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Combining fuzzy RES with GA for predicting wear performance of circular diamond saw in hard rock cutting process

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Abstract

Predicting the wear performance of circular diamond saw in the process of sawing hard dimensional stone is an important step in reducing production costs in the stone sawing industry. In the present research work, the effective parameters on circular diamond saw wear are defined, and then the weight of each parameter is determined through adopting a fuzzy rock engineering system (Fuzzy RES) based on defining an accurate Gaussian pattern in fuzzy logic with analogous weighting. After this step, genetic algorithm (GA) is used to determine the levels of the four major variables and the amounts of the saw wear (output parameter) in the classification operation based on the fixed, dissimilar, and logarithmic spanning methods. Finally, a mathematical relationship is suggested for evaluation of the accuracy of the proposed models. The main contribution of our method is the novelty of combination of these methods in fuzzy RES. Before this work, all Fuzzy RESs only use simple membership functions and uniform spanning. Using GA for spanning and normal distribution as membership function based upon our latest work is the first work in fuzzy RES. To verify the selected proposed model, rock mechanics tests are conducted on nine hard stone samples, and the diamond saw wear is measured and compared with the proposed model. According to the results obtained, the proposed model exhibits acceptable capabilities in predicting the circular diamond saw wear.

1. Introduction

In excavation and sawing operations, the feature of the stone that scrapes away the auger head is called abrasiveness [1]. Abrasiveness is one of the most effective parameters in stone sawability. Having a clear measure of this parameter plays a significant role in selecting the cutter tool in mine excavations as well as in cutting building stone operations [2]. Recognizing the characteristics of stones and investigation of the operational parameters specified for the cutting machines provide building stone production industry planners with a more facilitated cruise towards improving the processing speed and production enhancement. Therefore, in order to achieve an appropriate design in stone processing factories, predicting the diamond saw wear is what deemed to be necessary. Studies indicate that with increase in the uniaxial compressive strength, hardness, and stone abrasiveness, the excavation capability and stone sawability suffer a decline. The studies carried out in this section include offering a classified system accompanied by statistical relations [3-5]. Table 1 presents the most important research works that have been undertaken in the field of stone sawability and diamond saw wear.

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Table 1. Most important studies carried out in process of rock sawability and wear performance of circular diamond saw.

Researcher	Features Investigated
Birle & Ratterman, 1986 [6]	Offering a classification system based on laboratory studies for predicting saw wear performance in hard stones.
Pai, 1987, [7]	Offering a classification system based on saw wear performance and energy consumption.
Jening et al., 1989, [8]	Investigating the factors effective on diamond disc performance, cutting ability and the saw useful life relationship with the abrasiveness and hardness parameters.
Tonshoff et al., 2002, [9]	Investigating the factors effective in diamond tool wear (thermal and mechanical loads, tool characteristics, work piece and machining factors).
Konstanty, 2002, [10]	Analyzing the stone cutting according to the diamond tool performance.
Eyuboglu et al., 2003, [11]	Investigating the effect of stone parameters on saws wear in the process of Andesite stones cutting.
Engels, 2003, [12]	The effect of operational and instrument specifications on cutting rate and chip thickness in granite.
Kahraman et al., 2004, [13]	Surveying the relationship between the stone mechanical properties and cutting machine operational parameters.
Ersoy & Atici, 2005, [14]	The effect of various operational conditions on the behavior of the stone cutting saws.
Ersoy et al., 2005, [15]	Surveying the effect of diamond tool wear in hard stones.
Fener et al., 2007, [16]	Diamond discs performance in cutting carbonated stones according to the mechanical properties.
Buyuksagis, 2007, [17]	The effect of cutting methods on the wear of the diamond saw in the process of cutting granite.
Ozcelic, 2007, [18]	The effect of stone texture features on wear rate in the process of cutting carbonated stones.
Amaral et al., 2009, [19]	Surveying the diamond segment wear mechanism in the process of cutting granite stones.
Mikaeil et al., 2011, [20]	Developing a classification system for the prediction of carbonated stones cutting ability.
Yilmaz et al, 2011, [21]	Investigating the effect of stones physical and mechanical properties on diamond segment wear.
Turchetta, 2012, [22]	The effect of cutting conditions on cutting force and cutting energy and their relationships with the diamond segment wear.
Ataei et al., 2012, [23]	Offering a novel classification system for the evaluation of carbonated stones cutting ability.
Aydin et al., 2013, [24]	Offering a model for predicting the diamond saws wear rate in granite.
Karakurt, 2014, [25]	Optimizing the cutting forces in the process of cutting with diamond discs by the help of Taguchi method.
Mikaeil, et al., 2015, [26]	Developing the stones cutting predictability based on PROMETHEE method.
Mikaeil, et al., 2016, [27]	Predicting the cutting machine performance by exploitation competition algorithm and fuzzy clustering method.
Almasi et al., 2017a, [28]	Predicting the dimensional stones cutting rate based on stone characteristics and the intensity of the consumed energy by the use of tree model.
Almasi et al., 2017b, [29]	Developing a novel classification system based on abrasion, hardness and toughness for the prediction of hard stones cutting ability.

The substantial problem of the prior studies has been the adoption of separate measures for evaluating the effective parameters influencing the stone sawing speed and diamond segment wear. This is while the stone sawability and diamond saw wear depend on a great many of the parameters and these parameters are in close connection with one another. Therefore, attaining a comprehensive method by means of which the sawing speed in stones and finally the diamond saw wear can be evaluated is under the focus of the current research paper.

Classification systems are posited as effective tools in stone engineering for the purpose of evaluating the stone mass and material behavior. Therefore, according to the complicated nature and numerous effective factors influencing the stone sawing process and considering the diamond saw wear, it seems that the use of a classification system can be a solution in resolving the complicacies extent in evaluating the stone sawability as well as diamond saw wear prediction. The present work offers a novel classification system incorporating the effective stone physical and mechanical parameters according to the observation of principles like the non-existence of boundary constraints and inter-parameter overlapping to evaluate the diamond saw wear in the process of sawing dimensional stones. Up to the current point in time, the majority of the works performed in classifications area have been based upon classic measures. In such systems, some rocks are classified inaccurately due to the distinctions made between various classes as a result of a number of fixed constraints, and this is not optimum at all. According to the idea that the increase in the classification precision as well as the increase in the confidence level is always an optimum suitability, the present work makes use of fuzzy logic to elevate the precision and get close to the real conditions.

