus \tilde{Z}_3)^{-1} = [0.0411, 0.0785, 0.1537]$$

$$\tilde{W}_2 = \tilde{Z}_2 \otimes (\tilde{Z}_1 \oplus \tilde{Z}_2 \oplus \tilde{Z}_3)^{-1} = [0.044, 0.0785, 0.1454]$$

$$\tilde{W}_3 = \tilde{Z}_3 \otimes (\tilde{Z}_1 \oplus \tilde{Z}_2 \oplus \tilde{Z}_3)^{-1} = [0.0318, 0.064, 0.1373]$$

$$\tilde{W}_4 = \tilde{Z}_4 \otimes (\tilde{Z}_1 \oplus \tilde{Z}_2 \oplus \tilde{Z}_3)^{-1} = [0.0608, 0.1063, 0.1923]$$

$$\tilde{W}_5 = \tilde{Z}_5 \otimes (\tilde{Z}_1 \oplus \tilde{Z}_2 \oplus \tilde{Z}_3)^{-1} = [0.0621, 0.1117, 0.2047]$$

$$\tilde{W}_6 = \tilde{Z}_6 \otimes (\tilde{Z}_1 \oplus \tilde{Z}_2 \oplus \tilde{Z}_3)^{-1} = [0.0532, 0.0959, 0.1719]$$

$$\tilde{W}_7 = \tilde{Z}_7 \otimes (\tilde{Z}_1 \oplus \tilde{Z}_2 \oplus \tilde{Z}_3)^{-1} = [0.0276, 0.054, 0.1218]$$

$$\tilde{W}_8 = \tilde{Z}_8 \otimes (\tilde{Z}_1 \oplus \tilde{Z}_2 \oplus \tilde{Z}_3)^{-1} = [0.03, 0.056, 0.1089]$$

$$\tilde{W}_9 = \tilde{Z}_9 \otimes (\tilde{Z}_1 \oplus \tilde{Z}_2 \oplus \tilde{Z}_3)^{-1} = [0.0272, 0.0637, 0.1364]$$

$$\tilde{W}_{10} = \tilde{Z}_{10} \otimes (\tilde{Z}_1 \oplus \tilde{Z}_2 \oplus \tilde{Z}_3)^{-1} = [0.0608, 0.1175, 0.2047]$$

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$$\tilde{W}_{11} = \tilde{Z}_{11} \otimes (\tilde{Z}_1 \oplus \tilde{Z}_2 \oplus \tilde{Z}_3)^{-1} = [0.044, 0.0898, 0.1581]$$

$$\tilde{W}_{12} = \tilde{Z}_{12} \otimes (\tilde{Z}_1 \oplus \tilde{Z}_2 \oplus \tilde{Z}_3)^{-1} = [0.0456, 0.084, 0.1581]$$

The final weights of each parameter are calculated as follow:

$W_1 = (\prod_{i=1}^{3} \omega_j)^{1/3} = 0.07928$, W_2=0.0796, W_3=0.0655, W_4=0.1076, W_5=0.1125, W_6=0.0958, W_7=0.05675, W_8=0.0569, W_9=0.0619, W_{10}=0.1136, W_{11}=0.0857, W_{12}=0.0847. Mentioned priority weights have indicated for each criterion in table 4.

Criteria	Global weights
Uniaxial Compressive Strength	0.1136
Hardness	0.1125
Equal Quartz Content	0.1076
Abrasiveness	0.0958
Tensile Strength	0.0857
Young's Modules	0.0847
Grain Size & Shape	0.0796
Texture	0.0793
Matrix Type & Cementation	0.0655
Schmidt Hammer Rebound	0.0619
Density	0.0569
Weathering	0.0568

Table 4. Priority weights for criteria

5.2 Ranking the sawability of carbonate rock

In attempting to present a ranking system for assessing rock sawability, using all mentioned parameters is difficult from a practical point of view. In this ranking system three following rules have been considered: (a) the number of parameters used should be small, (b) equivalent parameters should be avoided, and (c) parameters should be considered within certain groups. Considering these rules, the parameters which have been chosen for assessing the rock sawability are listed as follows:

a. Uniaxial Compressive Strength (UCS)
b. Schmiazek F-abrasivity factor (SF-a)
c. Mohs Hardness (MH)
d. Young's Modulus (YM)

