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ORIGINAL ARTICLE

Performance prediction of circular saw machine using imperialist competitive algorithm and fuzzy clustering technique

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Abstract The purpose of this study is the application of meta-heuristic algorithms and fuzzy logic in the optimization and clustering to predict the sawability of dimension stone. Survey and classification of dimension stones based on their physical and mechanical properties can be so impressive in the optimization of machine applications that are in this industry such as circular diamond saw block cutting machine. In this paper, physical and mechanical properties were obtained from laboratory testing on dimension stone block samples collected from 12 quarries located in Iran and their results were optimized and classified by one of the strongest meta-heuristic algorithms and fuzzy clustering technique. The clustering of dimension stone was determined by Lloyd's algorithm (k-means clustering) based on imperialist competitive algorithm and fuzzy C-mean by MATLAB software. The hourly production rate of each studied dimension stones was considered as a criterion to evaluate the clustering efficacy. The results of this study showed that the Imperialist Competitive algorithm and fuzzy C-mean are very suitable for clustering with respect to the physical and mechanical properties of the dimension stone, and the results obtained showed the superiority of the ICA.

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1 Introduction

Nowadays, circular diamond saw blades are widely used to processing the dimension stone in stone processing plant and quarry. The performance and life of these tools represent a major factor in the cost of stone industry. Therefore, predicting the sawing performance for a particular stone is important. Sawing performance is affected by many factors. One of the most important factors that affect sawing performance is the physical and mechanical properties of stone. In this regard, many studies have been performed. Some of these studies are listed in Table 1.

This paper describes the application of meta-heuristic algorithm and fuzzy C-mean to predict the sawability of dimension stone based on some important physical and mechanical properties of rock. To achieve this goal, in the first step, four major properties of dimension stone including the uniaxial compressive strength, Schmiazek F-abrasivity, Mohs hardness and Young's modulus were tested in rock mechanics laboratory. During the research process, two groups of dimension stones were selected and analyzed. The dimension stone block samples were collected from a number of Iranian quarries. In the second step, the studied dimension stones were classified by imperialist competitive algorithm. The objectives are to minimize distance among members of a cluster and to maximize the distance of cluster centers from each other. The ICT is an evolutionary algorithm to solve optimization complex problems. This method was created by the simulation of the sociopolitically processes, and fuzzy C-mean was considered as a flexible

Table 1 Literature review of sawability studies

Researchers	UCS	BTS	YM	IS	SS	BS	H	A	D	Gs	Qc
Buyuksagis and Goktan [1]	●	●					●	●			●
Ersoy et al. [2]	●	●	●	●	●	●		●	●		●
Delgado et al. [3]							●				●
Kahraman et al. [4]					●						●
Fener et al. [5]	●	●		●			●	●			
Kahraman et al. [6]	●	●							●		●
Ozcelik [7]	●	●					●				●
Tutmez et al. [8]	●	●		●			●	●			
Buyuksagis [9]	●	●				●	●	●	●		●
Mikaeil et al. [10]	●										●
Mikaeil et al. [11]	●	●	●				●	●		●	●
Mikaeil et al. [12]	●	●					●	●			
Ataei et al. [13]	●	●					●	●			
Mikaeil et al. [14]	●	●									
Mikaeil et al. [15]	●	●	●				●	●		●	●
Mikaeil et al. [16]	●	●	●				●	●		●	●
Mikaeil et al. [17]	●	●									
Ataei et al. [18]	●	●					●	●		●	●
Ghaysari et al. [19]										●	
Mikaeil et al. [20]	●	●	●				●	●		●	●
Sadegheslam [21]	●		●					●			●
Mikaeil et al. [22]	●	●									
Mikaeil et al. [23]	●	●	●				●	●		●	●

UCS uniaxial compressive strength, *YM* Young's modulus, *BTS* indirect Brazilian tensile strength, *IS* impact strength, *SS* shear strength, *BS* bending strength, *H* hardness, *A* abrasivity, *D* density, *Gs* grain size, *Qc* quartz content

clustering method [24]. To show the efficiency of the proposed methods, the classification results were validated by test results. Finally, comparing the results of the proposed two methods with test results, it can be derived that the proposed methods can find an appropriate solution. Hence, the scope of this paper is the applications of ICA technique and fuzzy logic in mining engineering with focus on optimization of classification.