2. Methodology

The present research paper takes advantage of fuzzy logic combined with genetic algorithm (GA), as an evolutionary system, for the purpose of improving the rock engineering systems (RESs) and increasing the classification confidence, enhancing the stone sawing process, and predicting diamond saw wear. In rock engineering procedures, the choice of the important parameters and taking the effects of various variables into consideration and combining these parameters alongside one another are altogether the most important stages of the research work. Figure 1 illustrates a flow chart of the operations performed in the current research paper.

Fuzzy logic is enumerated a mathematical solution in classification problems and static boundary conditions problem-solving. There is no clear boundary in fuzzy logic, and the various element association with different concepts and subjects is relative, and the elements are not divided into two sets of members and non-members. The membership of the various elements ranges from 0 to 1 in fuzzy systems [30].

GAs are efficient in different non-linear non-analytical functions of the mathematical equations describing various phenomena in nature, and they are required to be solved and their answers to be found for various engineering designs. Optimizing the structure causes a reduction in the system's time and cost.

2.1. Classic RES method

Rock engineering system was first offered by Hudson in 1992, and it has been widely applied in problem-solving measures since then. Based on the Hill and Warfield's theory, the RES systems are displayed in matrix form in various applications, and these matrices exhibit the entire characteristics of the system including the components, interactions, and system's distinguished borders [31-32].

In RES, the factors mutually influence each other that these interactions are considered. The major effective factors in the corresponding problem are stretched along the matrix main diagonal, and the interactions between each pair of the aforementioned factors are found in the other entries.

There are five various methods available for coding the interaction matrices including binary, expert semi-quantitative (ESQ), parameters diagram slope, dissimilar method based on direct systematic approach, and explicit methods [33]. In the diagram exhibiting the parameters cause-effect, the influence of one parameter on the system is called cause, and the effect of system on the parameter is termed effect. These diagrams are obtained from the influence of interactive matrices' effects, and they demonstrate the possibility for the identification of prevalent design parameters as well as the intensity of the individual interactions on the system behavior. The sum of each row and column is calculated after matrix coding. The sum of the numerical amounts obtained for each line as the "cause" or P_1 influence on the system is designated by "C" on the coordinate system, and the algebraic sum of every column as the system "effect" on or result from P_1 is denoted by "E". The way a parameter influences the system as well as the way it is influenced by the system is shown on the coordinate system in Figure 2 [33].

After plotting the cause and effect diagrams and performing the necessary analyses, finally, Equation (1) is applied to calculate the weight of each parameter and the parameters' interaction intensity [34].

$$\alpha_i = \frac{C_i + E_i}{\sum_{i=1}^{n} C_i + \sum_{i=1}^{n} E_i} \quad (1)$$

where i is the number of major parameters, α_1 is the weight of the i_{th} parameter, C_1 is the effect of the i_{th} parameter, and E_1 is the effect on the i_{th} parameter.

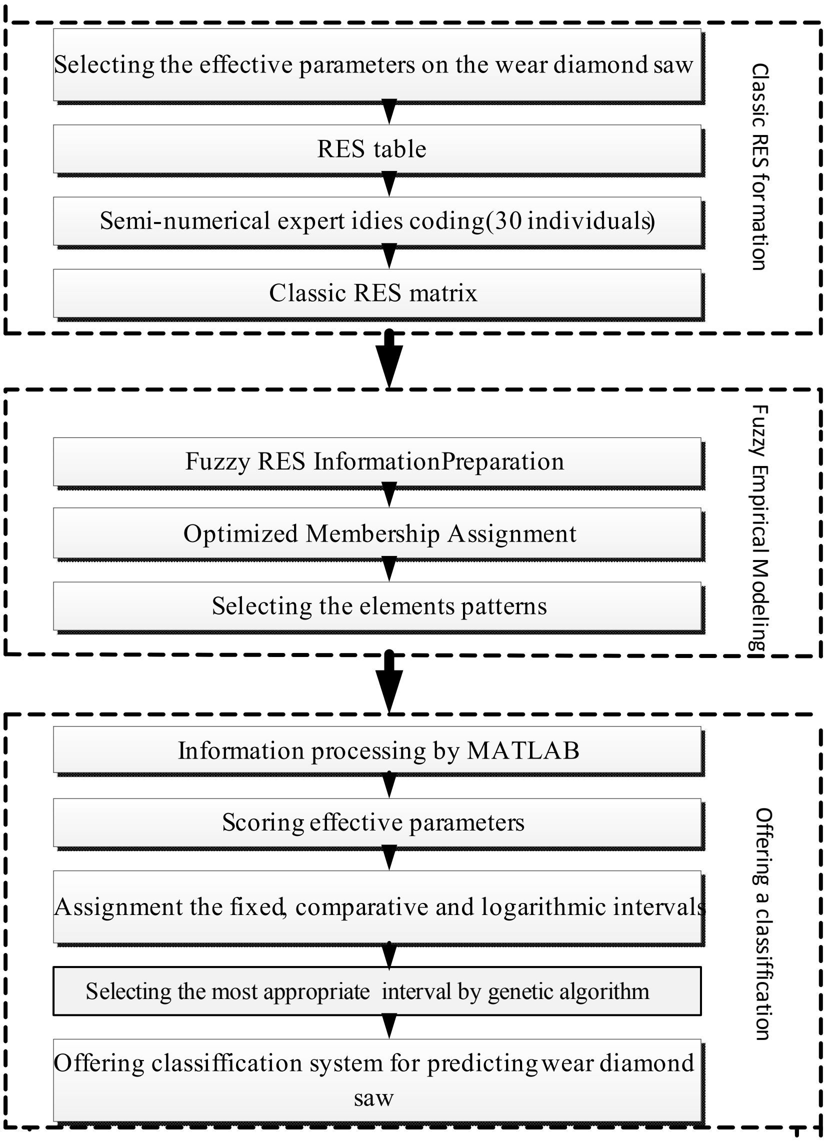

Figure 1. A new classification method flowchart to predict wear performance of circular dimond saw.

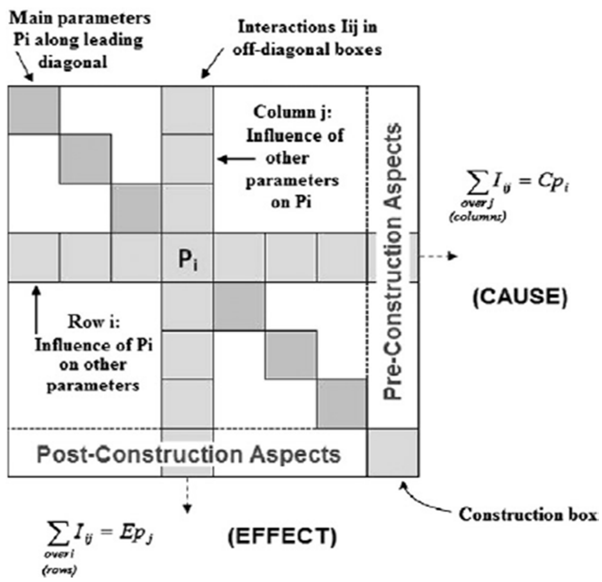

Figure 2. Summation of coding values in column and row through each parameter to establish cause and effect coordinates [33].

