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Evaluation of gang saws' performance in the carbonate rock cutting process using feasibility of intelligent approaches

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ABSTRACT

Gang saw is widely used in the dimension stone industry and stone cutting factories. One of the important factors in evaluating the efficiency of a machine is the electrical current consumed by the gang saw. Therefore, the evaluation of the electrical current consumed by the gang saw and study of the effective parameters are necessary in the rock cutting process. In the present research, considering the physical and mechanical properties of rock, including the uniaxial compressive strength (UCS), Mohs hardness (Mh), Schimazek's F-abrasiveness factors (SF-a) and Young's modulus (YM), it was attempted to study and evaluate the electrical current consumed by the gang saw using soft computing techniques. Thus, the Differential Evolution (DE) algorithm and Self-Organizing Map (SOM) algorithm were used as two intelligent techniques in this study. Results obtained from these studies showed that the DE algorithm could accurately classify 12 carbonate rocks under study into three groups, including travertine rocks sample with the average electrical current of 83.25 (A), crystal rocks sample with the average electrical current of 90 (A) and marble rocks sample with the average electrical current of 94 (A). Due to more details of output and results of the DE algorithm, it can be concluded that this algorithm has superiority over the SOM technique because it provides higher performance capacity in evaluating and classifying carbonate dimension stone samples in terms of the electrical current consumed by the machine and its physical and mechanical properties.

1. Introduction

Nowadays, rock cutting tools are significantly used in the dimension stone quarries and dimension stone processing factories. The complete knowledge of the cutting process and the performance of gang saw can enhance the efficiency and quality of the manufactured product. The comprehensive understanding of the cutting machines' performance can boost the productivity and quality of dimension stones. The final cost and product quality are important factors in this arena. Overall, the cost of a dimension stone plaque in stone cutting industries is highly influenced by factors such as tools wear and energy consumption [1,2]. In discussions on the optimization, it is continuously attempted to increase the ratio of production rate to the two aforementioned factors. The production rate usually has a direct relationship with two factors of diamond tools' wear and energy consumption, so that along with the increase of production rate, the tools' wear and energy consumption will also increase [3,4]. For this reason, it is necessary to make an ideal balance between the production rate and tools' wear and energy consumption. Various factors influence the amount and performance of cutting machines and the energy consumption by the cutting machine. The properties of rock, type and form of tools, force or load imposed and other environmental parameters are the most important factors [5–8]. Nowadays, with the advance of technology and use of new cutting machines such as saws a new path has been opened in the cutting process in stone processing plants, so that it can be predicted that for the next few years, these facilities (given their obvious superiority over circular diamond saws) have been completely substituted with circular diamond saws. So far, complete and comprehensive studies have been conducted on the circular diamond saw cutting equipment and diamond wire sawing. But, studies on the gang saw equipment are at the preliminary levels because it has been recently used widely [9]. Lons studied the cutting forces and diamond segments' abrasion in the saw machine. In this research, the relationship between diamond abrasion and

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cutting forces was investigated and the results showed a weak relationship between the aforementioned parameters [10]. Wiemann et al. investigated the saw machine. In their studies, it was shown that the diamond blades' tension had a significant role in the saw machine's cutting process. The results obtained from their studies showed that tensile stress of tip of blade moved toward its bottom and its value varied in different measurement situations (front, middle and end). Finally, in the sawing process, the tension frequency change in diamond blades and the effect of supply rate on the blades' tensile stress were important and effective factors on the performance of cutting [11]. Jansen studied the deformation of diamond saw blades. The results showed that deformation of diamond blades was a function of tension, eccentricity, friction coefficient and geometric parameters of the blade [12]. In this regard, Gerlach investigated the sawing tool in a laboratory scale using a saw machine. The obtained results indicated that the blade diversion was influenced by geometric parameters, eccentricity and tension of blade. Also, in practice, the friction between segment and rock reduces the effective tension of blade, so that in the sawing process, the effective tension of blade may be a function of vertical forces in the direction of supply which changes under different conditions in case of any change in the rocks' properties [13]. In researches conducted by Wang and Clausen in 2002, a carbonate rock sample was studied using single-point (single-segment) cutting tools under different cutting conditions. In their study, the conditions of the contact surfaces between the rock and the diamond grain and also the cutting mechanism of brittle failure were analyzed. The cutting test was done by a CNC milling machine. The cutting force Fc in the direction of cutting and the cutting force F_f perpendicular to cutting direction were measured and recorded by a Kislter dynamometer (type 5019). During the test, two carbonate rocks were studied under the dry and wet cutting conditions. During the research of Wang and Clausen, the cutting surfaces (the groove created by the contact of segment with the rock surface) were analyzed by a microscope [14]. In 2003, a computer simulation of the saw cutting process was performed by Wang and Clausen. The saw cutting simulation can be a practical alternative for designing, especially computing the number of diamond grains and their distribution on segments of the saw blades. Simulation was done by Visual Basic Software and Microsoft Access. Accordingly, their simulation, the cutting forces in the blade, segment and each diamond grain as well as effective cutting edges could be computed under different cutting conditions [15]. In 2003, a study was conducted by Wang and Rolf on the rock cutting process theory using the saw machine. Thus, the cutting motion of the blade and diamond grain was studied. Studies showed that the effective number of diamond grains and the effective cutting depth depended on the situation of segment and the height of the raised part of diamond grain. The cutting depth of the diamond grain is increased with the increase of supply rate, reduction of crankshaft rotation per minute and the length of impact. The maximum cutting depth of the diamond grain depends on its situation in contact with the rock in one cutting impact. In the cutting process, the contact surface between the blade and rock block changes every moment. The segments' distribution, cutting length and impact length are the most important factors in the contact surface versus the cutting time [16]. The effect of marble textural characteristics on the sawing efficiency of diamond segmented frame saws was investigated by Ozcelik. In this study, the relationships among the texture coefficients, wear on diamond segments and average sawing speed were studied and significant relationships were found between them [17]. A quality classification of dimensional stones was developed by Kahraman et al. based on P-wave velocity to estimate the slab production efficiency to stone cutting with gang saws [18]. The stone waste percentages generated from cutting stone blocks into slabs were studied by Alhaj using gang saw machine. The results showed that there was an inverse relation between the gang saw thickness and the volume waste percentages and productivity. Also, the volume waste percentages change around the ideal values which are 26% for 2 cm, 19% for 3 cm and 22% for the mixed 2 & 3 cm thicknesses [19]. Ersoy and Yeşilkaya carried out optimized investigations for selecting and ranking the cutting machines among 3 types of the most preferred machines in the marble quarry industry. The analytic hierarchy process approach was employed in this work. The results clearly showed the superiority of the gang saw machine in comparison with the other types of cutting machines [20].The slab production of the multiblade gang saw on 7 different carbonate stones was predicted by Neves et al. The results showed that slab production of carbonate rocks could be successfully predicted using the multiple linear regression [21]. The sawability of diamond frame saw was studied by Sun et al using Fuzzy Analytic Hierarchy Process (FAHP) and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) techniques in granites cutting process [22]. The energy consumption of gang saw machine wa predicted and evaluate by Dormishi et al. The linear and nonlinear regression analysis were employed in their study, and several developed models were presented. Based on their results, they made some recommendations for the investigation and prediction of the energy consumption of gang saw machines [23].