2 Imperialist competitive algorithm

Nowadays, meta-heuristic algorithms are widely used for optimization and solving engineering problems in engineering sciences. Several evolutionary algorithms are provided for optimization such that it can be noted to the genetic algorithm (GA) [25], particle swarm optimization algorithm (PSO) [26] and bat algorithm [27]. The imperialist competitive algorithm is one of the most effective methods to find optimal solution of different problems among meta-heuristic algorithms. This algorithm is for solving nonlinear integer programming such as dynamic programming (DP) [28]. This algorithm inspired from a sociopolitical phenomenon proposed by Atashpaz-Gargari and Lucas [29]. The ICA is a great algorithm in the field of evolutionary computation based on the sociopolitical evolution of humans. This algorithm has an application effective in various fields of sciences in optimization of complex issues. In general, the imperialist competitive algorithm can be used in any optimization problem without limitation. This matter has caused which this algorithm is used for solving lots of problems in the field of electrical engineering, mechanics engineering, industry, management, civil engineering and artificial intelligence, etc. [30–34]. The ICA established based on three main principles, which include assimilation policy, imperialistic competition and revolution. Assimilation policy is moving colonies toward their relevant imperialist in a randomly deviated direction. Imperialistic competition and revolution are competition of take possession of colonies from other empires and random changes in the characteristics of some countries, respectively. Finally, algorithm continues with these three main principles until a stop condition is satisfied.

Like other meta-heuristic algorithms, process begins with an initial population in this algorithm, each of them being called a country. The countries have two types:

imperialists or colonies. In fact, the country is an array of variable values like to chromosome in GA terminology. Each empire gets and controls one or more of the colonies of the weakest imperialist based their capacity and ability. Some of them that have the lowest costs of the fitness function selected as imperialist and also remaining population considered are as a colony. At first, normalized cost is calculated for per empire by Eq. (1), where the C_n is the normalized cost of empire, $\max\{c_i\}$ is the highest cost among imperialists and c_n is the cost of nth imperialist.

$$C_n = c_n - \max_i\{c_i\} \quad (1)$$

Then, with having cost of normalized, the normalized strength of each imperialist (P_n) is calculated by Eq. (2) which based on this process, colonies divided among the empire:

$$P_n = \left| \frac{C_n}{\sum_{i=1}^{N_{imp}} C_i} \right| \quad (2)$$

Therefore, the number of initial colonies obtained by Eq. (3) in which NC_n and N_{col} are the initial number of colonies of nth imperialist and the number of total colonies, respectively:

$$NC_n = \text{round}\left\{P_{n.(N_{col})}\right\} \quad (3)$$

Figure 1 shows moving colonies toward their relevant imperialist.

According to Fig. 1, the value of X is defined by Eq. (4) that (d) and (β) are distance between colony and imperialist and a parameter greater than one, respectively. The $\beta > 1$ causes to get closer to the imperialist from both sides. Also, for increasing search area around of the imperialist, this absorption occurs with a random amount of deviation in absorption direction of colony by empire. This deviation is shown with θ. This value is random number that selected randomly and uniform distribution according to Eq. (5).