2.2. Fuzzy RES method

In the fuzzy RES method, the parameters' weights are assigned in a fuzzy form in lieu of making use of the fixed values specified by Equation (1). In this mode, the allowable span selected based on the fuzzy membership function in the form of a given category will be divided into several categories, and each of these categories are assigned with corresponding weights based on the amount of effect each of them exerts. Gaussian (normal) membership function has been used in the proposed method based on natural system studies and variable interaction investigation.

Normal distributions are important in statistics, and are often used in the natural and social sciences to represent real-valued random variables whose distributions are not known [35]. As it can be seen in [35, 37], especially in statistics, normal distributions is the most important distribution to explain the behavior of variables with an unknown nature. As a result, membership functions in fuzzy systems use the PDF of variables to explain the fuzzy behavior of this, so as a direct result, the normal PDF is the best choice in natural systems.

The major parameters in the normal membership function are classification average and variance, and the membership function can be calculated by the use of numerical methods and each sample span certainty, and then it can be given certain variables.

In the Gaussian membership function, each new variable is replaced with a real value that shows its probability to occur in this distribution (membership) function. Obviously, if the value is far from the center (mean value) of distribution function, the probability of its occurrence is low, and if this value is near to center of MF (Membership Function) the probability is near to maximum. In fact, these probabilities form the fuzzy value for each variable, and a combination of them form the final result.

In assigning the weights in normal fuzzy function, instead of calculating the weight in the form of a fixed value in the entire span, the weight takes the highest likely value in the maximum average point, and its value decreases with it being placed at the extremes of the span, and then the effects of the variables in the points, the distances of which are considered more than what is expected will be decreased to the same extent. In case the parameters' patterns or the natural variables do not follow the normal membership function, there are certain statistical tests that exactly determine the membership function confidence level and show the membership function inefficiency in the parameter of concern.

Normal (Gaussian) membership function, due to its being closer to natural processes, its continuous mode and high precision is considered as one of the most common membership functions in the fuzzy systems. It is evident that fuzzy simple functions such as triangular and trapezoidal are not able to explain the real behavior of complicate natural variables accurately and only give a simplified explanation of these variables. Different from them, the Gaussian function is able to explain natural systems so accurate [36-37]. Under some reasonable assumptions, it can be proved that Gaussian functions are the most adequate choice of the membership functions for representing uncertainty in measurements [37].

Finally, a Gaussian membership function was selected as the appropriate membership function of choice in the proposed method, and its precision and correspondence to the perceived data was statistically tested. After attributing the membership function to the effective parameters in the classification, combining the parameters formed the final system in which case the final decision-making is carried out with a certain fixed threshold and usually quite similar to what takes place in classic systems.

3. Fuzzy empirical modeling

In the classic RES method adopted in the prior works, firstly, the expert ideas are considered fixed or absolute; secondly, according to the idea that sampling is performed on a smart community in the engineering area, the notion scattering and/or expert idea variance is neglected. The closeness or the distantness of the expert ideas in the proposed fuzzy system should be weighted based on a correct and authentic pattern.

3.1. Database compilation and information preparation

At first, a comprehensive questionnaire was administered to 30 experts. The questionnaire collected the data pertaining to the effects of the entire variables in a five-level format according to the effect they exert on abrasion as it is considered by the individuals expert in this field. In order to be able to retrieve the patterns defined by various experts in an appropriate manner by means of the MATLAB software (2016 edition), the entire information was identically inserted in Excel covering all the notions existent in the survey. A sample of the prepared matrix in Excel is given in Table 2.

Table 2. A sample of matrix completed by expert individuals.

	UCS	BTS	N	ρ	W	Sf-a	Ym	EQC	TC	Gs	IRB	LA	MH
UCS	UCS	2	0	2	1	2	2	0	1	0	2	1	1
BTS	3	BTS	0	1	2	1	1	0	1	0	1	1	1
N	2	4	N	2	4	1	2	0	1	0	2	2	0
ρ	3	3	3	ρ	3	2	3	0	1	1	2	2	1
w	2	3	4	3	W	2	2	0	1	2	2	2	2
Sf-a	3	2	2	2	1	Sf-a	2	1	1	2	2	2	1
Ym	3	2	2	2	1	1	Ym	0	2	1	2	2	1
EQC	3	3	2	3	2	3	3	EQC	2	2	3	3	2
Tc	3	2	1	2	1	2	2	1	Tc	1	2	2	1
Gs	2	3	2	3	3	2	3	1	1	Gs	3	3	2
IRB	3	3	3	3	2	2	3	1	2	1	IRB	3	4
LA	3	2	2	3	2	2	2	1	1	1	3	LA	3
MH	3	3	2	3	2	3	3	2	2	2	3	3	MH

where UCS is the uniaxial compressive strength, BTS is the indirect Brazilian tensile strength, N is the porosity, ρ is the density, W is the water absorption percentage, SF-a is the Shimazaki abrasion, YM is the Young's modulus, EQC is the quartz content, Tc is the tissue coefficient, Gs is the grains size, IRB is the Schmidt hammer rebound hardness, LA is the Los Angles abrasion, and MH is the Mohs hardness. As a specimen, the first row and the third column in Table 2 are indicators of the extent to which N influences UCS.

3.2. Membership function allocation

At this stage, there are thirty 13×13 matrices. According to the probability density function being specified, it is now necessary to control the minimum number of the samples required by the experts so as to save a sufficiently high confidence margin for the results, and the outputs can be offered as statistically significant as possible.

The minimum quantity of the sample so as to make a distribution follow the normal patterns corresponding to a central limit theorem is that the sample dimensions must exceed 20. In case that the sample dimensions are very large, the probability density pattern disregarding the type of the variable and its pattern will necessarily shift towards a normal pattern [38]. This is one of the most important principles for reasoning the use of normal probability density function in fuzzy pattern of the proposed method. To determine the sample size, and according to the maximum standard deviation existent in the extracted information, and considering a very high confidence level, a number of thirty samples was envisaged appropriate.