5.3 Uniaxial Compressive Strength (UCS)

Uniaxial compressive strength is one of the most important engineering properties of rocks. Rock material strength is used as an important parameter in many rock mass classification systems. Using this parameter in classification is necessary because strength of rock material constitutes the strength limit of rock mass (Bieniawski, 1989). Factors that influence the UCS

of rocks are the constitutive minerals and their spatial positions, weathering or alteration rate, micro-cracks and internal fractures, density and porosity (Hoseinie et al. 2009). Therefore, uniaxial compressive strength test can be considered as representative of rock strength, density, weathering, texture and matrix type. Thus, the summation of the weights of five parameters (texture, weathering, density, matrix type and UCS) is considered as weight of UCS. In total, the weight of UCS is about 0.372.

5.4 Schmiazek F-abrasivity factor (SF-a)

Abrasiveness influences the tool wear and sawing rate seriously. Abrasiveness is mainly affected by various factors such as mineral composition, the hardness of mineral constituents and grain characteristics such as size, shape and angularity (Ersoy and Waller, 1995). Schimazek's F-abrasiveness factor is depend on mineralogical and mechanical properties and has good ability for evaluation of rock abrasivity. Therefore, this index has been selected for using in ranking system. F-abrasivity factor is defined as

$$F = \frac{EQC \times Gs \times BTS}{100} \tag{16}$$

Where F is the Schimazek's wear factor (N/mm), EQC is the equivalent quartz content percentage, Gs is the median grain size (mm), and BTS is the in direct Brazilian tensile strength. Regarding the rock parameters which are used in questionnaires, summation of the weights of abrasiveness, grain size, tensile strength and equivalent quartz content is considered as weight of Schimazek's F-abrasiveness factor. In total the weight of this factor is 0.3687.

5.5 Mohs Hardness (MH)

Hardness can be interpreted as the rock's resistance to penetration. The factors that affect rock hardness are the hardness of the constitutive minerals, cohesion forces, homogeneity, and the water content of rock (Hoseinie et al. 2009). Thus, hardness is a good index of all above given parameters of rock material. Considering the importance of hardness in rock sawing, hardness, after Schmiazek F-abrasivity factor, is considered the most relevant property of rock material. Regarding the questionnaires, summation of the weights of Mohs hardness and Schmidt hammer rebound value was considered as total weight of mean Mohs hardness. In total the weight of this factor is 0.1745.

5.6 Young's Modulus (YM)

According to rock behaviour during the fracture process, especially in sawing, the way that rocks reach the failure point has a great influence on sawability. The best scale for rock elasticity is Young's modulus. Based on ISRM suggested methods (ISRM, 1981), the tangent Young's modulus at a stress level equal to 50% of the ultimate uniaxial compressive strength is used in this ranking system. Regarding the questionnaires, the weight of this factor is about 0.0847 in total. According to FDAHP results the final weights of major parameters are shown in fig. 4.

5.7 Laboratory tests

For laboratory tests, some rock blocks were collected from the studied factories. An attempt was made to collect rock samples that were big enough to obtain all of the test specimens of