$$x \sim U(0, \beta \times d) \quad (4)$$

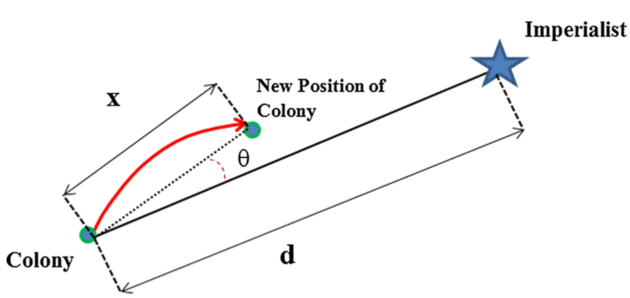


Fig. 1 Moving colonies toward their relevant imperialist in a randomly deviated direction

$$\theta \sim U(-\gamma, \gamma) \quad (5)$$

γ is a parameter that controls the angle of deviation range and is considered equal to $\frac{\pi}{4}$ (Rad). At the final step, time of empire competitive is among the imperialists. At this stage, each colony separated from the weakest empire and joins to a stronger colonial. Whatever colonial is stronger and it is more likely to be selected by colony. Finally, each empire that lost their colony becomes as a new colony. This process will continue to establish the stop condition in the algorithm [35].

3 Fuzzy C-mean

Fuzzy C-means clustering is an evolutionary model for creating the hard C-means clustering. In the meantime, application of the fuzzy sets theory in the clustering process is very effective and beneficial. In other words, the fuzzy clustering technique is one of the most effective methods in the determination of the set member's membership degree. Fuzzy clustering is viewed as a flexible clustering method. This method was proposed by Bezdek et al. [36] in 4 steps based on the iteration optimization [37].

In the first step, the number of clusters represented by the symbol c is determined ($2 \le c \le n$) and a value is also determined for the weighting parameter of m'. This parameter plays a key role in the clustering process's fuzziness. Then, a primary partitioning matrix of $U(0)$ is calculated, which will be updated per iteration of the algorithm. Each algorithm's iteration is determined with an r value where $r = 0, 1, 2, 3$ and …

In the next step, the centroid of clusters, {Vi(r)}, is calculated per iteration.

Using Eqs. (6)–(10), the partition matrix for the rth iteration will be updated as $U^{(r)}$. $\mu_{ik}^{(r+1)}$ is the degree of membership of the kth data in the ith cluster for the algorithm's ($r + 1$) th iteration in the third step. d_{ik} represents the Euclidean distance between kth data and ith cluster center. In Eq. (6), φ indicates the equation hardness.

$$\mu_{ik}^{(r+1)} = \left[\sum_{j=1}^{c} \left(\frac{d_{ik}^{(r)}}{d_{jk}^{(r)}} \right)^{\frac{2}{(m'-1)}} \right]^{-1} \quad \text{for } I_k = \varphi \quad (6)$$

$$\mu_{ik}^{(r+1)} = 0 \quad \text{for all classes } i \text{ where } i \in \tilde{I}_k \quad (7)$$

$$I_k = \left\{ i | 2 \le C < n;\ d_{ik}^{(r)} = 0 \right\} \quad (8)$$

$$\tilde{I}_k = \{1, 2, \ldots, c\} - I_k \quad (9)$$

$$\sum_{i \in I_k} \mu_{ik}^{(r+1)} = 1 \quad (10)$$

In the last step, the clustering's precision level is controlled by Eq. (11), where ε_L is the precision level, i.e., calculations have reached the desired precision level of ε_L and clustering has led to a proper optimization, and therefore, the calculations end here. Otherwise, we should return to the second step and repeat the calculations. This loop is repeated until the desired precision level is obtained. Due to the complexity and heavy calculations and the risk of error in manual computations, a MATLAB code is used for calculations.