3.3. An appropriate fuzzy pattern

In the compiled 13×13 matrix, there are totally 144 fuzzy patterns required for displaying the variables' relationships. If each variable is assigned with a normal fuzzy pattern, for each one of the variables in the thirteen-fold variable set, there will be totally 12 fuzzy membership functions (other than the variable with itself), and these membership functions can model the relationship pattern of this variable with the others with a high precision rate; in addition, the efficiency of the modeling will be increased.

In MATLAB, expert ideas are inputted to the system as random fuzzy samples, and based on this, a normal probability density function will be generalized as the membership function. To obtain the normal pattern according to the 30 aforementioned samples, various numerical methods like core method and B-splines can be used [36, 38]. In case that the information does not follow the normal pattern, the maximum similarity scale as an authentic test can be excluded, and it enjoys a greater reliability with respect to the other tests [39]. To assure the confidence of the replies acquired in the proposed method, the pattern authenticity was again evaluated in the form of questionnaires administered to the experts by taking advantage of the Anderson-Darling statistical test [40]. The test is of use in analyzing the similarity or the identicalness of the type of change between two random variables, and it delivers high efficiency, particularly in calculating the goodness of fitness or the model-information match [41]. The results obtained in this test for all of the 144 cases indicated that the model information absolutely complied with the pattern. The mean and standard deviation values per the entire obtained samples were tabulated in Table 3, which provides information regarding the preliminary fuzzy membership functions including the entire figures and elements pertaining to the produced matrices.

For instance, in column 8, there are smaller figures that are indicative of the trivial effect of various variables on EQC. The form of the numbers presented in the table completely justifies the use of the proposed fuzzy pattern in terms of the experts' ideas discrepancies or consensus. Several sample values regarding the expert ideas' scattering were given in Table 4.

In Table 4, the first line shows the name of the two variables about which the experts' ideas do not conform, and the second line indicates the standard deviation. For instance, the figure "1.035" in the first column is reflective of the idea that the UCS's effect on MH is regarded as featuring too much scattering in terms of the experts' ideas.

Table 3. Mean and standard deviation of variables and Gaussian fuzzy membership functions (mean and standard deviation).

	UCS	BTS	N	ρ	W	Sf-a	Ym	EQC	Tc	Gs	IRB	LA	MH
UCS	0.000	2.250, 0.463	0.750, 0.463	2.500, 0.756	1.375, 0.518	1.375, 0.916	2.000, 0.756	0.500, 0.756	0.750, 0.463	0.125, 0.354	2.500, 0.926	2.000, 0.926	1.250, 1.035
BTS	2.875, 0.354	0.000	0.500, 0.535	1.750, 0.886	1.625, 0.518	2.375, 1.061	1.875, 0.835	0.750, 1.389	0.875, 0.641	0.250, 0.707	1.875, 1.356	1.375, 0.518	1.000, 1.309
N	3.000, 0.535	2.750, 1.035	0.000	2.375, 0.518	3.375, 0.916	1.500, 0.926	2.000, 0.756	0.000, 0.000	1.250, 0.707	0.250, 0.707	2.250, 0.463	2.000, 0.000	0.625, 0.518
ρ	3.250, 0.707	2.750, 0.707	3.000, 0.000	0.000	2.875, 0.835	1.625, 0.518	2.625, 0.518	0.000, 0.000	1.375, 0.744	1.000, 0.000	2.625, 0.518	2.250, 0.463	1.625, 0.916
W	2.375, 0.744	2.625, 0.518	2.875, 1.246	2.250, 1.035	0.000	1.125, 0.835	2.125, 0.835	0.000, 0.000	0.875, 0.354	0.875, 0.835	1.750, 0.463	1.625, 0.518	1.500, 0.535
Sf-a	2.375, 0.744	2.000, 0.535	1.375, 0.916	1.375, 0.916	0.750, 0.463	0.000	1.500, 0.926	0.750, 1.035	1.375, 0.744	1.250, 0.707	2.000, 0.000	2.500, 0.756	1.625, 0.518
Ym	2.500, 0.535	2.000, 0.000	1.250, 0.886	1.750, 1.165	0.750, 0.463	0.875, 0.641	0.000	0.125, 0.354	1.500, 0.756	0.500, 0.535	2.000, 0.000	2.375, 0.518	1.375, 0.518
EQC	3.375, 0.518	2.500, 0.535	1.125, 0.835	2.500, 0.756	1.750, 0.463	3.250, 0.707	2.750, 0.463	0.000	1.250, 1.035	0.875, 0.735	2.875, 0.835	3.000, 0.000	2.750, 1.389
Tc	2.750, 0.707	2.250, 0.463	1.875, 0.835	2.500, 0.535	1.750, 0.886	2.500, 0.535	2.125, 0.354	0.875, 0.641	0.000	1.750, 1.035	2.250, 0.463	2.250, 0.463	1.625, 0.916
Gs	2.750, 1.035	2.500, 0.756	2.250, 0.707	2.375, 0.744	2.500, 0.756	2.875, 0.835	2.375, 0.518	0.500, 0.535	1.875, 0.835	0.000	2.500, 0.756	2.250, 0.707	1.875, 0.354
IRB	3.750, 0.463	2.875, 0.354	1.875, 1.246	2.250, 1.035	1.250, 1.035	2.250, 0.463	2.375, 0.518	0.500, 0.535	1.500, 0.926	1.500, 0.926	0.000	2.500, 0.535	3.375, 1.061
LA	2.625, 0.744	1.750, 0.463	1.625, 1.188	2.375, 1.061	1.500, 0.926	2.500, 0.535	1.750, 0.463	1.000, 0.926	1.125, 0.835	0.875, 0.641	2.000, 0.926	0.000	2.250, 0.707
MH	2.750, 0.463	2.375, 0.744	1.375, 0.916	2.375, 0.916	1.625, 0.518	2.625, 0.518	2.125, 0.835	1.375, 1.302	1.375, 0.916	1.375, 0.916	2.750, 0.707	2.875, 0.354	0.000

Table 4. Expert ideas scattering.