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each rock type from the same piece. Each block sample was inspected for macroscopic defects so that it would provide test specimens free from fractures, partings or alteration zones. Then, test samples were prepared from these block samples and standard tests have been completed to measure the above-mentioned parameters following the suggested procedures by the ISRM standards (ISRM, 1981). The results of laboratory studies are listed in table 5 and used in next stage.
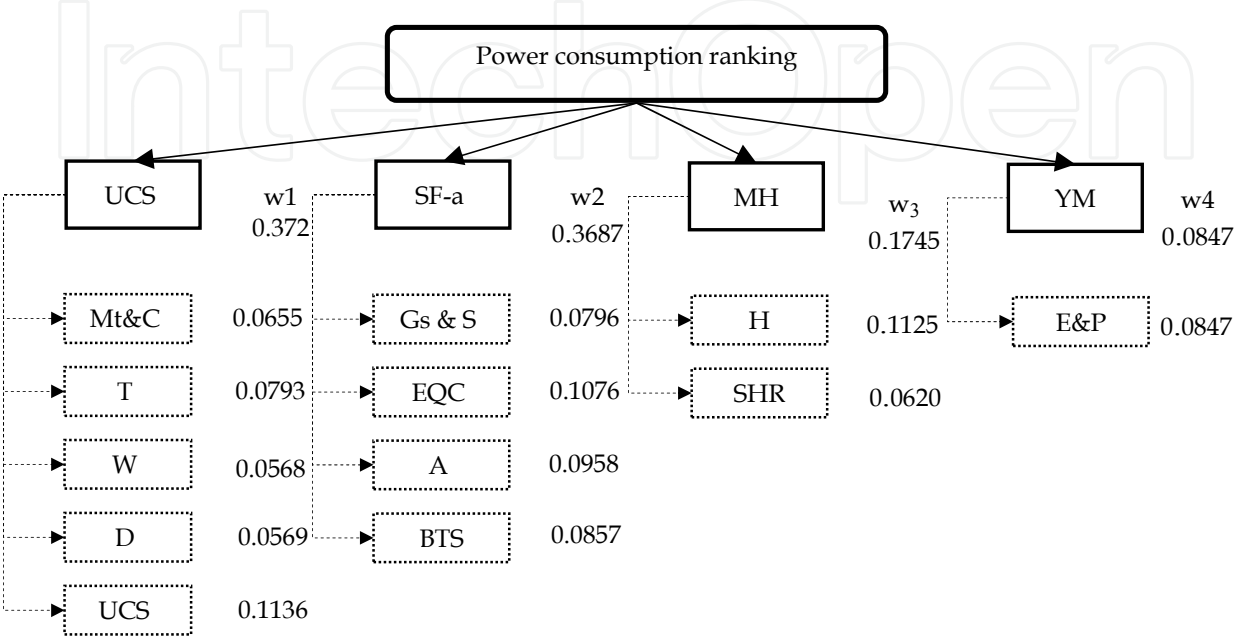
Fig. 4. The final weights of major parameters in power consumption ranking system

	Rock sample	UCS	BTS	EQC	Gs	SF-a	YM	MH
		MPa	MPa	%	mm	N/mm	GPa	n
1	MHAR(Marble)	71.5	6.8	3.6	0.55	0.135	32.5	3.5
2	MANA(Marble)	74.5	7.1	3.4	0.45	0.109	33.6	3.2
3	TGH(Travertine)	53	4.3	2.8	1.01	0.122	20.7	2.9
4	THAJ(Travertine)	61.5	5.6	2.6	0.85	0.124	21	2.9
5	TDAR(Travertine)	63	5.4	2.7	0.87	0.127	23.5	2.95
6	MSAL(Marble)	68	6.3	3.2	0.52	0.105	31.6	3.1
7	MHAF(Marble)	74.5	7.2	4	0.6	0.173	35.5	3.6

Table 5. The result of laboratory studies

After determining the weights of the criteria with FDAHP method and laboratory studies, ranking the sawability of carbonate rocks is performed by TOPSIS method. Firstly, the amount of each criterion is filled in decision matrix for each criterion.

Decision matrix is obtained with respect to important rock properties (Table. 6). Decision matrix is normalized via Eq. (9) (Table. 7). Then, weighted normalized matrix is formed by multiplying each value with their weights (Table. 8). Positive and negative ideal solutions are determined by taking the maximum and minimum values for each criterion:

$$A^* = \left\{ 0.1547, 0.1863, 0.0393, 0.0748 \right\}$$

$$A^- = \left\{ 0.1101, 0.1130, 0.0229, 0.0602 \right\}$$

Then the distance of each method from PIS (positive ideal solution) and NIS (negative ideal solution) with respect to each criterion are calculated with the help of Eqs. (13) and (14). Then closeness coefficient of each rock is calculated by using Eq. (15) and the ranking of the rocks are determined according to these values.