$$\| \tilde{U}^{(r+1)} - \tilde{U}^{(r)} \| = \varepsilon_L \tag{11}$$

4 Studied quarries

Iran is among the countries that possess great potentials and capabilities in the production of dimension stones. There is a wide range of sedimentary, igneous and metamorphic dimension stone resources in Iran. Due to the high quality, beautiful color and texture of dimension stones of Iran, these resources are distinguished and superior as compared their compared to their counterparts from other parts of the word, and in some cases, they are one of a kind in market. Therefore, the dimension stones industry can be accounted as a strong point of mining sector from different aspects such as exploitation, domestic production, export and foreign exchange revenue. The exploitable dimension stone deposits of Iran can be summarized as travertine about 59 million tons, marble about 500 million tons and granite about 60 million tons [38]. In this paper, 12 quarries with famous dimension stones as follows: Red Granite (A1), Black Granite (A2), White Granite (A3), Chocolate Granite Khoramdeh (A4), Pearl Granite (A5), Cream Marble Harsin (A6), Pink Marble Anarak (A7), Red Travertine (A8), Travertine Hajiabad (A9), Travertine Darebokhari (A10), Marble Salsali (A11) and Pink Marble Haftoman (A12) are considered and studied. The location, geological and discontinuities of studied quarries are given in Fig. 2 and Table 2. The samples of stones which have been studied were collected from these mines and transferred to laboratory.

5 Laboratory studies

For laboratory tests, sample blocks were collected from the studied quarries. Standard tests were done to measure the four major of physical and mechanical properties of rock were chosen for assessing the sawability of dimension stone. These parameters are listed as follows:

(a) Schmiazek abrasivity factor (SF-a)
(b) Uniaxial compressive strength (UCS)
(c) Mohs hardness (MH)

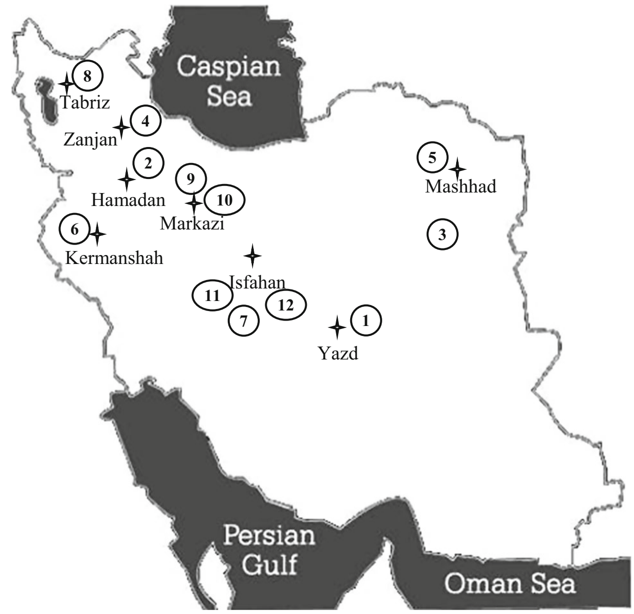


Fig. 2 Location of studied quarries

(d) Young's modulus (YM)

The reasons of the selections of these parameters are given below.

5.1 Schmiazek F-abrasivity factor (SF-a)

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 [39]. Schimazek's F-abrasiveness factor is the most common factor for evaluation of rock abrasivity. It is depended on textural and mechanical properties. The Schimazek's F-abrasiveness factor is defined as

$$\mathrm{SFa} = \frac{\mathrm{EQC} \times \mathrm{Gs} \times \mathrm{BTS}}{100} \tag{12}$$

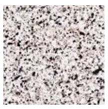
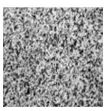
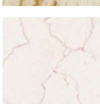
where F is the Schimazek's wear factor (N/mm), EQC is the equivalent quartz content percentage, Gs is the median grain size (mm) and BTS is the indirect Brazilian tensile strength.

The Schimazek's F-abrasiveness factor was selected as an abrasiveness index of rock in clustering system. The results of laboratory studies to determine this index are given in Table 3.