UCS, MH	BTS, Sf-a	BTS, EQC	BTS, IRB	BTS, MH	N, BTS	W, N	W, ρ	Sf-a, EQC
1.035	1.061	1.389	1.356	1.309	1.035	1.246	1.035	1.035

3.4. Information processing

To sum up a value from each variable in an active or interactive mode, the membership functions should be appropriately intermingled so as to be able to obtain a fuzzy number, indicating the degree to which each variable is significant. To combine the fuzzy membership functions, a specific mathematical method based on a randomized process is applied. In this method, 10000 random samples are generated by taking advantage of the probability density pattern. According to the complicacy of this stage, Normrnd instruction in the MATLAB software is used. The instruction is a generator of the randomized figures based on Gaussian pattern with pre-determined mean and standard deviation [42-43]. Randomized samples are again mixed, and a Gaussian pattern is obtained in every line, and it is somehow the output of the entire variable aggregation. After calculating a thousand figures for each one of the elements, twelve elements of every line or column are placed at the side of one another, the result of which is a 120-thousand-tuple vector for every line or column. Using this 120-thousand-tuple vector, a fuzzy pattern was again calculated in a unitary format [39]. The mean and the standard deviation of this pattern is in fact the final output of the method or the same final fuzzy value of the variables. This procedure was repeated separately for the lines and the columns. Another advantage of this proposed method is the direct effect of the mean and the standard deviation of the entire membership functions in the final response. All responses unexceptionally exert a fuzzy effect on the final response in mathematical terms. As a final response and overall summation of the results, Table 5 presents the amount of effect each one of the variables, as distinguished by every line and column, has on the diamond saw wear considering the ideas and notions by the experts and the statistical and fuzzy computations. Finally, combining lines and columns' sums for each of the variables according to Equation (2) provides the final fuzzy weight of each variable that can be seen in the ending line of Table 5.

$$\alpha = \frac{Z_{row_i} + Z_{Col_i}}{\sum_{i=1}^{N} Z_{row_i} + Z_{Col_i}} \quad (2)$$

where Z_{row_i} is the lineal fuzzy weight for variable i, Z_{Col_i} is the columnar fuzzy weight of variable i, and N is the total number of the variables. The maximum and minimum weights belong to IRB and EQC, respectively.

The Z values are mean of normal probability density function that can be estimated from the value of input variables with many numerous methods such as maximum likelihood method, which maximize the log-likelihood function [44].

Table 5. Linear, columnar, and final fuzzy weights of variables.

Variable name	Column		Row		Final fuzzy weights
	Mean	Variance	Mean	Variance	
UCS	2.862	0.769	1.448	1.060	0.0900
BTS	2.383	0.684	1.424	1.176	0.0802
N	1.659	1.153	1.782	1.233	0.0715
ρ	2.199	0.952	2.081	1.095	0.0888
W	1.759	1.049	1.664	1.090	0.0710
Sf-a	2.071	1.025	1.573	0.911	0.0761
Ym	2.135	0.756	1.417	0.946	0.0742
EQC	0.533	0.886	2.332	1.129	0.0594
Tc	1.26	0.822	2.039	0.838	0.0686
Gs	0.883	0.892	2.215	0.939	0.0642
IRB	2.28	0.801	2.166	1.199	0.0921
LA	2.249	0.704	1.784	0.993	0.0840
MH	1.741	1.134	2.088	0.993	0.0798

4. Classification of saw wear evaluation

To compile and offer a classification system in rock engineering, the selection of key parameters and their combinations are among the most important principles of designing and creating a classification system [45]. A classification system becomes acceptable when, besides featuring simplicity (minimum time and test costs), it can capture the entire physical and mechanical characteristics of rocks with the minimum quantity of parameters.

4.1. Selecting effective parameters

The four parameters, namely Schmidt hammer rebound hardness, uniaxial compressive strength, Los Angles abrasion, and elasticity module, due to the higher final weight (Figure 3 and Table 6), have been, respectively, proposed and utilized as the representatives of the four important features of the rocks including hardness, abrasion, compressive strength, and elasticity properties.

A) Schmidt Hammer

Hardness is a function of the intrinsic factors like the type of the mineral, the elastic-plastic behavior of the rock, and the grain dimensions. The combination of these factors determines the hardness of a rock. The final weight attributed to Schmidt hardness is also obtained via summing the weights belonging to two parameters Schmidt hardness and Mohs hardness equal to 17.3.

B) Uniaxial Compressive Strength

This parameter represents many physical and mechanical characteristics of the rock including the texture, density, compressive strength, indirect Brazilian tensile strength, porosity, and water content. The weight sum of all these parameters equal to 46.9 is considered as the final weight of the uniaxial compressive strength in the new classification system.

C) Los Angles Abrasion

The rocks' wearing and abrasion ability depend on the type and amount of the mineral, the number of micro-cracks, and weathering degree as well as the inter-grain adhesion. To investigate the stone abrasion in laboratories, there are numerous methods offered by a great many of the researchers some of which are being widely used. Abrasion tests based on Los Angles method are being frequently used today. The method is applied to determine the rock material strength against abrasion upon receiving impacts. Los Angles abrasion is utilized as the quantitative index of rock abrasion evaluation. This parameter weight also calculated from the sum of Schimazek's F-abrasiveness grain size and the quartz content is 28.4.

D) Elasticity Module

By focusing on the way rocks behave in failure process as well as on the formation of chips in the process of sawing stones, it can be found out that the way a stone sample reaches its maximum compressive strength highly influences the diamond sae wear. Although this parameter influences the other properties of rocks, the effects it exerts are more considerable than its being influenced by the other parameters. Elasticity module is utilized as the parameter indicative of the rock's elastic behavior with a final weight equal to 7.4.

Thus this way, the weight of each one of the four parameters, namely Schmidt hardness, uniaxial compressive strength, Los Angles abrasion, and elasticity module, should be determined for the evaluation of diamond saw wear. Figure 3 illustrates the final weight of these parameters.

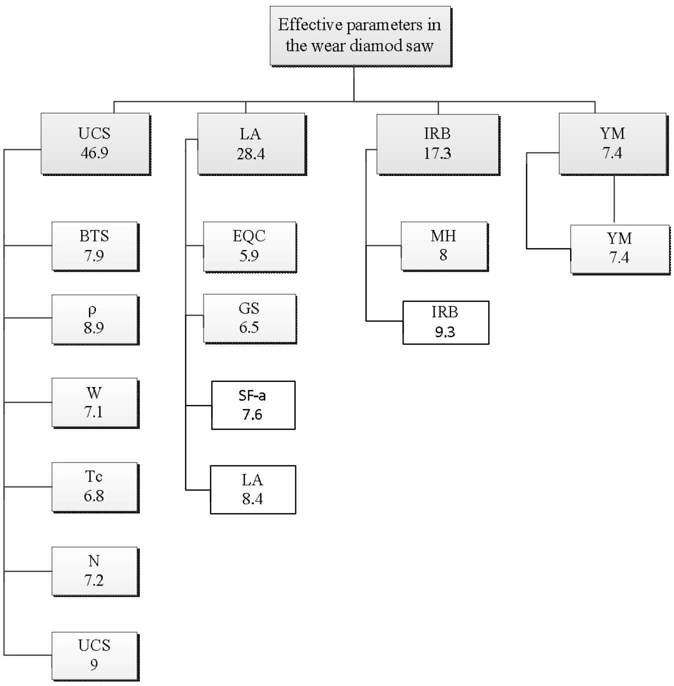

Figure 3. Final weight values of effective parameters in new classification.

