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Assessing the System Vibration of Circular Sawing Machine in Carbonate Rock Sawing Process Using Experimental Study and Machine Learning

Reza Mikaeil · Mojtaba Mokhtarian · Sina Shaffiee Haghshenas · Nicola Careddu ⬤ · Aref Alipour

Abstract Predicting the vibration of the circular sawing machine is very important in examining the performance of the sawing process, as it shows the amount of energy consumption of the circular sawing machine. Also, this factor is directly related to maintenance cost, such that with a small increase in the level of vibration, the maintenance cost increases to a large extent. This paper presents new prediction models to assess the vibration of circular sawing machine. An evaluation model based on the imperialist competitive algorithm as one of the most efficient artificial intelligence techniques was used for estimation of sawability of the dimension stone in carbonate rocks. For this purpose, four main physical and mechanical properties of rock including Schimazek's F-abrasivity, uniaxial compressive strength, mean Mohs hardness, and Young's modulus as well as two operational parameters of circular sawing machine including depth of cut and feed rate, were investigated and measured. In the predicted model, the system vibration in stone sawing was considered as a dependent variable. The results showed that the system vibration can be investigated using the newly developed machine learning models. It is very suitable to assess the system vibration based on the mechanical properties of rock and operational properties.

Keywords Dimension stone · Carbonate rocks · Sawing process · Vibration · ICA

1 Introduction

In dimension stone industry, a range of igneous, metamorphic, and sedimentary rocks are used. These types of dimension stones are commonly known as granite, limestone, marble, travertine, sandstone, and quartzite. The market value of these materials is far higher than that of most minerals currently extracted and varies considerably. Thus, special attention has been given to this issue in the world. One of the most important parts in stone processing is sawing process of extraction blocks. Sawing machines in the building stone processing industry can be divided into circular diamond saw, gang saw and diamond wire saw. Among these devices, circular diamond saw is the most used.

Iran is a mineral-rich country with a high potential in dimension stone. Studies show that Iran is ranked among the 15 major mineral-rich countries (Reichl et al. 2013; Adibi and Ataee-pour 2015). Over the last

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Table 1 Literature review of sawability studies

References	Saw type		Physical and mechanical properties											
	W	C	UCS	BTS	YM	IS	SS	BS	H	A	D	Gs	Qc	Ws
Burgess (1978)		●										●	●	
Wright and Cassapi (1985)		●	●		●				●	●			●	
Birle and Ratterman (1986)		●							●					
Jennings and Wright (1989)		●	●		●				●				●	
Clausen et al. (1996)		●										●	●	
Ciccu et al. (1998)	●					●			●					●
Agus et al. (2003)	●								●			●	●	
Wei et al. (2003)		●	●						●	●			●	
Eyuboglu et al. (2003)		●	●	●	●				●					
Ersoy and Atıcı (2004)		●	●	●	●	●	●	●	●	●	●	●	●	
Kahraman et al. (2004)		●	●	●	●		●		●	●				
Gunaydin et al. (2004)		●	●	●	●		●							
Ozcelik et al. (2004)	●		●	●	●				●		●		●	
Buyuksagis and Goktan (2005)		●	●	●	●				●	●			●	
Ersoy et al. (2005)		●	●	●	●	●	●	●	●	●			●	
Delgado et al. (2005)		●							●				●	
Kahraman et al. (2005)		●					●						●	
Cai et al. (2007)	●		●			●	●		●		●			
Fener et al. (2007)		●	●		●	●			●	●				
Kahraman et al. (2007)		●	●		●						●		●	
Özçelik (2007)	●		●		●				●				●	
Tutmez et al. (2007)		●	●		●	●			●	●				
Buyuksagis (2007)		●	●		●			●	●	●	●		●	
Mikaeil et al. (2008)	●		●										●	
Kahraman and Gunaydin (2008)		●							●		●			
Ataei et al. (2011)		●	●		●				●	●				
Mikaeil et al. (2011)		●	●		●									
Ataei et al. (2012)	●		●		●				●	●		●	●	
Yurdakul and Akdas (2012)		●	●		●			●	●	●	●			
Ghaysari et al. (2012)	●											●		
Mikaeil et al. (2013)		●	●	●	●				●	●		●	●	
Sadegheslam et al. (2013)	●		●		●					●			●	
Careddu and Cai (2014)	●	●												
Careddu and Lanceni (2015)	●	●												
Tumac (2015)		●							●	●				
Mikaeil et al. (2015)		●	●	●	●				●	●		●	●	
Aryafar and Mikaeil (2016)		●	●	●	●				●	●		●	●	
Tumac (2016)		●	●		●				●		●			
Almasi et al. (2017a)	●		●	●	●				●	●		●	●	
Almasi et al. (2017b)	●		●	●	●				●	●		●	●	
Almasi et al. (2017c)	●		●	●	●				●	●		●	●	
Kamran et al. (2017)	●		●	●	●				●	●		●	●	
Akhyani et al. (2017)		●	●	●	●				●	●		●	●	