5.2 Uniaxial compressive strength (UCS)

Uniaxial compressive strength is an important mechanical parameter to present the engineering property of rock. Rock material strength is used as an important parameter in

Table 2 Geology and discontinuities characteristics of studied quarries

Dimension stone sample	Commercial name	Name of quarry	Geological age	Major mineral	Rock mass quality	Joint set	Joint spacing Cm
A_1 	Granite	Ghale Khargoshi	Eocene	Plagioclase	Good	1–2	300<
A_2 	Granite	Chayan	Cretaceous	Aluminosilicate	Good	1–2	300<
A_3 	Granite	Nehbandan	Cretaceous	Alkali feldspar	Excellent	1	–
A_4 	Granite	Khoshtinat	Post-Eocene	Feldspar Quartz	Fair–Good	1–2	300<
A_5 	Granite	Khatam	Mesozoic	Alkali feldspar Quartz	Good	1	–
A_6	Marble	Zolfaghar	Oligo-Miocene	Calcite	Fair–Good	2–3	250–300
A_7 	Marble	Golsang	Oligo-Miocene	Calcite	Fair	2	150–200
A_8 	Travertine	Azarshahr	Quaternary	Calcite	Good	2	250–300
A_9	Travertine	Hajiabad	Quaternary	Calcite	Fair–Good	2–3	200–250
A_{10} 	Travertine	Darebokhari	Quaternary	Calcite	Fair	2–3	200–250
A_{11} 	Marble	Salsali	Oligo-Miocene	Calcite	Good	2–3	200–300
A_{12} 	Marble	Haftoman	Oligo-Miocene	Calcite	Fair–Good	2	150–200

many rock mass classification systems [40]. Uniaxial compressive strength test can be considered as characteristic of rock strength, density, weathering, texture and matrix type. Therefore, using this parameter in this study to predict the sawability of dimension stone is necessary. To determine the uniaxial compressive strength of studied dimension stones, the 5 standard NX core samples with a length-to-diameter ratio of 2.5:1 were taken using a diamond rotating drill from block sample. A circular diamond saw blade was used to cut the specimens to their final lengths. After that, the surfaces of specimens were grinded using a grinding machine to achieve a high-quality surface for the axial loading. The mechanical tests were carried out by a servo-controlled testing machine designed for rock

Table 3 Result of laboratory studies to determine the SF-a

Dimension stone sample	BTS MPa	EQ_C %	Gs mm	SF-a N/mm
A_1	8.52	57.65	2.9	14.24
A_2	15	60.06	0.87	7.6
A_3	9.2	64.3	4.1	24.25
A_4	8.3	32.2	3.9	10.42
A_5	7.4	30.3	3.8	8.5
A_6	6.8	3.6	0.55	0.135
A_7	7.1	3.4	0.45	0.109
A_8	4.3	2.8	1.01	0.122
A_9	5.6	2.6	0.85	0.124
A_{10}	5.4	2.7	0.87	0.127
A_{11}	6.3	3.2	0.52	0.105
A_{12}	7.2	4	0.6	0.173

Table 4 Result of laboratory studies

Dimension stone sample	UCS MPa	SF-a N/mm	YM GPa	MH N
A_1	142	14.24	43.6	6.1
A_2	173	7.6	48.6	6.6
A_3	145	24.25	35.5	5.95
A_4	133	10.42	28.9	5.65
A_5	125	8.5	31.2	5.6
A_6	71.5	0.135	32.5	3.5
A_7	74.5	0.109	33.6	3.2
A_8	53	0.122	20.7	2.9
A_9	61.5	0.124	21	2.9
A_{10}	63	0.127	23.5	2.95
A_{11}	68	0.105	31.6	3.1
A_{12}	74.5	0.173	35.5	3.6

test. The standard uniaxial compressive strength test of core samples was carried out under a loading rate of 1 MPa/s [41]. Finally, the average uniaxial compressive strength was calculated for each studied dimension stones. The results are given in Table 4.