4.2. Determining span (spanning)

4.2.1. Fixed spanning

Diamond saw wear is specified in the format of a scale from as very low to very high. Boundary selection takes place in a five-level scale including "very low", "low", "medium", "high", and "very high". This grading method is the most widely applied method in acquiring the experts' ideas [46]. Wear rate calculation based on fuzzy weights is carried out according to Equation (3):

$$\mathrm{Y}_{Model} = \alpha_1 \mathrm{UCS}_{group} + \alpha_2 \mathrm{IRB}_{group} + \alpha_3 \mathrm{Ym}_{group} + \alpha_4 \mathrm{LA}_{group} \tag{3}$$

where, $\mathrm{Y}_{\mathrm{model}}$ is the predicted wear (output), and α_1, α_2, α_3, and α_4 are, respectively, the weights of the fuzzy groups UCS, IRB, YM, and LA, which are obtained from every group based on Figure 3 and with a final fuzzy summing of the corresponding variables, as presented in Table 5. The final fuzzy weights are given separately in Table 6.

The values allocated to each variable in Equation (3) are determined though the grading method, and they range from 1 to 5. In grading by the use of equal spans, the variations take a linear form. Table 7 presents the results for the grading based on the method mentioned above for the four major variables and the wear value (output). The figures, respectively, specify the various spans' floor and top values. In case that the selected spanning method is exercised accurately and correctly, an appropriate span limit of the wear (Y_{model}) should be obtained via substituting the spans obtained and multiplying them by the fuzzy values of all the four aforementioned variables.

At this stage, uniform spanning was also used for the dependent variable, Y_{model}. Since the measured wear amounts are very small, the entire measured wear amounts were multiplied by 10^7 so as not to allow for the rounding errors. The wear rate was measured between 4.5 and 72 in this work (Table 10). Utilizing this classification standard and comparing the responses by the extracted information, it was found out that there was a high error rate in Table 10. The performed classifications could be accepted even with an error step but there still exists ten other errors, and this is reflective of a 66% error in estimating the figures for every set. In this way, Equation (3) and the exercised fixed classification are by no means applicable in predicting the error level wear of circular diamond saw.

Table 6. Final fuzzy weight of each variable group.

Coefficient	α_1	α_2	α_3	α_4
Final fuzzy weight	0.470	0.172	0.074	0.284

Table 7. Classification based on fixed spanning for effective variables and wear rate (output).

Parameters	Grading				
UCS	50-88	88-126	126-164	164-202	202-240
IRB	50-56	56-62	62-68	68-74	74-80
YM	20-30	30-40	40-50	50-60	60-70
LA	15-21	21-27	27-33	33-39	39-45
Saw wear (output)	3.6-20.16	20.16-36.72	36.72-53.28	53.28-69.84	68.84-86.4
Classification	**Very low**	**Low**	**Medium**	**High**	**Very high**

4.2.2. Using GA and Dissimilar method to spanning

GA is a relatively optimum and effective method capable of being applied in a wide spectrum of the problems without creating divergence issues that make it an efficient method utilized by a great majority of the researchers and designers in various fields of study [47-48]. GA was used for the determination of the spans in a dissimilar form in MATLAB software. In the GA step, for all the input and output variables, unequal boundary numbers in each variable interval area were found. The cost function of the GA step is Error in final classification. The determined boundary numbers are used for classification. The error percentage in this mode (classification error) is the cost function of GA that should be minimized. Please note that a one-level mistake in predicting Saw wear is negligible and does not count in errors. For each set of variables, four boundary numbers should be found (the start and end of interval are known). The results obtained are given in Table 8.

At this stage, a minimum limit of 0.16 was selected for every span so as to prevent every span value to go below a certain figure. In this way, in a 190-unit span, the minimum width of every category should be approximately 30.4. This 0.16 limit was chosen based on trial and error with the purpose of maximizing the accuracy percentage. With the selection of such a figure, none of the spans would go below this value. As for the span roof, no roof was considered, and the only condition was that the spans after the selected span should be able to take the minimum foresaid length in order to not allow for contradicting the lowest boundary for any of the variables.

The designed GA possesses 20 variables, and it has to be able to obtain four certain values for each of the five-level sets. At this stage, use should be made of binary GA. Every variable precision rate was considered to be 8 bits according to the existent limited spans and based on the most open span, i.e. UCS. In case that this figure is increased, and accordingly, the precision increased, no effect is observed in the table, and only the algorithm calculation load and implementation time would be increased. The figure selection accuracy suffers a decrease, and the error level worsens with narrowing the span. Due to having 20 variables and allocating 8 bits to each of them, at the end, the gene obtained for each sample would be a 160-bit gene, which is considered as an appropriate figure for a GA with normal complicacy. The mutation likelihood that is an important parameter of GA was considered equal to 0.01, according to the problem structure. The number of overlapping points was 9 and the overlap algorithm, a multi-point algorithm, was selected based on stochastically selecting the points. The number of preliminary samples, the studied sample volume, was considered to be equal to 512 at first. No special effect was observed in responses with lowering or increasing the number of this variable. The spans were dissimilarly obtained with respect to the span recommended by GA, and the response accuracy in this mode was improved in contrast to the previous mode. In this mode, as compared with the linear mode with equal span, the first span showed a relatively high expansion in the UCS variable, and the next spans became shorter in length. Regarding the other variables, the dissimilar response differs from the normal one but it is not considerable. As for the spanning for the output variable (Y_{model}) in dissimilar mode in respect to the normal mode, again changes were observed in some of the parameters. For instance, in the dissimilar mode, the first span for UCS was initiated from 3.6 and ended in 23.5; whereas, in the span featuring a fixed length, the first span had a shorter length. In fact, GA takes lower values for the spans in middle levels so as to increase the accuracy in the middle sections and compensate for the higher number of the samples and the centralization of the figures in the middle sections. However, there are still a total of 4 classification errors in the model of Table 8, with the real information (Wr column of Table 10), and this is not an acceptable error level for grading procedures, so the model of Table 8 is not good. The accuracy percentage in this mode, assuming an allowable tolerance equal to 1 in responses, was 55.5%, which is not acceptable. The responses obtained indicate that the spanning output, albeit dissimilar, is still unable to correctly model the real variables.