Table 1 continued

References	Saw type		Physical and mechanical properties											
	W	C	UCS	BTS	YM	IS	SS	BS	H	A	D	Gs	Qc	Ws
Mikaeil et al. (2017)	●		●	●	●				●	●		●	●	
Yilmazkaya et al. (2018)	●		●		●	●	●	●		●		●	●	
Tumac and Shaterpour-Mamaghani 2018)		●			●	●	●					●	●	
Aryafar et al. (2018a)		●	●	●	●				●	●		●	●	
Aryafar et al. (2018b)		●	●	●	●				●	●		●	●	
Akhyani et al. (2018)		●	●	●										
Mikaeil et al. (2018a)		●	●	●	●				●	●		●	●	
Mikaeil et al. (2018b)		●	●	●	●				●	●		●	●	
Careddu et al. (2018)	●		●					●		●	●			
Careddu et al. (2019)	●		●					●		●	●			
Akhyani et al. (2019)		●	●	●	●				●	●		●	●	
Mohammadi et al. (2019)		●	●	●	●				●	●		●	●	
Dormishi et al. (2019a)		●	●	●	●				●	●		●	●	
Dormishi et al. (2019b)		●	●	●	●				●	●		●	●	
Mikaeil et al. (2019a)		●	●	●	●				●	●		●	●	
Haghshenas et al. (2019)		●	●	●	●				●	●		●	●	
Hosseini et al. (2019)		●	●	●	●				●	●		●	●	
Hosseini et al. (2020a)		●	●	●	●				●	●		●	●	
Hosseini et al. (2020b)		●	●	●	●				●	●		●	●	

W, Diamond wire saw; C, Circular saw, Frame saw and Chain saw; 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; Ws, Wave speed

four decades, many studies in the field of dimensional stone have been done in the world (Table 1). By reviewing the previous studies in Table 1, it can be seen that the five parameters including uniaxial compressive strength (UCS), indirect Brazilian tensile strength (BTS), hardness (H), abrasivity (A), and quartz content (Qc) have been used widely for modeling and evaluation of sawing process. It was concluded that these parameters are significant in the rock sawing process with diamond wire saw and circular diamond saw.

One of the effective factors in sawing costs is maintenance cost. Along with other cost factors such as labor, energy, water, this factor is very important. This factor can be considered directly related to the vibration of the sawing machine. As a result, predicting machine vibration can play an important role in predicting the cutting costs. In addition, in the sawing process, system vibration is a significant factor of cutting performance in terms of maintenance cost. The