Despite the important the classical and experimental methods, the soft computing techniques serve a key role to solve complex and uncertain problems, which have received attention recently in the field of rock mechanics. The wear rate of diamond wire saw wasv evaluated by Mikaeil et al. based upon the some major dimension stone properties. They obtained a logical relationship between rock characteristics and wire rate using the harmony search algorithm [24]. An optimized model for predicting the areal slab production rate of large diameter circular saw was developed by Tumac. The Uniaxial compressive strength (UCS), Brazilian tensile strength (BTS), Cerchar abrasivity index (CAI), porosity, and density were considered as input parameters. The proposed model was an effective and efficient model [25]. In another study by Mikaeil et al., the circular saw machine's performance was investigate using the imperialist competitive algorithm and fuzzy C-mean based 4 striking characteristics of dimension stone. The classification results were validated by hourly production rates. The results obtained demonstrated the effectiveness of the imperialist competitive algorithm in evaluating the performance of circular saw machine [26].

As mentioned, in the past research works, researchers often had been trying to establish reasonable relationships between some parameters and production rate based on the classical and experimental methods. On the other hand, cutting processes are traditionally classified as one of the issues dealing with uncertainty in quarries and laboratory studies, especially in the preparation of cylindrical specimens from stone samples and determination of physical and mechanical properties and the cutting phase. The literature shows that the hard (conventional) computing approaches are suitable for dealing with systems with a precise and certainty value, while the soft computing techniques are able to tackle unpredicted and uncertain conditions in different kinds of industrial, economic and technological problems compared to the mathematical and deterministic methods. In fact, the soft computing approaches have been providing a more widely frame compared to the conventional computing, contributing to very promising results. It is worth noting that an additional advantage of the soft computing approaches is striking results in modeling non-linear functions in comparison to the hard computing techniques. Accordingly and given the unreliability of laboratory tests, two stochastic techniques, namely differential evolution (DE) and self-organizing map (SOM) algorithms are used for the clustering in order to improve the analysis of the laboratory results. Although in previous research works, there are some studies based on soft computing techniques, this kind of analysis was not used in previous studies for gang saws performance evaluation in carbonate rock cutting process based on conditions of this study such as the kind of cutting machine and rock properties. In fact, in this study by contribution of two algorithms as novel approaches and the some physical and mechanical properties of the rock are considered to evaluate to study and evaluate the electrical current in the carbonate rocks' cutting process.

2. Materials sources and data collection

Field studies were conducted in one of the dimension stone processing factories in Mahalat city, Iran. For this reason, the blocks extracted from 12 quarries were transferred to a factory to be used for conducting studies. Each rock sample under study was cut using the saw cutting machine with diamond blades under the same operational conditions. Fig. 1 shows a view of the saw cutting machine and ammeter under study. The characteristics of the saw machine are provided in Table 1. The machine is composed of the main chassis of the saw, bases, blades, water pipes, flywheel, belt, main generator, two arms, generator for raising and lowering blades, and variator generator. The machine's main engine is 55 kW which has 23 A at the time of initial start and 65 A at the second impact. The machine blades are 4.4 m long and about 27 segments are welded on these blades. The distance between the first blade and the pincer holding the blade is about 6 cm from both heads of the blade. The distance between two segments on the blade is about 12–13 cm. The distance of each blade from the next is adjusted through 22-mm-diameter mediators and the front and rear of the blade are installed on the chassis using pincers, and then are strongly tightened.

(a)

(b)

Fig. 1. Gang saw machine (a) and ammeter (b) used in this study.

Table 1
Machine operating characteristics during performance studies.

Characteristic	Units	Value
Blade run	mm	750
Cutting width	mm	1440
Cutting length	mm	3300
Cutting height	mm	1950
Blade length	mm	4400
Max. no. blades	No.	50
Main engine power	kW	55
Total weight of machine	t	47

According to the fracture theory of brittle materials indentation, Fig. 2 demonstrates the principal cutting process of diamond grit in the gang saw machine. The depth of cut plays a key role in the deformation of stone. It does mean, the main deformation with small depth of cut is represented as plastic deformation, which by increasing the depth of the cut, this plastic deformation is reduced. It is due to the fact that the lateral cracks propagate to the surface and lead to chipping. Certain small lateral cracks expanding on the surface emerge scaly at the underneath of the grooves. The lateral cracks at various locations include a set of half-circles behind the sliding diamond tool on the surface. The area of plastic deformation by having the crushed stone powers is kept at the bottom of the cutting grooves. When the surface shear cracks extend zone, the crushed area's deflection turns into a continuous chip [14].

The locations and names of the studied quarries and electrical current during cutting process are given in Fig. 3 and Table 2.