Table 8. Dissimilar classification with a fixed span for effective variables and wear rate (output).

Parameters	Grading				
UCS	50-116.59	116.59- 148.69	148.69-179.12	179.12-209.58	209.58-240
IRB	50-59.01	59.01-64.42	64.42-69.56	69.56-74.82	74.82-80
YM	20-37.39	37.39-45.91	45.91-53.94	53.94-61.95	61.95-70
LA	15- 23.09	23.09-28.09	28.09-34.98	34.98-39.82	39.82-45
Saw wear (output)	3.6- 23.51	23.51-41.95	41.95-57.65	57.65-72.04	72.04-86.4
Classification	**Very low**	**Low**	**Medium**	**High**	**Very high**

4.2.3. Choosing boundary numbers based on logarithmic mapping and Dissimilar GA

Logarithm operator can correct the output classification performance via limiting the changes in relatively big spans and heightening the precision in relatively small changes. The intrinsic weak point of the logarithmic operator is in taking negative figures and 0, while there is no zero or negative wear in saw wear tests. In the proposed method, the grading was carried out in logarithmic space after multiplying the output values by 10^7 by the use of logarithmic operator.

As it can be seen from the rounded figures, in this mode, the expanded span of the changes will be appropriately limited by the use of logarithmic operator and the differences in the lower spans show more appropriate results. In this mode, the inputs keep their linear span form and logarithmic mapping was only exerted on the output variable (wear) of the classification. After getting the novel dissimilar spanning done, wear was computed by the use of logarithmic operator. The obtained response per all the samples is given in Table 9 with a precision of three decimal numbers after being transferred to logarithm space. To score a value for the various amounts of a parameter in the new classification system, the highest score (very high) was assigned to the best status. Maximum scores of 70%, 50%, 25%, and 10% were, respectively, allocated to different states including “high”, “medium”, “low”, and “very low”.

In comparison with the no-logarithm mode, the changes in the second variable are not so much evident but variations are clearly observed in variables 1, 3, and 4. Considering a unit tolerance in reporting the results obtained through this method, no error was observed. The final Equation takes the form of Equation (4):

$$\log_{10}(Y_{Model}) = \alpha_1 \mathrm{UCS}_{group} + \alpha_2 \mathrm{IRB}_{group} + \alpha_3 \mathrm{Ym}_{group} + \alpha_4 \mathrm{LA}_{group} \quad (4)$$

where the coefficients and the variables are described similar to Equation (3).

At a glance, the task of fuzzy logic and GA is fully different in our work. Fuzzy logic is used to find membership functions and assign a fuzzy value to each input. After this step, GA finds a spanning value for each fuzzy output to maximize system accuracy. The cost function of GA is the error rate of the model that should be minimized, and the GA variables (genes) are spanning levels for fuzzy outputs. Fuzzy outputs are fuzzy values of each input. In fact, these methods are used in a hierarchical situation. Firstly, fuzzy logic changes the input variables to fuzzy values, and then the levels found by GA classify these fuzzy values and apply them to a final model. The output of the model is the circular diamond saw wear.

Table 9. New classification for prediction of diamond saw w in process of cutting hard dimensional stones.

	Parameters	**Value rows**				
1	**Uniaxial compressive strength (MPa)**	<103	103-144	144-177	177-209	209<
		Strength very low	Strength low	Strength medium	Strength high	Strength very high
	Score	4.7	11.7	23.4	32.8	46.9
2	**Schmidt hardness**	< 60	60-65	65-70	70-75	75<
		Very low	Low	Medium	Hard	Very hard
	Score	1.7	4.3	8.7	12.1	17.3
3	**Elasticity Module (GPa)**	<37.7	37.7-45.8	45.8-53.9	53.9-62	62<
		Very low	Low	Medium	High	Very high
	Score	0.7	1.9	3.7	5.2	7.4
4	**Los Angles Abrasion**	<22.8	22.8-27.7	27.7-34.6	34.6-39.8	39.8<
		Abrasion very low	Abrasion low	Abrasion medium	Abrasion high	Abrasion very high
	Score	2.9	7.1	14.7	19.9	28.4
Saw wear (output)		0.52-0.85	0.85-1.16	1.16-1.60	1.60-1.92	1.92-2.23
Classification		Very low	Low	Medium	High	Very high

5. Validation of results

To assess the proposed model's authenticity, rock mechanics tests were carried out on 9 hard dimensional stone types. Also the diamond saw wear rate was examined and measured in the process of cutting. Figure 4 exhibits a sample of uniaxial compressive strength test.

Figure 4. Uniaxial compressive strength test.

The results of the conducted tests are presented in Table 10. To measure the wear rate, and validate the proposed model, a dimensional stone sawing machine was built lab-sized. A maximum spindle motor power of 4 kw was used in manufacturing the machine, and the machine is comprised of three main parts, namely sawing blade, measurement tools, and a personal computer. The changes in operating parameters like advance rate, peripheral speed, and sawing depth are measured and recorded by the machine (Figure 5).

Figure 5. Dimensional stone sawing machine.

Diamond saws average wear rate was obtained in the form of the reductions in the length, width, and height in 18 diamond segments, each with a size of 35 mm × 2.5 mm × 6.0 mm impregnated at the margin of a steel core by taking advantage of a digital micrometer with a resolution of 0.001 mm (Figure 6).

Figure 6. Digital micrometer for measuring saw wear.

Also the results of the spanning based on Table 9 and the proposed model output are inserted in Table 10. Correlation coefficient (R^2) between the results obtained for the proposed model and the results of the undertaken tests is 0.83, which is acceptable.
where Wr is the saw wear measured in the sawing process.

To confirm the authenticity and efficiency of the proposed method, a row was eliminated from the 9 existing samples, and the model was again computed for the remaining samples and the results obtained were exerted on the omitted row in terms of spanning. This was repeated nine times for the entire samples in total, and relatively identical results and correct omitted row set were obtained in all the cases, which is indicative of the proposed method's credibility and reliability.
Finally, 9 evaluated rock samples were classified into three categories based on the proposed model. Samples 1 and 2 in category 2 were classified with a low abrasion rate, which is reflective of high sawability. Similarly, samples 3, 4, 5, 6, 7, and 9 in category 3 were classified with a medium abrasion rate (ranging in value from 5.00E-06mm3 to 8.00E-07mm3), and they were found to have a good sawability. Sample 8 in category 4 was found with a high saw wear rate (7.20E-06mm3), which is reflective of the weak sawability of the sample. According to the results obtained, it can be concluded that the new proposed model is capable of evaluating and classifying the sawability in the process of sawing hard dimensional stones. Based upon the section 4.2.2 results, there are a total of 4 errors in the model designed by Table 8 that decreased in the final model (Y model of table 10) to 0.