5.3 Mohs hardness scale (MH)

Hardness can be defined as the rock's resistance to fracture or plastic deformation due to scratching and cracking from circular diamond saw. The factors that affect rock hardness are the hardness of the constitutive minerals, cohesion forces, homogeneity and the water content of rock [42]. Hardness is a good index of all above given parameters of rock material. Mohs hardness scale is the common and useful index to evaluate the hardness of rock. It was selected as hardness index in the clustering system. The mean hardness of each dimension stone is calculated based on the hardness of contained minerals using the following equation:

$$\text{Mean Hardness} = \sum_{i=1}^{n} M_i \times H_i \tag{13}$$

where M_i is mineral amount (%), Hi is Mohs hardness and n is the total number of minerals in the dimension stone. The mean Mohs hardness of each studied dimension stone is given in Table 4.

5.4 Young's modulus (YM)

According to rock behavior during the fracture process, especially in sawing, the way that rocks reach the failure point has a great influence on sawability. The best scale for rock elasticity is Young's modulus. Based on ISRM suggested methods [41], the tangent Young's modulus at a stress level equal to 50 % of the ultimate uniaxial compressive strength is used in this clustering system. The results are given in Table 4.

Then, the pseudo-code must be written for the fitness function and the other parts of the algorithm in MATLAB. Afterward, for more evaluation and data analysis the samples are evaluated in 2, 3, 4 and 5 clusters. The results of classification were not agreeable with properties of the studied dimension stones for 2, 4 and 5 clusters. The lowest and the most appropriate cost function achieved for 3 clusters.

6 Application of imperialist competitive algorithm in dimension stone sawability prediction

One of the most impressive applications of ICA is data clustering of information. The objective function is one of the most significant parts in meta-heuristic algorithms. In fact, the fitness function of an optimization problem is to maximize the distance of cluster centers from each other and to minimize distance among members of a cluster. The Lloyd's algorithm (k-means clustering) is the fitness function in imperialist competitive algorithm. It shows in Eq. (14):

$$\text{Obj.Function} = \sum_{i=1}^{n} \min_{1 \le j \le k} \mathrm{d}(x_i, m_j) \tag{14}$$

In fact, for the optimization of data clustering, Lloyd's algorithm (k-means clustering) is used based on the imperialist competitive algorithm in this research and the main results of optimization obtained from ICA.

6.1 Data clustering by 3 clusters

In data mining for the total sample dimension stones, the considered limits in the clustering are maximum iteration of 150, minimum acceptance precision of $\varepsilon_L = 0.0001$ and 75 population as initial population for ICA. The Lloyd's algorithm conducted an optimization as the fitness function and found to maximize the distance of cluster centers from each other and to minimize distance among samples of a cluster based on the considered limits of ICA and four important physical and mechanical properties of samples. The algorithm process stops after the calculations. For fuzzy C-mean, considered limits in the clustering are maximum iteration of 100, minimum acceptance precision of εL = 0.00001 and the weighting parameter of $m' = 2$. Distance of clusters' centers from criteria and classification of samples for each method are given in Tables 5 and 6, respectively.

Table 7 represents the difference between the results of step 120 and 121 in which it is less than the minimum acceptance precision of 0.0001 and this process is fixed from 121th to 150th iteration; therefore, the computing stops at the 200th iteration for ICA. Furthermore, as listed in Table 7, the difference between the results of stages 47 and 48 is less than the minimum acceptance precision of 0.00001; therefore, the calculations stop at the 17th iteration.