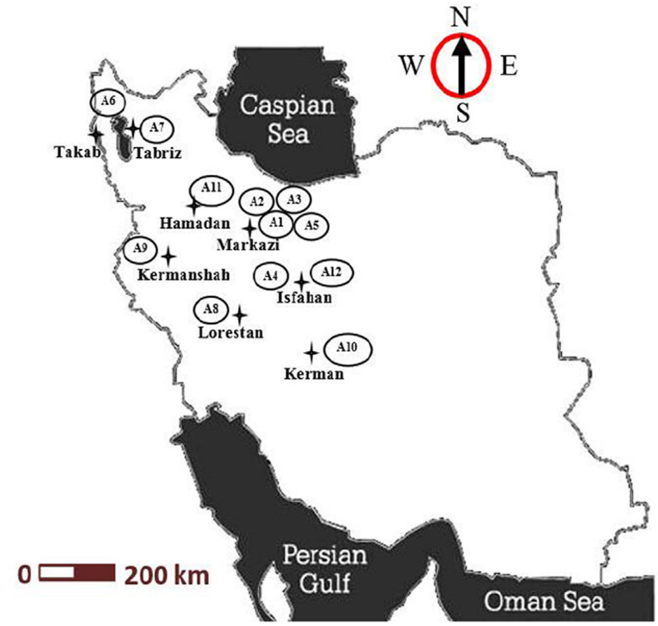

Fig. 3. The location of studied quarries.

3. Laboratory studies

For laboratory tests, sample blocks were collected from the studied quarries. A sample of blocks prepared for conducting experimental studies is shown in Fig. 4.

Standard tests were done to measure four major physical and mechanical properties of rock such as the Schmiazek abrasivity factor (SF-a), Uniaxial Compressive Strength (UCS), Mohs Hardness (MH) and Young's Modulus (YM).

Abrasiveness influences the wear of sawing tools. Abrasiveness is mainly affected by various factors such as mineral composition, the hardness of mineral constituents and grain size, grain shape and grain angularity [27]. Schimazek's F-abrasiveness factor is the most common factor for evaluation of rock abrasivity. It depends on textural and mechanical properties. The Schimazek's F-abrasiveness factor is defined as Eq. (1) [28].

$$SFa = \frac{EQC \times Gs \times BTS}{100} \tag{1}$$

where SF-a 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 Brazilian tensile strength (MPa).

Thin microscopic sections were studied to determine the grains' sizes and amount of quartz in the rock samples under study. A sample of thin microscopic section for Qorveh crystal (A11) is shown in Fig. 5.

The results of laboratory studies to determine this index are given in Table 3.

Uniaxial compressive strength is considered as a significant mechanical element present in the engineering property of rock. Rock material strength is a very important parameter used in numerous systems of rock mass classification [29]. A characteristic of rock strength, density, weathering, texture, and matrix type is

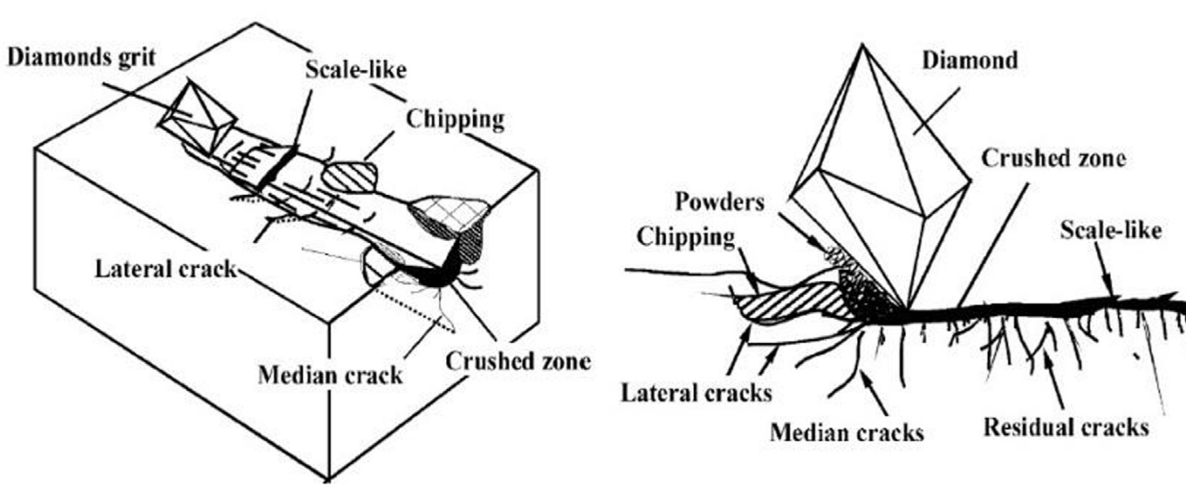

Fig. 2. Cutting mechanism of marble by abrasive [14].

Table 2
The names of the studied rocks and consumed electrical current in cutting process.

Samples No.	Commercial name	Name of quarry	Electrical current (Ampere)
A1	Hajiabad Travertine	Hajiabad	83
A2	Darebokhari Travertine	Kohbar	86
A3	Atashkoh Travertine	Atashkoh	85
A4	Chocolate Travertine	Kashan	84
A5	Abbas Abad Travertine	Abbas Abad	88
A6	Takab Travertine	Takab	83
A7	Azarshahr Travertine	Azarshahr	79
A8	Khalkhal Travertine	Khalkhal	78
A9	Harsin Marble	Harsin	95
A10	Kerman Marble	Mirzaei	93
A11	Ghorveh Crystal	Ghorveh	89
A12	Laybid Crystal	Laybid	91

Table 3
The result of laboratory studies to determine the SF-a.