	UCS	SF-a	YM	MH
	C1:	C2:	C3:	C4:
1	71.5	0.135	32.5	3.5
2	74.5	0.109	33.6	3.2
3	53	0.122	20.7	2.9
4	61.5	0.124	21	2.9
5	63	0.127	23.5	2.95
6	73	0.105	31.6	3.1
7	74.5	0.173	35.5	3.6

Table 6. Decision matrix

	UCS	SF-a	YM	MH
	C1:	C2:	C3:	C4:
1	0.3991	0.3937	0.4243	0.4166
2	0.4158	0.3176	0.4387	0.3809
3	0.2958	0.3556	0.2703	0.3452
4	0.3432	0.3619	0.2742	0.3452
5	0.3516	0.3709	0.3068	0.3511
6	0.4074	0.3065	0.4126	0.3690
7	0.4158	0.5052	0.4635	0.4285

Table 7. Normalized decision matrix

	UCS	SF-a	YM	MH
	C1:	C2:	C3:	C4:
1	0.1485	0.1452	0.0360	0.0727
2	0.1547	0.1171	0.0372	0.0665
3	0.1101	0.1311	0.0229	0.0602
4	0.1277	0.1334	0.0232	0.0602
5	0.1308	0.1368	0.0260	0.0613
6	0.1516	0.1130	0.0350	0.0644
7	0.1547	0.1863	0.0393	0.0748

Table 8. Weighted normalized matrix

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The power consumption ranking of carbonate rocks are also shown in Table 9 in the descending order of priority.

Rank	Carbonate rock	dj*	dj-	CCj
1	MHAF(Marble)	0	0.0886	1
2	MHAR(Marble)	0.0418	0.0532	0.5602
3	MANA(Marble)	0.0697	0.0475	0.4050
4	MSAL(Marble)	0.0742	0.0434	0.3693
5	TDAR(Travertine)	0.0582	0.0317	0.3528
6	THAJ(Travertine)	0.0632	0.0270	0.2992
7	TGH(Travertine)	0.0743	0.0181	0.1958

Table 9. Rankings of the sawability of carbonate rocks according to CCj values

6. Discussion and validation of the new ranking

A new hierarchical model is developed here to evaluate and ranking the sawability (power consumption) of carbonate rock with using of effective criteria and considering of decision makers' judgments. The proposed approach is based on the combination of Fuzzy Delphi and Analytic Hierarchy Process (FDAHP) methods. Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is also used in this study. FDAHP was used for determining the weights of the criteria according to decision makers then rankings of carbonate rocks were determined by TOPSIS. The proposed method was applied for Iranian ornamental stone to evaluation the power consumption in rock sawing process. The sawability ranking results of tested carbonate rocks are shown in section 5.

For validation of applied ranking system, experimental procedure was carried out. For this purpose, a fully-instrumented laboratory cutting rig was used. The rig was based on a commercially available machine and was capable of simulating realistic cutting conditions. It consists of three major sub-systems, a cutting unit, instrumentation and a personal computer. Sawing tests were performed on a small side-cutting machine, with a maximum spindle motor power of 7.5 kW. Cutting parameters such as feed rate, depth of cut, and peripheral speed control in the monitoring system. The variation of ampere was measured with a digital ampere-meter. The circular diamond saw blade used in the present tests had a diameter of 410 mm and a steel core of thickness 2.7 mm, 28 pieces of diamond impregnated segments (size 40×10×3 mm) were brazed to the periphery of circular steel core with a standard narrow radial slot. The grit sizes of the diamond were approximately 30/40 US mesh at 25 and 30 concentrations. This blade is applied for travertine, limestone and marble types of the stones, which are non-abrasive and medium hard. During the sawing trials, water was used as the flushing and cooling medium and the peripheral speed and depth of cut were maintained at constant 1770 rpm and 35 mm. Each rock was sawn at particular feed rate (200, 300 and 400 cm/min). During the sawing trials, the ampere and power consumption were monitored and calculated. The monitored ampere and calculated power consumption are listed in Table 10. According to Tables 9 and 10, the first rock in ranking (MHAF) has a maximum value of power consumption among other rock samples. It means that the new developed ranking is correct.