Table 5 Distance of clusters' centers from criteria by ICA and fuzzy C-mean for 3 clustering

Criteria	ICA			Fuzzy C-mean		
	C_1	C_2	C_3	C_1	C_2	C_3
MH	0.877	0.902	0.485	0.391	0.813	0.84
YM	0.697	0.73	0.641	0.006	0.412	0.954
UCS	0.782	0.838	0.413	0.585	0.755	0.744
SF-a	0.411	1	0.005	0.48	0.897	0.905

Table 7 Precision level and calculation termination of ICA and fuzzy C-mean

Step (n)	$\tilde{U}^{(n-1)}$	$\tilde{U}^{(n)}$	$\varepsilon_L = \tilde{U}^{(n)} - \tilde{U}^{(n-1)}$	Result
Precision level and calculation termination of ICA				
120	1.6942	1.6944	$0.0002 > 0.0001$	Continue
121	1.6944	1.6945	$0 < 0.0001$	Continue
150	1.6945	1.6945	$0 < 0.0001$	Stop
Precision level and calculation termination of fuzzy C-mean				
47	0.294659	0.294648	$0.000011 > 0.00001$	Continue
48	0.294648	0.294643	$0 < 0.00001$	Stop

Figure 3 shows data clustering based on 3 clusters, and Fig. 4 shows minimum cost per iteration in which the 121th iteration is reached to the optimal point.

7 Validation of results

Validation of results is an important phase of search. For validation of the applied algorithm and its results, field studies were carried out. The production rate of each studied dimension stones was used as a criterion for evaluating and validating the results. For this purpose, some stone factories in Shamsabad located in Tehran were selected, and the performance of the diamond circular saw was measured in term of hourly production rates (P_h). The production rate and sawability classification of the studied dimension stones are given in Table 8.

According to Table 5, the applied algorithm is almost able to classify the studied dimension stone into two geological groups based on physical and mechanical

Table 6 Optimization and classification of samples of ICA and fuzzy C-mean

Samples	Optimum partition of ICA			Classification		Optimum partition of fuzzy C-mean			Classification of fuzzy C-mean	
A1	0.273	0.446	0.874	First class	A1	0.046	0.72	0.235	First class	A1
A2	0.405	0.762	0.913		A2	0.094	0.739	0.167		A2
A3	0.593	0.000001	1.163		A4	0.002	0.007	0.992		A4
A4	0.107	0.592	0.669		A5	0.055	0.862	0.084		A5
A5	0.107	0.667	0.589	Second class	A3	0.064	0.876	0.06	Second class	A3
A6	0.659	1.145	0.053	Third class	A6	0.971	0.021	0.008	Third class	A6
A7	0.666	1.155	0.054		A7	0.964	0.026	0.01		A7
A8	0.811	1.257	0.244		A8	0.936	0.043	0.021		A8
A9	0.781	1.236	0.221		A9	0.947	0.036	0.017		A9
A10	0.755	1.218	0.169		A10	0.974	0.018	0.008		A10
A11	0.681	1.165	0.02		A11	0.986	0.01	0.004		A11
A12	0.631	1.131	0.109		A12	0.922	0.057	0.021		A12