Samples No.		BTS MPa	EQC %	Gs mm	SF-a N/mm
A_1	Hajiabad Travertine	5.60	2.60	0.25	0.04
A_2	Darebokhari Travertine	5.40	2.70	0.57	0.08
A_3	Atashkoh Travertine	5.90	2.65	0.26	0.04
A_4	Chocolate Travertine	5.70	2.50	0.34	0.05
A_5	Abbas Abad Travertine	4.40	2.30	0.36	0.04
A_6	Takab Travertine	5.60	2.50	0.14	0.02
A_7	Azarshahr Travertine	4.30	2.80	0.32	0.04
A_8	Khalkhal Travertine	3.60	1.93	0.48	0.03
A_9	Harsin Marble	6.80	3.60	0.25	0.06
A_{10}	Kerman Marble	6.50	3.10	0.27	0.06
A_{11}	Ghorveh Crystal	6.20	3.00	0.90	0.17
A_{12}	Laybid Crystal	6.35	2.87	0.80	0.15

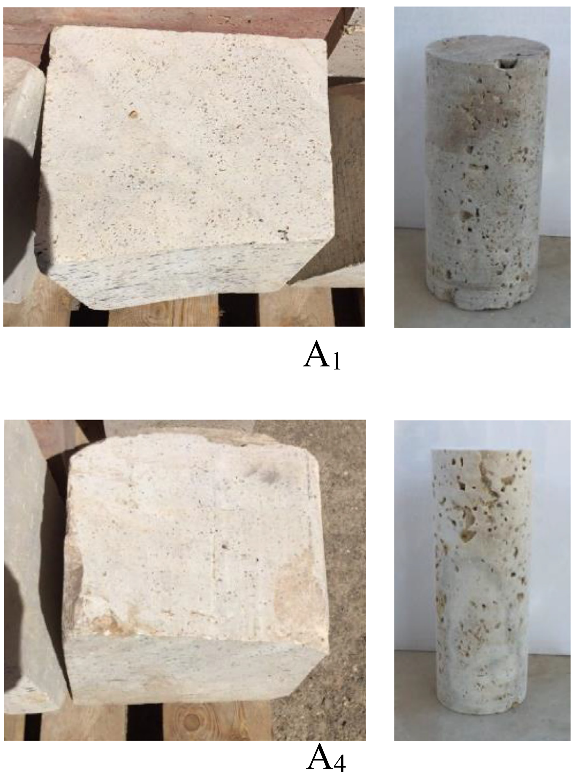

Fig. 4. Block and core samples prepared for conducting experimental studies.

Fig. 5. Microscopic thin-section image of A11.

the uniaxial compressive strength test. Thus, it is necessary to use this parameter in the study of sawability. For identifying the uniaxial compressive strength of the dimension stones studied, 5 standard NX core samples with a length to diameter ratio of 2.5:1 were considered through the use of a diamond rotating drill from the block sample (Fig. 4). For cutting the specimens into their final lengths, a circular diamond saw blade was utilized. Then, using a grinding machine, the specimens' surfaces were grinded to reach a high quality surface for the axial loading to be imposed. Researchers carried out mechanical tests using a servo controlled testing machine designed for rock testing. The pressuring rate of 1 MPa/s was used for the standard uniaxial compressive strength test of core samples [30]. At the final stage, the average uniaxial compressive strength was computed for each dimension stones studied. The results are shown in Table 4.

Hardness means the rock's resistance to fracture or plastic deformation because of scratching and cracking from circular diamond saw. The factors influencing the rock hardness include the cohesion forces, the hardness of the constitutive minerals, homogeneity, and the water content of rock. Hardness is a good index of all the above mentioned elements of the rock material. One of the most common and useful indices for evaluating the hardness of a rock is the Mohs hardness scale. This index was chosen as a hardness index in the clustering system. The mean hardness per dimension stone is computed on the basis of the contained minerals' hardness using the following Eq. (2) [31]:

$$Mean\ \ Hardness = \sum_{i=1}^{n} M_i \times H_i \tag{2}$$

where M_i, Hi and n are the mineral amount (%), Mohs hardness, and the total number of minerals in the dimension stone, respectively. Table 4 shows the mean Mohs hardness for each studied dimension stone.

Table 4
The results of laboratory studies.

Sample No.		UCS MPa	SF-a N/mm	YM GPa	MH n
A_1	Hajiabad Travertine	61.5	0.04	21.0	2.90
A_2	Darebokhari Travertine	63.0	0.08	23.5	2.95
A_3	Atashkoh Travertine	62.8	0.04	22.8	2.80
A_4	Chocolate Travertine	54.5	0.05	14.5	2.20
A_5	Abbas Abad Travertine	67.0	0.04	27.0	2.70
A_6	Takab Travertine	60.0	0.02	20.0	2.60
A_7	Azarshahr Travertine	53.0	0.04	15.0	2.90
A_8	Khalkhal Travertine	50.5	0.03	16.4	2.60
A_9	Harsin Marble	71.5	0.06	26.0	4.30
A_{10}	Kerman Marble	72.0	0.06	32.0	4.00
A_{11}	Ghorveh Crystal	65.0	0.17	25.0	3.80
A_{12}	Laybid Crystal	63.5	0.15	23.5	3.90

Considering to the rock behavior during the fracture process, especially in sawing, how rocks reach the failure point has a great effect on the sawability. Young's modulus is the best scale for the rock elasticity is based on ISRM suggested methods [30]. In this clustering system, the tangent Young's modulus at a stress level of 50% of the ultimate uniaxial compressive strength is utilized. The results are shown in Table 4.

4. Differential evolution (DE) algorithm

One of the most dynamic computing branches is the soft computing. Soft computing includes a wide spectrum of methodologies based on biological sciences, neural systems structures, motions, and collective and social behaviors of the biological species. In fact, soft computing analyzes scientific and complex problems in the engineering world using natural systems [32–39]. Meta-heuristic algorithms as a branch of soft computing have a significant role in optimizing and solving problems under uncertain conditions [40–43]. Differential Evolution (DE) algorithms are among meta-heuristic algorithms which show very proper performance in the optimization of engineering problems. DE algorithms were introduced by Storn and Price in 1995 and obtained the first rank in the IEEE optimization competitions [44]. This algorithm works randomly and begins the optimization process by creating an initial population and a series of suggested responses. DE gives all the responses an equal initial chance; then by creating the next generation (the next response), it compares the responses with the initial ones and selects the best one. In the DE algorithm, there are four operators which conduct the optimization process, including initialization, mutation, crossover and selection, respectively [45,46]. In fact, the optimization process in this algorithm starts by creating a series of initial generations and then the merits of the produced responses are evaluated and fitted based on the objective function. One of the remarkable and interesting points in this algorithm is that it works like the genetic algorithm in terms of generating initial responses, but its main difference with the genetic algorithm and other meta-heuristic ones is the order of operators, i.e. in this algorithm, first mutation operator and then the crossover operator work. As mentioned, the main stages are introduced as follows [47–49]:

1: Initialization of Population
2: Mutation
3: Crossover
4: Selection
5: This loop repeats until the stop conditions are achieved such as the desired precision level and maximum iteration.