rock sawing process inevitably leads to the production of vibrations that are transmitted both on the stone to be sawed and on the tool and the machine. These machines that, when sawing the stone, produce a large amount of vibrations (such as gang saw) require special and expensive reinforced concrete foundations; multi-wire machines certainly have the advantage of producing a lower amount of vibrations thanks to the lower rigidity of the system (Careddu and Cai 2014). However, it is undeniable that the vibrations produced during rock sawing can lead to various problems in the rock (poor flatness of the cut, and/or excessive surface roughness), in the tool (irregular wear, breakage) and in the machine (breakage). The problem of vibration has been studied by many researchers in rock sawing by diamond wire, some kind of "irregular" wear of diamond beads could be explained just by vibration phenomenon of the wire (Cai and Careddu 2013). Dunda and Kujundžić (2001) observed that high velocities of diamond wires
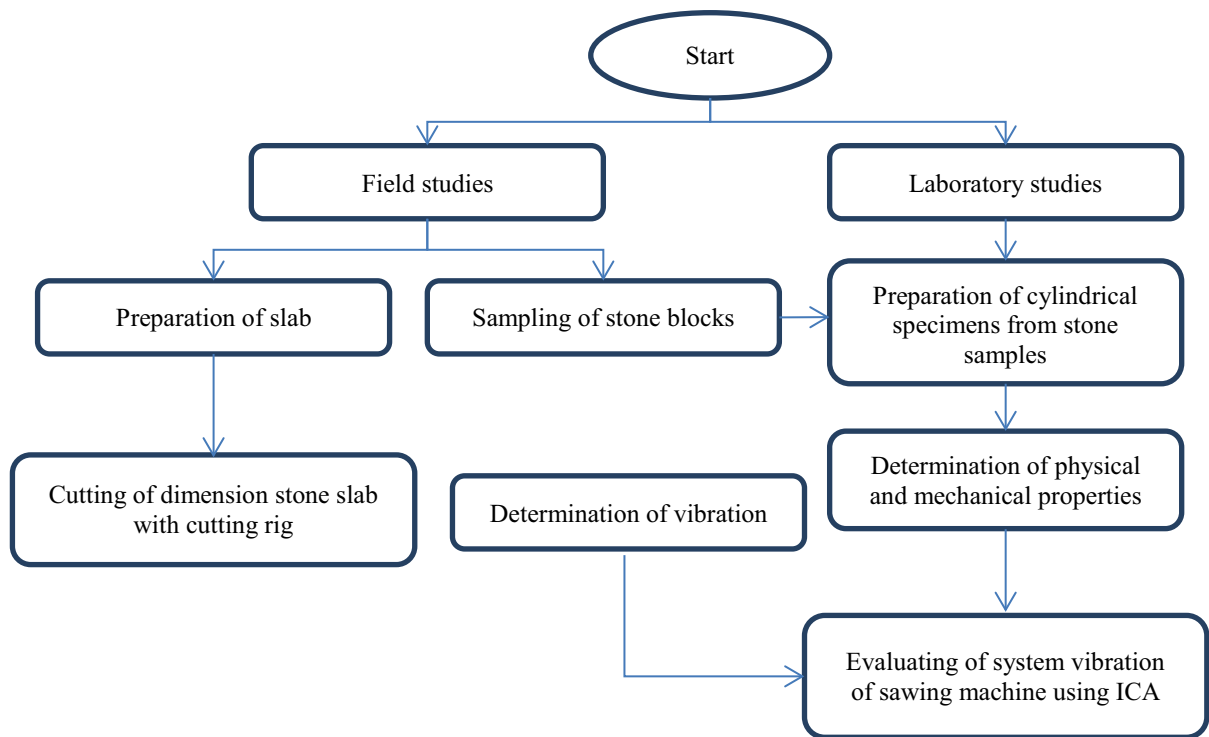
Fig. 1 Flowchart of study

produce vibrations of the rope, caused by dynamic forces, which lead to fatigue-breakage. Polini and Turchetta (2007) monitored tool wear using force and acceleration sensors and found that axial force and vibration affected the amount of tool wear. Tumac (2016) stated that operational parameters of the circular sawing process, such as peripheral speed, saw blade type and diameter have a significant effect on vibration. Geology and rock nature can also affect the development of vibrations in the chain saw cutting process the discontinuities and cracks within the rock mass limit the chain speed since larger chain speed increases vibrations on chain saw arm causing the breakage of the tools (Dagrain et al. 2012).

The major factors that need consideration in evaluating the system vibration, particularly for stone cutting, are the properties of the rock and the operational parameters of the saw as well as the type of equipment (gang-saw, multi-wire, and block-cutter). In this study, new models were developed to evaluate the system vibration in the stone sawing process by means of a circular diamond saw. Using these developed models, more economic analysis as a decision-making index can be done for project planning.

This study is organized as follows. After introduction in the first section, the methodology of the study is presented. In the third section, the studied quarries and laboratory study are explained. In the fourth section, the new models are developed to predict the system vibration using the imperialist competitive algorithm. Finally, the fifth section reviews the results of the models. This section concludes and discusses the paper.

2 Methodology

This study is generally organized into two main sections. Field and laboratory studies were performed to create statistical data in the first section. Finally, soft computing was carried out to evaluate the cutting performance of circular sawing machine. Figure 1 displays the flowchart of this study.