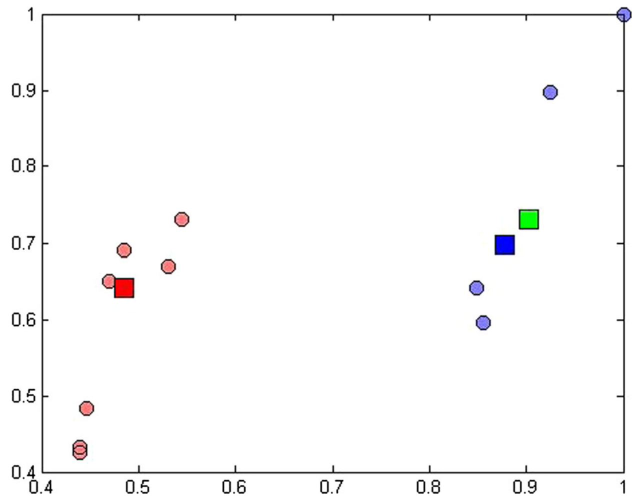


Fig. 3 Position of samples in clustering

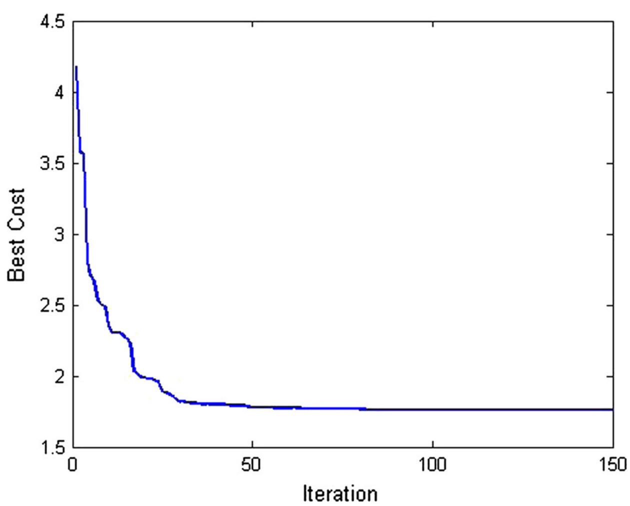


Fig. 4 Minimum cost per iteration in ICA

properties. The first group (Class 1) is hard dimension stone and the second group (Class 3) is soft dimension stone such as marble and travertine. In addition, the applied algorithm can be used to predict and classify the dimension stone sawability or the performance of circular diamond saw. The sawability of studied dimension stones was classified into two major groups. The first group (Class 1) has a poor sawability with a P_h less than 6.5 m^2/h, and the second group (Class 3) has a good sawability with a P_h greater than 8.5 m^2/h. The results show the capability of the imperialist competitive algorithm (ICA) and fuzzy clustering technique for solving optimal classification in stone industry.

8 Conclusion

The circular saw machine is one of the most important machines used in the stone processing factories. The performance prediction of circular diamond saw blade is very important in the cost estimation and the planning of the factories. In this paper, it was aim to evaluate and classify the dimension stone by imperialist competitive algorithm and fuzzy C-mean based on some important physical and mechanical properties of dimension stone. To achieve this goal, two groups of Iranian famous dimension stones were studied. The studied dimension stones were classified by applied algorithms, and the classification results were validated by the performance of the diamond circular saw was measured in term of hourly production rates (P_h) at some stone factories in Shamsabad. According to the results of this study, the applied algorithms were almost able to classify the studied dimension stones into two geological groups such as hard dimension stone (Class 1) and soft dimension stone (Class 3). Moreover, the

Table 8 Production rate and sawability classification of the studied dimension stones

Dimension stone sample		Type	Classification			P_h
			Class 1	Class 2	Class 3	m^2/h
A_1	Red	Granite	*			5.5
A_2	Black	Granite	*			5
A_3	White	Granite		*		5
A_4	Chocolate	Granite	*			6
A_5	Pearl	Granite	*			6.5
A_6	Cream Harsin	Marble			*	8.5
A_7	Pink Anarak	Marble			*	9
A_8	Red	Travertine			*	11
A_9	Hajiabad	Travertine			*	10
A_{10}	Darebokhari	Travertine			*	10
A_{11}	Salsali	Marble			*	9
A_{12}	Pink	Marble			*	8

sawability results of studied dimension stones confirm the capability of applied algorithm. The first class has a poor sawability, and the third class 3 has a good sawability. The results of ICA algorithm showed that the identified samples are similar to that obtained from fuzzy C-mean. In addition, based on optimal and comparative results and prediction of the dimension stone sawability, ICA and fuzzy C-mean make it possible to evaluate the hurly production rate of circular diamond saw although ICA is superior to fuzzy C-mean based on the results of optimum partition. Finally, the results showed that the sawability of dimension stone can reliably be classified from some important physical and mechanical properties of dimension stone such as uniaxial compressive strength, Schmiazek F-abrasivity, Mohs hardness scale and Young's modulus by using imperialist competitive algorithm and fuzzy clustering technique.

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