In the first step, DE is started from an initial set of solutions called the initial population produced by Eq. (3):

$$X_{i0} = X_{Min} + \delta_i[X_{Max} - X_{Min}] \quad i = 0, 1, 2, 3, \ldots., NP \tag{3}$$

where X_{Min} and X_{Max} demonstrate the lower and upper bounds of the parameter vectors X_{i0}, respectively. δ_i is a uniformly distributed random number that ranges between 0 and 1. Also, NP introduces the number of population.

In the mutation section, the search space is expanded and a mutant solution vector V_{ig} is obtained at generation g by Eq. (4) and must also satisfy $x_{r_1,g}, x_{r_2,g}, x_{r_3,g} \,|\, r_1 \neq r_2 \neq r_3 \neq i$.

$$V_{ig} = x_{r_1,g} + F\left[x_{r_3,g} - x_{r_2,g}\right] = 0, 1, 2, 3, \ldots., NP \tag{4}$$

where F is the scaling factor that ranges between 0 and 1. In addition, the amplification of the differential variation is controlled by F. $x_{r_1,g}, x_{r_2,g}$ and $x_{r_3,g}$ are the solution vectors and are randomly chosen. Also, i is the index of current solution.

In the next step, the creation of the trial vector ($U_{j,i,g}$) is carried out by the crossover operation through combining the mutated vector ($V_{j,I,g}$) and target vector ($X_{j,I,g}$) based on Eq. (5).

$$U_{j,i,g} = \begin{cases} V_{j,i,g} & R_j \leq CR \\ X_{j,i,g} & Otherwise \end{cases} \tag{5}$$

where CR is the crossover constant and R_j indicates a randomly selected real number at the interval [0,1] and j shows the jth component of the corresponding array.

In the selection step, the next generation is selected between the trail vector and the corresponding target vector. Finally, it continues to reach the most optimized response.

DE algorithm is used in many engineering and industrial designs due to its high compatibility and flexibility in different complex problems. For the optimal design of water distribution networks, meta-heuristic algorithms were used by Suribabu. He studied and investigated DE algorithm in comparison with other algorithms and the obtained results showed higher superiority in terms of optimal design of water distribution networks [50]. In a study conducted by Gurarslan and Karahan, a model was provided for solving problems of groundwater-pollution-source identification. First, the numerical simulations were performed for the flow and pollutant transport in the groundwater. Next, the optimization was done using DE algorithm. The obtained results in this study were more precise and effective than those of other researches [51]. In a case study conducted by Atashnezhad et al, the porosity prediction was investigated using data from three offset wells in Alberta, Canada. The obtained results not only had high precision, but also were creative and included estimation and evaluation using the collected drilling data in the real time. Finally, the appropriate performance results of DE algorithm were shown in this study [52].

5. Self-Organizing map (SOM) algorithm

Engineers like neurophysiologists have a significant contribution in developing neural networks. Due to the complex biological structure of brain in the data and concept analysis and process, brain is used as a pattern for creating a complete system and different neural computing techniques. Artificial neural networks have been significantly developed in recent years both in theoretical and practical researches, including image processing, signal processing, and pattern recognition in control systems [53–62]. There is a wide spectrum of artificial neural networks' users in the science and other fields. A computing model was developed by Khandelwal and Singh based on artificial neural networks and evaluated and provided a prediction model for blast-induced ground vibration in coal mines in India [63]. In researches conducted by Trivedi et al, Flyrock distances were predicted using two models of artificial neural network (ANN) and multi-variate regression analysis (MVRA). The exact results obtained from this research showed the superiority of artificial neural network over the multi-variate regression analysis [64]. In a study conducted by Khandelwal et al, the dump slope stability of a coal mine was studied and evaluated using artificial neural networks. In this research, factors affecting the slope stability such as geotechnical properties and hydrological conditions were considered. Finally, a comparison was done between the results of ANN and numerical modeling based on the value of factor of safety, showing the superiority of artificial neural networks [65]. Artificial neural networks include a wide spectrum of neural computing techniques. A special class of neural computing methods is Kohonen's method which was provided in 1980s from the biological neural network and based on the regular maps found in the brain cortex [53,66]. One of the data analysis principles in this algorithm is the reduction of computations and complexities in the data analysis. In this algorithm, based on the mutual behavior of some of the neural cells normally placed together with a flat topology, a self-organizing network is implemented. Kohonen method or Kohonen model algorithm or self-organizing map (SOM) is a non-supervised algorithm which is designed in three phases, including competition phase, cooperation phase and adaptation phase, respectively, although unlike other neural networks, SOM algorithm is generally formed by two layers, including input layer and Kohonen layer or competition layer [53,67]. This algorithm uses a network to predict the probability density function of the input space. In fact, it keeps the topological structure of the input space [68]. Fig. 6 shows an overall structure of SOM algorithm based on which, Kohonen layer or competition layer has m node which could be organized in a one-dimensional or two-dimensional layer.

In the algorithm optimization process, the winner neuron is selected based on the similarity criterion which is usually the Euclidean distance, then the weight of the winner neuron is adjusted based on Kohonen rule, i.e. the input data of each node in the input layer is attached to the competition layer from every x_i = (for i = 1,2,3,. . .,n) with a determined weight equal to w_{tj} = (for j = 1,2,3,. . .,n). For this reason, a learning rate (η) is defined and the coefficient of η controls the moderation rate that ranges between 0 and 1 by the following Eq. (6):

$$\eta(t) = \eta_0 \exp\left\{-\frac{t}{\tau}\right\} \tag{6}$$

where τ is exponential decay time constant and η_0 is initial value. Also, t is the number of times of learning.