2.1 Imperialist Competitive Algorithm

Artificial intelligence techniques are one of the most popular ways to solve complex problems in industry and economics sectors (Mahdevari et al. 2017;
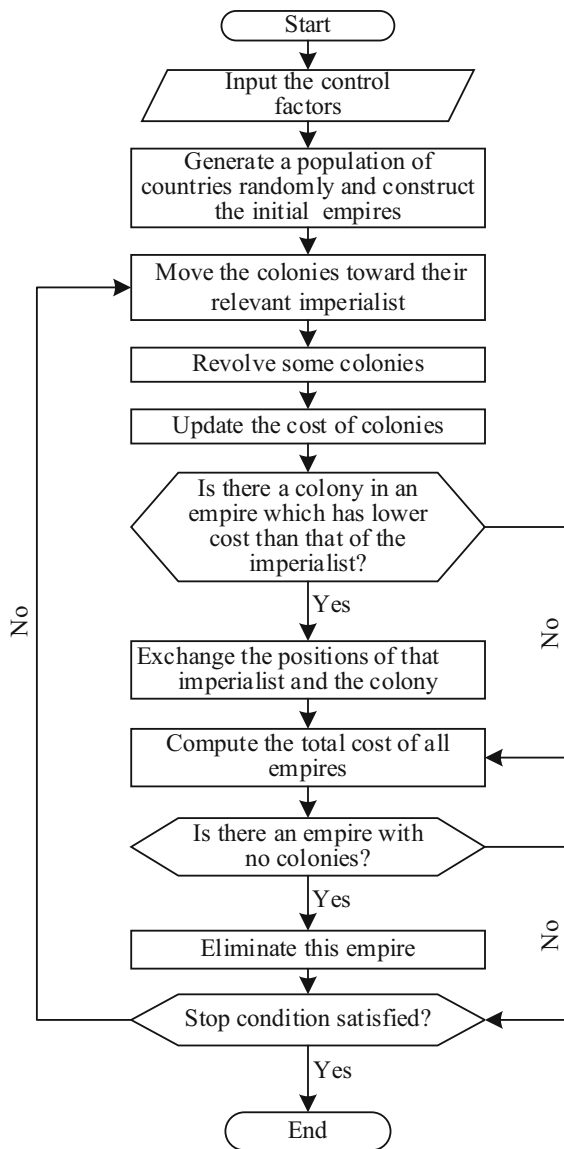
Fig. 2 Flowchart of imperialist competitive algorithm

Naderpour et al. 2019; Zhang and Geem 2019; Kayabekir et al. 2020; Daneshvar and Behnood 2020; Guido et al. 2020a; Kandiri et al. 2020). In recent years, several studies have been conducted on the application of artificial intelligence in engineering problems (Geem and Kim 2018; Mikaeil et al. 2018c, 2019b, c, d; Salemi et al. 2018; Gnawali et al. 2019; Park et al. 2020; Shaffiee Haghshenas et al. 2020; Noori et al. 2020; Fiorini Morosini et al. 2020; Guido et al. 2020b). One of the most efficient methods of artificial intelligence is the imperialist competitive algorithm (ICA), suggested by Atashpaz-Gargari and Lucas (Khabbazi et al. 2009;

Haghshenas et al. 2017). The capability of algorithm to solve the different types of optimization problems has been studied by the authors in Atashpaz-Gargari and Lucas 2007; Nazari-Shirkouhi et al. 2010; Shokrollah-pour et al. 2011; Maroufmashat et al. 2014; Ardalan et al. 2015; Sadaei et al. 2016; Sharifi and Mojallali 2016; Mokhtarian Asl and Sattarvand et al. 2016. As other evolutionary algorithms, the ICA begins with an initial number of solutions that are called countries. Each solution represents the concept of the nations and reflects the quality of objective function in each solution. The best solutions or countries are elected as 'imperialists' while the remaining solutions are categorized as the 'colonies' of those imperialists. An imperialist and the colonies form an 'empire' (Shokrollahpour et al. 2011). Gradually, imperialists seek to extend their characteristics to the colonies under their control. Still, the procedure is not fully controlled and revolutions are expected. Countries may also leave one empire to join another provided that the new one gives them more chance of promotion. Figure 2 displays the flowchart of the ICA. In the following, the methodology for implementation of ICA will be explained step by step.