Table 10. Results of rock mechanics tests, measured saw wear, and proposed model and corresponding span.

Sample Number	UCS		IRB		YM		LA		Wr	10^7Wr	Log(10^7Wr)		Y_{model}	
	(MPa)	Class no.	-	Class no	(GPa)	Class no	-	Class no	(mm3)	10^7 mm3	-	Class no	-	Class no
1	157	3	71	4	37	1	22.3	1	4.50E-07	4.5	0.653	1	2.46	2
2	138	2	69.5	3	29	1	29.8	2	5.00E-07	5	0.699	1	2.1	2
3	141	2	70.5	4	41.5	2	31.2	3	8.00E-07	8	0.903	2	2.63	3
4	173	3	71.5	4	46	3	21.23	1	1.56E-06	15.6	1.193	3	2.6	3
5	155	3	71	4	39	2	29.4	2	5.00E-06	50	1.699	4	2.81	3
6	150	3	71.5	4	43	2	38.1	4	2.50E-06	25	1.398	3	3.38	3
7	185	4	72	4	49	3	18.8	1	1.50E-06	15	1.176	3	3.07	3
8	239	5	74	4	52	3	16.7	1	7.20E-06	72	1.857	4	3.54	4
9	199	4	71	4	49.5	3	21.1	1	1.00E-06	10	1	2	3.07	3

6. Conclusions

In this paper, the effective parameters on the diamond saw wear in the process of sawing rocks were identified, and then their weight and importance were measured by rock engineering system (RES). RES is one of the most common and popular methods for determination of effective parameters in rock mechanics systems. In the classic RES method, at start, the expert ideas are collected, then according to these ideas, the correlation and importance of the all parameters were determined. In the last step of classic RES, some fixed weights based on the correlation and importance of each variable versus other variables were assigned to each variable. In modern systems, fuzzy RES, as a powerful method, is used instead of classic RES. The main advantage of fuzzy RES is its ability to model human ideas better than the classic method. One of the main weaknesses of the fuzzy RES methods in rock mechanics systems is its membership functions and the method for finding the membership function parameters. In the proposed method, a novel sampling process was added to the model for finding the interaction between variables more accurately. This step enables a method to determine the significance of the parameters influencing the saw diamond wear. For modelling each variable in the fuzzy step, the Gaussian membership function was selected as the best choice in complicate fuzzy systems. The proposed method converts the experts' ideas as a Gaussian pattern in fuzzy logic. The mean and standard deviation of the obtained membership functions were verified with a 95% confidence level using the Anderson-Darling test. Each variable had 12 membership functions related to other variables. For combining these membership functions belonging to each variable precisely, firstly, a random number generator was used to produce 10000 random numbers (in fact, this step is the sampling step) with the Gaussian function form for each one of 12 membership functions related to other variables. These random numbers merged, and a vector with length 120000 was assigned to each variable. This vector was used to calculate each variable final fuzzy pattern. Using this step, the mean and variance of fuzzy membership functions both have an effect on the final pattern.

Based on the results obtained in the mentioned step, four parameters, namely uniaxial compressive strength, Schmidt hardness, Los Angles abrasion, and Young's modulus with final weights of 46.9, 17.3, 28.9, and 7.4 were selected in the proposed system as representatives of the four important properties of the rocks: hardness features, strength, abrasion, and elastoplasticity properties.

Finally, wear grading was computed by the use of the four effective variables based on fixed, dissimilar, and logarithmic boundary intervals whose models were optimized by GA. The cost function of GA is to minimize the classification error. Based on the results obtained, the logarithmic dissimilar boundary selection had the lowest error. After the Gaussian membership function and random number generation step, i.e. the main contribution of the proposed method, GA and optimization boundary intervals by a logarithmic mapping is the next novelty of our method.

To validate the proposed model, real tests were carried out on 9 hard stone samples, and the saw diamond wear was measured. The experimental results were compared by the results of the proposed model. Eventually, it is clear that the proposed model is capable of evaluating the stones sawability by rock mechanics properties.

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ترکیب سیستم‌های مهندسی سنگ فازی با الگوریتم ژنتیک برای پیش‌بینی عملکرد سایش دیسک الماسی دایره‌ای در فرآیند برش سنگ سخت

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چکیده:

پیش‌بینی عملکرد سایش دیسک‌های الماسی در فرآیند برش سنگ‌های ساختمانی سخت یک گام مهم و اساسی برای دست‌یابی به شرایط بهینه برای کاهش هزینه‌های تولید در صنعت برش سنگ است. در این تحقیق، پارامترهای مؤثر در سایش دیسک‌های الماسی تعیین و سپس وزن هر کدام از این پارامترها با رویکرد سیستم‌های مهندسی سنگ فازی با یک الگوی گاووسی دقیق در منطق فازی با وزن‌دهی متناظر با آن مورد بررسی قرار گرفت. پس از این مرحله، سطح‌بندی چهار متغیر اصلی و میزان متغیر سایش دیسک (پارامتر خروجی) در سیستم طبقه‌بندی، بر اساس روش‌های بازه‌بندی ثابت، تطبیقی و لگاریتمی با استفاده از الگوریتم ژنتیک صورت گرفت. در نهایت یک رابطه ریاضی برای ارزیابی دقت مدل پیشنهادی ارائه شد. هدف اصلی روش، نوآوری ترکیب این روش‌ها با روش سیستم‌های مهندسی سنگ فازی است. قبل از ارائه این تحقیق، در روش سیستم‌های مهندسی سنگ فازی تنها از توابع عضویت ساده و بازه‌بندی ثابت استفاده شده بود. استفاده از الگوریتم ژنتیک برای بازه‌بندی و توزیع نرمال به عنوان تابع عضویت، بر اساس آخرین بررسی انجام شده برای اولین بار در سیستم‌های مهندسی سنگ فازی استفاده شد. به منظور صحت‌سنجی مدل پیشنهادی، آزمایش‌های مکانیک سنگ بر روی ۹ نمونه سنگ سخت انجام و مقدار سایش دیسک الماسی اندازه‌گیری شده، با نتایج مدل پیشنهادی مقایسه شد. بر اساس نتایج، مدل پیشنهادی توانایی قابل قبولی در پیش‌بینی سایش دیسک‌های الماسی دارد.

کلمات کلیدی: سایش دیسک الماسی دایره‌ای، سیستم‌های مهندسی سنگ فازی، الگوریتم ژنتیک.