This process is repeated until it reaches a special criterion. For example, certain numbers of iterations could be one stop criterion. The weight vector of the excited neuron is updated. Updating process of the algorithm is shown in the Eq. (7) [67,68].

$$w_{ij}(t+1) = w_{ij}(t) + \eta\left[x_i - w_{ij}(t)\right] \tag{7}$$

If t as the number of times of learning is equal to the learning number T, the learning process stops and completes the independent survey, otherwise this loop repeats and returns to Eq. (7).

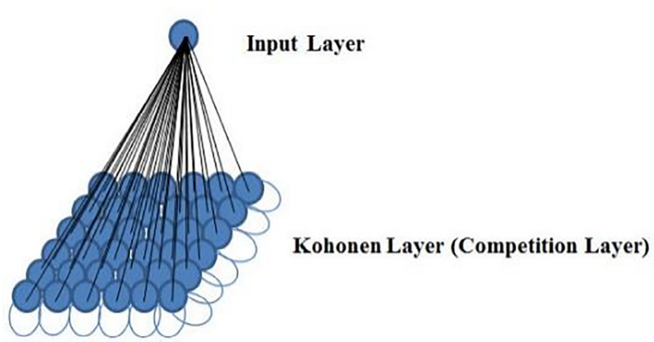

Fig. 6. A typical structure of self-organizing networks.

Table 5
The Control Parameters of Differential Evolution algorithm.

Maximum Number of Iterations	Population Size	Crossover Probability	Minimum Acceptable Error
500	75	0.2	0.00001

6. Clustering modelling based upon physical and mechanical characteristics

6.1. Modelling using Differential Evolution

One of the most influential applications of DE algorithm is in the area of data mining for optimizing the objective function's performance process [69]. In fact, the aim is to create a powerful an accurate optimization and analysis system based on the DE algorithm. Therefore, in this paper, a dataset for 12 rock blocks based on four physical and mechanical criteria of rocks are considered for analyzing the electrical current by the rock cutting machine, including the UCS, YM and SF-a which were fitted and analyzed by the combination of Lloyd's algorithm (k-means) as an objective function and DE meta-heuristic algorithm as a system optimizer algorithm. Furthermore, for implementing this optimization system, the combination of algorithms from MATLAB software is used as one of the most powerful optimization software in different areas such as artificial intelligence. Lloyd algorithm (k-means) is introduced based on Eq. (8), in which m_j is the center of cluster and k is the number of clusters. In addition, x_i is data in a set in which the value of i is i = [1,2,3,. . .,n]. d indicates the Euclidean distance of the center of cluster from the center of each member [70]. The purpose of this clustering is to reduce the Euclidean distance (increase similarity) between members of a cluster and increase the Euclidean distance (reduce similarity) between members of different clusters.

$$Obj.Function = \sum_{i=1}^{n} \min_{1 \le j \le k} d(x_i, m_j) \tag{8}$$

As mentioned, k-means algorithm is considered as an objective function for DE optimization algorithm. In fact, although the Lloyd algorithm may be highly used in simple data sets, there are some drawbacks, including the determining of the precise and accurate Euclidean distance in large or complex data sets. Hence, DE algorithm as a meta-heuristic algorithm can be a reliable technique for the training and optimization k-means algorithm. Therefore, considering the nature of complex problems and big datasets and also its full compliance with DE algorithm concepts, after the analysis, a precise and accurate clustering is obtained. The accurate determination of the algorithm's control parameters has a significant role in the convergence process and increases the precision level of optimization responses. Thus, control parameters for DE algorithm were adjusted and considered based on the previous studies using the certified experts' opinions, as seen in Table 5 [51,52].

After the adjustment of control parameters, data were evaluated and analyzed in 2, 3, 4 and 5 classes and the most appropriate and exact optimization process was obtained for the triplet class. The distance of each criterion from the center of clusters is shown according to Table 6. Additionally, the distance of each data under study from each class and clustering of each data are shown in Table 7.

According to the results obtained from the Euclidean distance of each criterion under evaluation in this analysis from the center of clusters in Table 6, it is determined that SF-a has the highest

Table 6
Distance of clusters' centers from criteria with 3 clusters.

	The First Class	The Second Class	The Third Class
UCS	1	0.84	0.89
Mh	0.95	0.63	0.89
YM	0.97	0.63	0.74
SF-a	0.33	0.23	0.91

Table 7
Optimization results of clustering by Differential Evolution algorithm.

Samples No.	Optimum partition			Clusters
	First Class	Second Class	Third Class	
A_1	0.457	0.055	0.727	2
A_2	0.41	0.298	0.456	2
A_3	0.423	0.095	0.704	2
A_4	0.721	0.235	0.79	2
A_5	0.368	0.235	0.743	2
A_6	0.557	0.111	0.847	2
A_7	0.638	0.194	0.774	2
A_8	0.659	0.182	0.816	2
A_9	0.171	0.462	0.571	1
A_{10}	0.032	0.514	0.643	1
A_{11}	0.71	0.832	0.103	3
A_{12}	0.604	0.712	0.042	3

impact on the samples of the first and second classes and the UCS has least impact the first and second classes, respectively. Furthermore, YM and Mh have an equal impact on the rock samples under evaluation in the first and second classes, respectively. In contrast with these classes, in the third class, SF-a has the least significance and impact, while YM has the highest significance and impact on the samples of this class. Also, Mh and UCS have an equal impact on the samples under study in this group. Table 7 shows the optimized Euclidean distance between the centers of each cluster from each rock sample, according to which, the first 8 research cases are placed in the second class and samples A_9 and A_{10} as well as A_{11} and A_{12} are placed in the first and third classes, respectively. The process of optimization based on iterations is depicted in Fig. 7. According to Fig. 7, the process is reached to the desired precision level from 360th iteration and it is fixed from 360th to 500th iteration.

It is worth mentioning that the best cost is the fitness value of objective function and it is a non-dimensional term. Fig. 6 shows this value in each iteration. Also, the absolute value of the difference between the two corresponding best costs is defined as the error. According to Table 5, the convergence condition of algorithm about the minimum acceptable error was 0.00001 which is obtained from 360th iteration and is fixed until the latest iteration. Consequently, it can be concluded that algorithm was converged, because the convergence condition of algorithm was reached.