Step 1 Generating initial empires: The optimization algorithm starts with an initial population that is created consisting of N_{pop} solutions including N_{imp} of the strongest that represent the imperialists. The remaining members of the population ($N_{col} = N_{pop} - N_{imp}$) represent the colonies of the empires. The primary empires and colonies are separated among the imperialists given their power as the higher the power of an empire, the more the colonies covered by it. To distribute the colonies among imperialists based on their power, the normalized cost of nth imperialist is given as follows (Atashpaz-Gargari and Lucas 2007):

$$C_n = \max\{c_i\} - c_n, \quad i = 1, 2, \ldots, N_{imp} \qquad (1)$$

where c_n and C_n represent the cost and the normalized cost of nth imperialist respectively. Thus, each imperialist's normalized power is determined as follows (Atashpaz-Gargari and Lucas 2007):

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

The number of colonies that can be controlled by an imperialist is determined by its normalized power. Hence, the count of colonies of an empire at beginning is given as (Atashpaz-Gargari and Lucas 2007; Haghshenas et al. 2017):

$$ColEmp_n = round(pow_n \times N_{col}) \qquad (3)$$

where $ColEmp_n$ is the starting number of the colonies of nth empire that are determined in the whole colony population randomly.

Step 2 Assimilation process: The colony can move towards the imperialist on different socio-political axes such as culture and language. The colony can approach the imperialist by x units, while x stands for a random number with uniform distribution.

Step 3 Revolution: The operator diversifies ICA to examine new regions. The mechanism protects the algorithm from being trapped in local optima. Thus, each iteration selects the weakest colony and randomly replaces it with a new one.

Step 4 Imperialist and a colony substitution: It is possible for a colony to reach the position where cost function is less than that of its imperialist. When this happens, the colony and imperialist replace their position.

Step 5 Calculating the total power of an empire: It is obtained based on the power of its imperialist country, while the powers of its individual colonies have also important influence, which is relatively insignificant. Thus, the total cost of an empire is as:

$$TC = \text{cost}(imperialist_n) \\ + \xi \text{mean}(\cos t(colonies\ of\ empire_n)) \qquad (4)$$

where TC represents the total cost of the nth empire and ξ stands for positive number which is considered less than 1.

Step 6 Imperialistic competition: The competition is modeled by choosing one of the weakest colonies that belongs to the weakest empire and making a competition among all empires to possess this colony. The possession probability of each empire is proportional

to its total power. The normalized total cost of each empire is determined as follows (Eq. (5)):

$$NTC_n = \max\{TC_i\} - TC_n \quad i = 1, 2, \ldots, N_{imp} \qquad (5)$$

where TC_n and NTC_n represent the total cost and normalized total cost of nth empire respectively. Now the chance of possession for each empire is given by:

$$p_n = \left| \frac{NTC_n}{\sum_{i=1}^{N_{imp}} NTC_i} \right| \qquad (6)$$

To determine the share of each empire of the noted colonies, vector P is formed as follows:

$$P = [p_1, p_2, p_3, \ldots, p_{N_{imp}}] \qquad (7)$$

Afterwards, the vector R equal to P in size is created of which the elements are uniformly distributed random numbers between 0 and 1.

$$r = [r_1, r_2, r_3, \ldots, r_{imp}], \quad r_1, r_2, r_3, \ldots, r_{imp} \sim U(0, 1) \qquad (8)$$

Then, vector D is formed by subtracting R from P.

$$D = P - R = [d_1, d_2, d_3, \ldots, d_{N_{imp}}] \\ = [p_1 - r_1, p_2 - r_2, p_3 - r_3, \ldots, p_{N_{imp}} - r_{N_{imp}}] \qquad (9)$$

Based on vector D, the colonies will be subjected to an empire whose corresponding index of empire in D is maximum. (Atashpaz-Gargari and Lucas 2007; Haghshenas et al. 2017).

Step 7 Removing the empires without power: Empires without power will not survive in the imperialistic competition and the colonies they have are taken by other empires. Here, an empire falls when all its colonies are lost.

Step 8 Stopping criteria: when no iteration remains or only one empires controls the whole world, the algorithm stops.