	Rock sample	Test 1 Fr=200 (cm/min)		Test 2 Fr=300 (cm/min)		Test 3 Fr=400 (cm/min)	
		I(A)	P(W)	I(A)	P(W)	I(A)	P(W)
1	MHAF(Marble)	12	2280	17.5	4370	28.6	8588
2	MHAR(Marble)	11.5	2090	16.4	3952	22	6080
3	MSAL(Marble)	11.5	2090	15.7	3686	20.2	5396
4	MANA(Marble)	11.2	1976	16.5	3990	22.2	6156
5	THAJ(Travertine)	11.2	1976	15.4	3572	19	4940
6	TDAR(Travertine)	10.6	1748	15.6	3648	17.2	4256
7	TGH(Travertine)	9.5	1330	12	2280	18	4560

Table 10. Ampere and calculated power consumption in sawing trials

The calculated power consumption of each carbonate rock in Figure 5 shows that the new ranking method for carbonate rock is reasonable and acceptable for evaluating them.
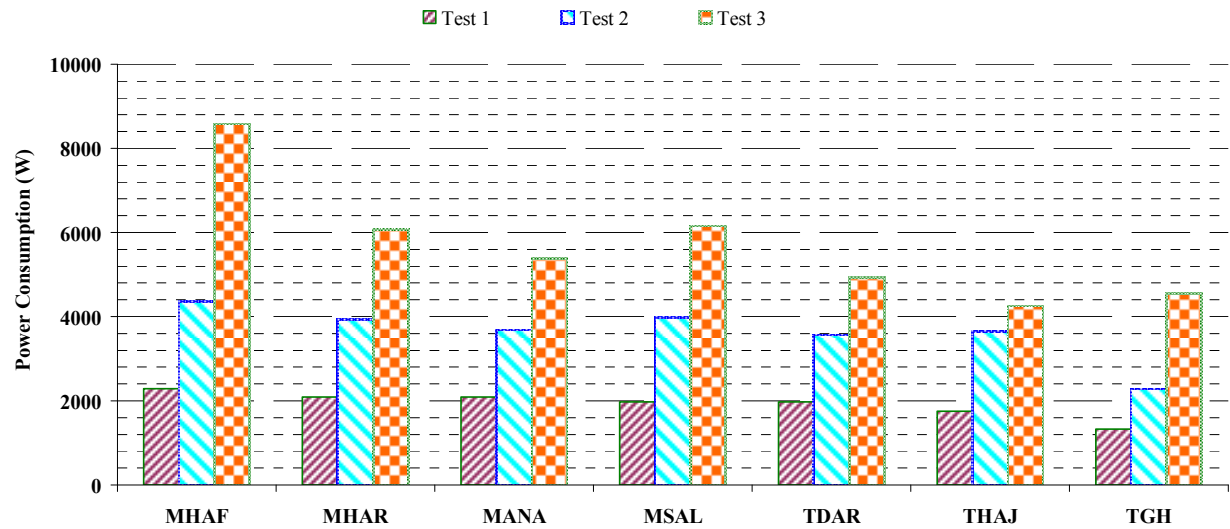
Fig. 5. The power consumption of carbonate rocks in sawing trials

7. Conclusion

In this chapter, a decision support system was developed for ranking the power consumption of carbonate rocks. This system designed to eliminate the difficulties in taking into consideration many decision criteria simultaneously in the rock sawing process and to guide the decision makers for ranking the power consumption of carbonate rocks. In this study, FDAHP and TOPSIS methods was used to determine the power consumption degree of the carbonate rocks. FDAHP is utilized for determining the weights of the criteria and TOPSIS method is used for determining the ranking of the power consumption of carbonate rocks. During this research a fully-instrumented laboratory sawing rig at different feed rate for two groups of carbonate rocks were carried out. The power consumptions were used to verify the result of applied approach for ranking them by sawability criteria. The experimental results confirm the new ranking results precisely.

This new ranking method may be used for evaluating the power consumption of carbonate rocks at any stone factory with different carbonate rock. Some factors such as uniaxial compressive strength, Schmiazek F-abrasivity, mohs hardness and young's modulus must be obtained for the best power consumption ranking.

8. Acknowledgment

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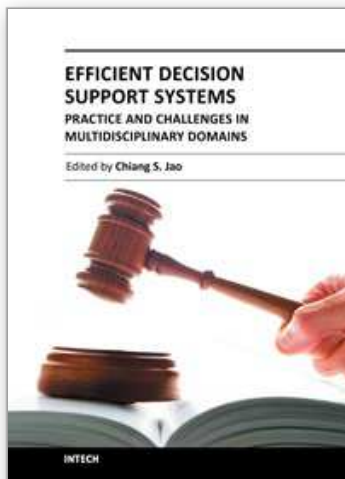
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