6.2. Modelling using Self-organizing map (SOM)

As mentioned before, control parameters have a key role in the algorithms' convergence process leading to the determination of more precise and proper responses. In fact, the selection and adjustment of these parameters have an experimental process and depend on some issues i.e. the number of studied samples, the complexity of the problem and the suggestions of experienced experts, and previous studies. Considering the opinions of experts and previous studies [54,67] in this modelling, for determining a robust and accurate intelligent modelling system using self-organizing map, some of the networks' control parameters are adjusted, as mentioned in Table 8 [67,68].

After adjusting control parameters and inserting data under study to perform clustering in MATLAB software, data are analyzed for doublet, triplet and quartet classes which in this optimization process based on the clustering by the SOM algorithm, the most appropriate clustering belongs to the triplet class. Fig. 8 shows the number of neurons (classes) and the number of samples. For instance, the first neuron could attract 2 samples, and the second and third have attracted 6 and 4 samples, respectively. For more transparency, according to the obtained results from this clustering, Samples A_1, A_3, A_4, A_6, A_7 and A_8 in the second class, and samples A_9 and A_{10} are placed in the first group, also samples A_2, A_5, A_{11} and A_{12} are placed in the third one. It is worth noting that x and y axes just indicate the Euclidean distances in Fig. 8.

In Fig. 9, the effect of each physical and mechanical properties of rocks under study on each class is shown. According to the colorbar in Fig. 9, the darkness of colors shows the high influence of the parameter on that class, i.e. if the colorbar is darker, the Euclidean distance between the center of cluster and the criterion is lower. Based on the images obtained from data analysis, it is obvious that four criteria of SF-a, YM, Mh and UCS have the least impact on the sample attracted by the second neuron (second class) because the color of the second class shows a dark color, meaning that these four parameters have the least Euclidean distance with the center of the second class. In addition, three parameters of YM, Mh and UCS have the lowest impact on the samples of the first class. While, SF-a has the lowest impact on the samples of the third

Table 8
The Control Parameters of SOM algorithm.

Maximum Epoch (Iterations)	InitNeighbor (initial neighborhood size)	Cover Steps (number of training steps for initial covering of the input space)
100	3	30

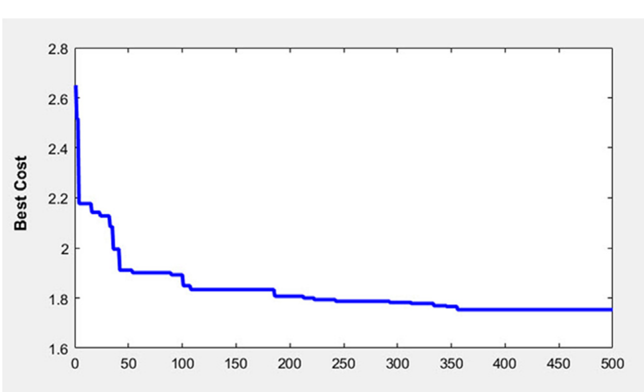

Fig. 7. The best cost per iteration by DE algorithm.

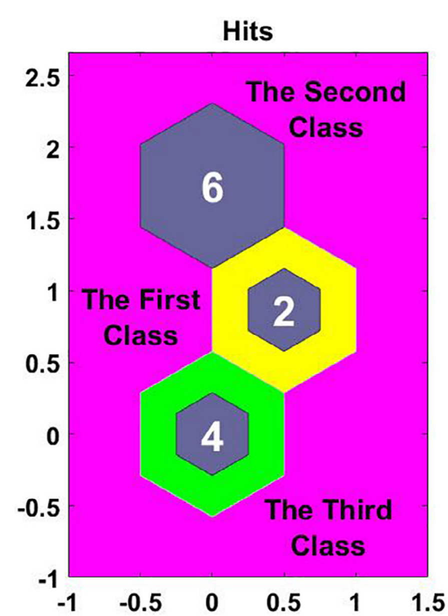

Fig. 8. The clustering with 3 classes.

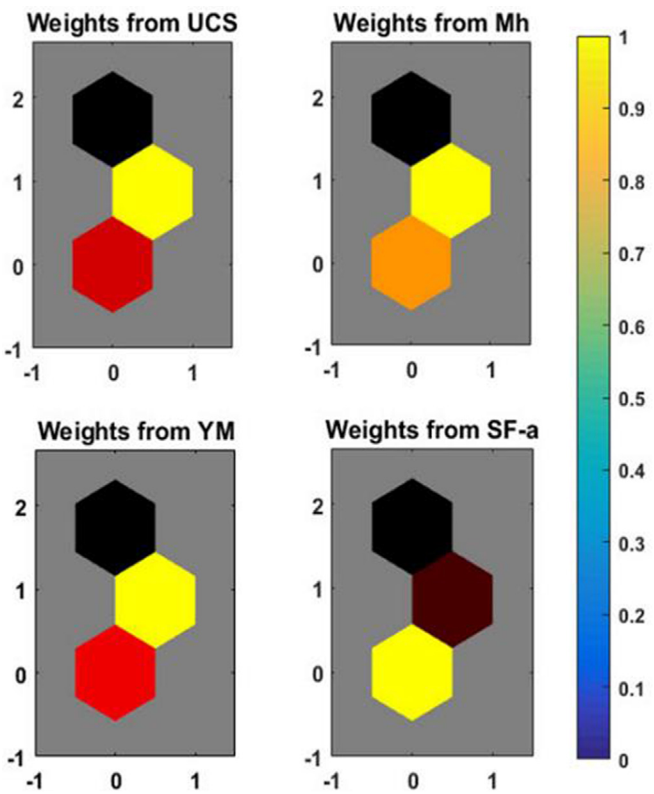

Fig. 9. The impact of each creation's weight on 3 classes.

class. Hence, there is a considerable point indicating that in this analysis, the darker the color of classes (neurons) is, the most irritability of that class (neuron) by the desired criteria will be.