3 Studied Quarries and Laboratory Study

In this paper, twelve famous Iranian quarries are studied. The names and locations of these quarries are presented in Table 2 and Fig. 3, respectively.

Table 2 The names of studied quarries

	Name samples		Rock sample	Type	Quarry
S1		CHM	Cream Harsin	Marble	Zolfaghar
S2		PAM	Pink Anarak	Marble	Golsang
S3		RT	Red	Travertine	Azarshahr
S4		HT	Hajiabad	Travertine	Hajiabad
S5		DT	Darebokhari	Travertine	Darebokhari
S6		SM	Salsali	Marble	Salsali
S7		PM	Pink	Marble	Haftoman
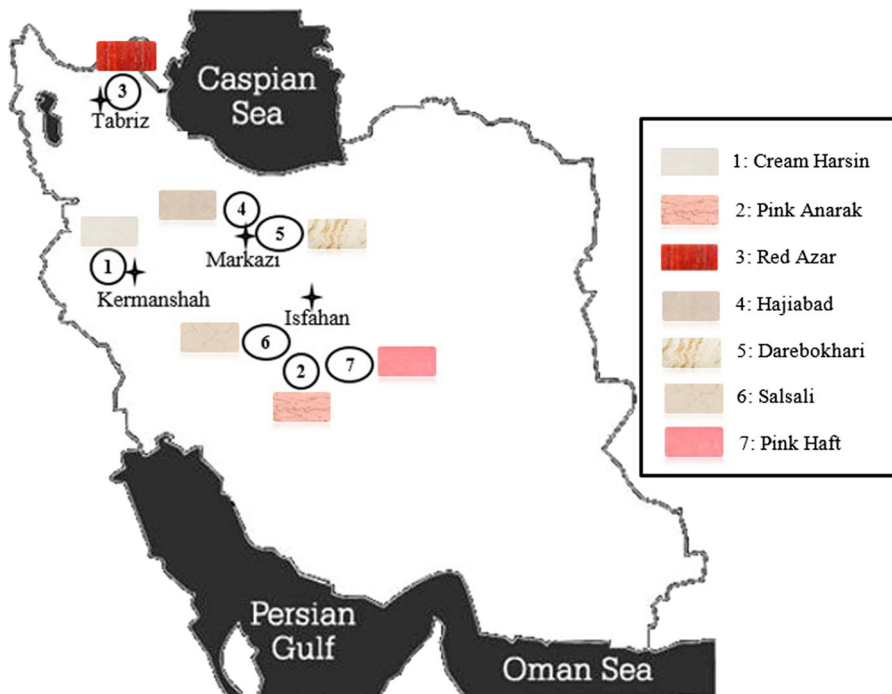
Fig. 3 The location of studied quarries

Table 3 The results of laboratory studies

Name samples	UCS MPa	BTS MPa	Q_C %	Gs mm	SF-a N/mm	YM GPa	MH n
S1	71.5	6.8	3.6	0.55	0.135	32.5	3.5
S2	74.5	7.1	3.4	0.45	0.109	33.6	3.2
S3	53	4.3	2.8	1.01	0.122	20.7	2.9
S4	61.5	5.6	2.6	0.85	0.124	21	2.9
S5	63	5.4	2.7	0.87	0.127	23.5	2.95
S6	68	6.3	3.2	0.52	0.105	31.6	3.1
S7	74.5	7.2	4	0.6	0.173	35.5	3.6
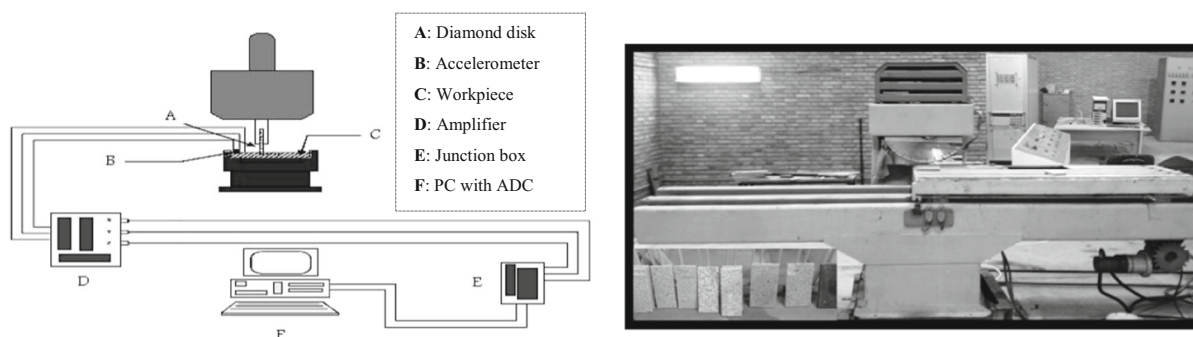
Fig. 4 A schematic diagram of the adopted sensor system and laboratory sawing rig
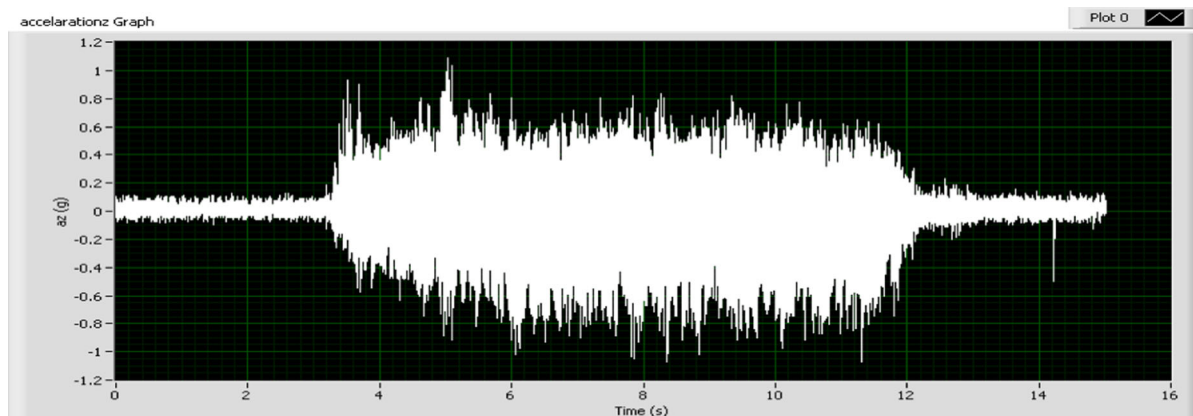
Fig. 5 Typical time-domain acceleration signals monitored at the different time interval

The samples of the studied dimension stones were prepared from quarries. Then, they were transferred to the rock mechanics laboratory to determine four major physical and mechanical parameters including, Schmiazek F-abrasivity factor (SF-a), Mohs Hardness (MH), Uniaxial Compressive Strength (UCS), and Young's Modulus (YM). Finally, standard tests were completed to measure these parameters according to the procedures suggested by the ISRM standards (ISRM 1981).

The UCS test was carried out using a servo controlled testing machine designed for rock test under a loading rate of 1 MPa/s. Finally, the average UCS was considered for each studied dimension stone.

The Schimazek's F-abrasiveness factor is calculated by Eq. 10 (Schimazek and Knatz 1970).

Table 4 The range of used parameter in this study

Parameter	Unit	Category	min	mean	max
Depth of cut	cm	input	1.50	2.53	3.60
Feed rate	m/s	input	1.00	2.50	4.00
Mohs hardness	n	input	2.90	3.18	3.60
Young's Modulus	GPa	input	20.70	28.65	35.50
Uniaxial Compressive Strength	MPa	input	53.00	67.55	74.50
Schmiazek F-abrasivity factor	N/cm	input	1.05	1.28	1.73
RMS	m/s^2	output	0.98	2.16	3.92

$$SFa = \frac{EQC \times Gs \times BTS}{100} \tag{10}$$

where SFa is the Schimazek's F-abrasiveness factor in N/mm, EQC denotes the equivalent quartz content percentage in %, Gs represents the median grain size in mm, and BTS is the indirect Brazilian tensile strength in MPa. The mean hardness of each studied rock is determined according to the hardness of contained minerals by Eq. 11 (Hoseinie et al. 2009):

$$Mean\ Hardness = \sum_{i=1}^{n} M_i \times H_i \tag{11}$$

where M_i is the mineral content in %, H_i is Mohs hardness, n denotes the total number of minerals in the thin section of the studied dimension stone.