7. Discussion

Two soft computing techniques including the DE and SOM algorithms were used to investigate the performance of the gang saw and effective parameters on cutting. In addition, the models with the four physical and mechanical properties of 12 carbonate rocks, including the UCS, Mh, SF-a and YM were studied. The results obtained by using two clustering techniques are shown in Fig. 10. It is found that there is a slight difference between the final obtained results from the two algorithms. Although, the outputs of the DE algorithm has more details than the SOM algorithm, which results in a reliable system modeling technique for the better evaluation of gang saws.

In this section, for validating the results of modellings, a comparison is made among the DE clustering, SOM clustering and the measured average electrical current of the gang saw. The result of comparison is shown in Table 9. In fact, the columns of the DE clustering and SOM clustering show each sample class.

Furthermore, the following remarks can be evaluated and concluded:

- With respect to Table 9, all samples are classified in three classes by the two clustering algorithms, and also the first cluster is A_9 and A_{10} as marble types with measured electrical current for above 93 (A). The second cluster is from A_1 to A_8 as travertine types with the measured electrical current from 78 (A) to 88 (A). In the last class, the samples as crystal types have measured electrical current equal to 89 and 91. The results of comparisons show that the DE algorithm was successfully used to classify 12 carbonate rocks. In fact, travertine rock samples of A_1–A_8, crystal rock samples of A_{11} and A_{12} and marble rock samples of A_9 and A_{10} were classified in three groups with the average electrical current of 83.25 (A), 90 (A) and 94 (A), respectively. While, there are 2 errors in the SOM algorithm. A_1 and A_8 as travertine rock samples with 86 (A) and 88 (A) are classified in third cluster as crystal rock samples with the average electrical current of 90 (A).

Table 9
The Comparison of results of two modellings and measured electrical current.

Sample No.	DE Clustering	SOM Clustering	Measured Electrical Current (A)	Measured Average Electrical Current (A)
A_1	2	2	83	83.5
A_2	2	3	86	
A_3	2	2	85	
A_4	2	2	84	
A_5	2	3	88	
A_6	2	2	83	
A_7	2	2	79	
A_8	2	2	78	
A_9	1	1	95	94
A_{10}	1	1	93	
A_{11}	3	3	89	90
A_{12}	3	3	91	

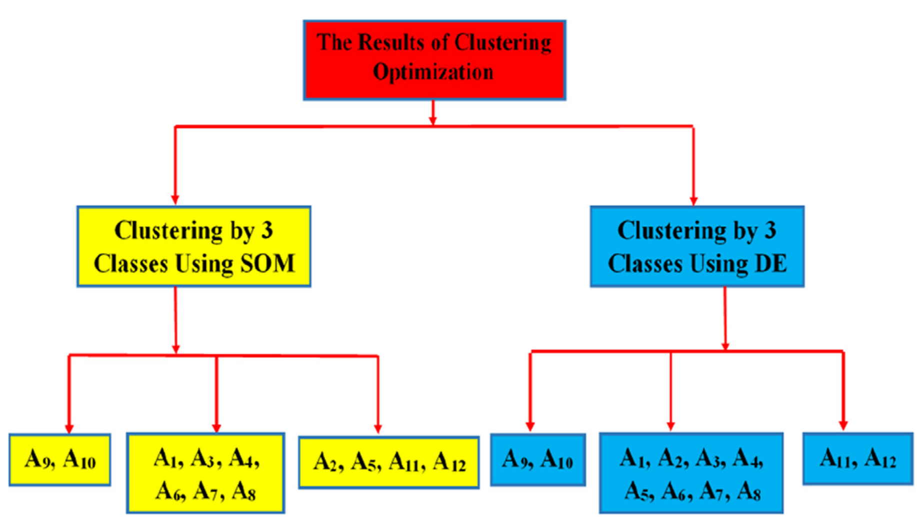

Fig. 10. The structure of clustering process by the DE and SOM algorithms.

- In Marble and Travertine classes with the average electrical current of 94 and 83.25 (A), respectively. SF-a is the most effective factor, which contributes greatly to the values of electrical current in gang saws. Also, YM plays a key role in the values of electrical current in Crystal class. It's worth mentioning that the exact amount of these results demonstrated in Table 6 by the DE algorithm, however these results obtained from colorbar and Fig. 10 using the SOM, which indicated a range of values. For example, in the second class there is no salient difference between the impact of parameters, and determination of them is difficult based on colorbar.
- DE algorithm is a reliable system modeling technique for evaluating electrical current with highly acceptable degrees of accuracy and robustness (with the accuracy rate of 100%). While, the results of the SOM algorithm describes its low capability in the evaluation of electrical current (with the accuracy rate of 83.33%).
- The results of this study can be very useful and effective for owners of rock industry and designers for a more reliable planning and design based upon the electrical current. Finally, it can be concluded that due to the multiplicity of factors affecting the cutting process and the performance of gang saw, these two soft computing techniques can be applied for the evaluation of gang saw performance.

8. Conclusions

The electrical current of gang saws is one of the important costly factors in the rock cutting industries. One of effective strategies for reducing costs and increasing the income obtained from sales is to increase the efficiency and reduce the amount of electrical current by the rock cutting machines. The first step in this arena is to identify the factors influencing the amount of electrical current by the cutting machine and measure this amount during the process of different dimension stones. The studies conducted in this research attempted to address the clustering of dimensional stones from the perspective of the amount of electrical current consumed by the gang saw using the soft computing and considering the physical and mechanical properties, including the UCS, Mh, SF-a and YM. Results obtained from studies after adjusting control parameters and inserting data relating to 12 carbonate rock samples in MATLAB software showed that samples were accurately classified into three classes with the low, average and high electrical current amounts. Consequently, it is concluded that the DE algorithm can accurately evaluate and classify carbonate rock samples from the electrical current perspective due to having physical and mechanical properties. Considering the full compliance of clustering results with the measured electrical current, this study demonstrates that the DE and SOM algorithms are applicable for evaluation of electrical current; however, DE algorithm can be better applied based on higher performance capacity. Future studies must focus on comparing the DE and SOM clustering processes to other meta-heuristic algorithms within the framework of this application, including the Genetic algorithm (GA), Artificial Bee Colony (ABC) algorithm and machine-learning approaches such as support vector machines (SVM).

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