The tangent Young's modulus has been considered in this study. This modulus is obtained at a stress level equal to 50% of the ultimate UCS. The results of rock mechanic laboratory studies are reported in Table 3.

To conduct and complete laboratory studies, an experimental procedure was performed. For this purpose, seven carbonate rocks were cut at different feed rates (FR) including FR: 100, 200, 300 and 400 cm/min and depth of cut (DC) including, DC: 35, 30, 22 and 15 mm using a fully-instrumented laboratory cutting rig. Samples of studied dimension stones were prepared in 50 × 20 × 4 cm for sawing studies. Water was used as a coolant during the sawing tests. The circular diamond saw blade used in this study had a diameter of 410 mm and a steel core of thickness 2.7 mm, 28 pieces of diamond impregnated segments (size 40 × 10 × 3 mm) were brazed to the periphery of circular steel core with a standard narrow radial slot. The grit sizes of the diamond were approximately 30/40 US mesh at 25 and 30 concentrations. The acceleration signal was acquired along the whole cut.

For monitoring the vibration in stone cutting, an adopted sensor system was designed (Fig. 4).

An accelerometer (ADXL105-3) was used to measure the acceleration of workpiece in the sawing process. A monitoring strategy was adopted based on time domain characteristics. Figure 5 illustrates monitored time-domain signals.

Then, the signals were analyzed using a feature extraction program in Labview. The Root Mean Square Amplitude feature (RMS) according to Eq. (12) was extracted for the acceleration signals. Equation (12) shows the RMS value of a function x(t) over an interval of T.

$$X_{rms} = \sqrt{\frac{\int_0^T x(t)^2 dt}{T}} \tag{12}$$

During the sawing trials, the acceleration signal and RMSaz for each rock were monitored and calculated at different FRs and DCs. The results of experimental studies were taken into account to establish the models. The range of the parameters used in this study is summarized in Table 4.

4 Prediction of System Vibration by ICA

The present section describes the model development procedure of ICA in estimating RMSa. In this regard, two models are proposed for predicting the RMSa and then ICA is used for determining their coefficients. The general forms of proposed models are presented in Eqs. (13) and (14):

$$RMS_I = k_0 + k_1 \times DC_i^{k_2} + k_3 \times FR_i^{k_4} + k_5 \times MH_i^{k_6} + k_7 \times YM_i^{k_8} + k_9 \times UCS_i^{k_{10}} + k_{11} \times SF - a_i^{k_{12}} \tag{13}$$

$$RMS_{II} = k_0 + k_1 \times DC_i^{k_2} \times FR_i^{k_3} \times MH_i^{k_4} \times YM_i^{k_5} \times UCS_i^{k_6} \times SF - a_i^{k_7} \tag{14}$$

where DC is depth of cut in mm, FR denotes feed rate (cm/min), MH (n), YM (GPa), UCS (MPa), and SF-a (N/mm). These parameters were set as the independent parameters of the model, while RMSa was considered as the dependent parameter. k_0, k_1, k_2, … k_{12} are unknown coefficients that must be adjusted to minimize the dependent parameter prediction error. The ICA approach has been used for this purpose. First, 800 random values for coefficients was considered as a first countries. Out of 800 randomly selected countries, 25 countries with the least estimation error were considered as imperialists. Then the primitive countries were according to the imperialists to form empires and colonial competition according to flowchart shown in Fig. 2, was done between empires to set the best values for the coefficients. Indeed, based on the lowest values of fitness function, ICA tries to find the fittest model to the available data. This is possible through minimizing errors between the measured values of RMSa and the estimated ones. Hence, the used fitness function for solving the problem of this study is the Mean Squared Error (MSE) function, which can be defined as follows:

$$Minimize \ \frac{1}{n}\sum_{i=1}^{n}(RMSa_{Esti} - RMSa_{Meas})^2 \tag{15}$$

$RMSa_{Meas}$ and $RMSa_{Esti}$ are the measured RMSa data, and the estimated ones by the model, respectively and n denotes the number of data.

The procedure proposed for applying ICA to predicting RMSa has been implemented in C++ programming language. In order to achieve the optimum ICA parameters, some of the previous studies were studied (Atashpaz-Gargari and Lucas 2007; Ahmadi et al. 2013; Ebrahimi et al. 2014). The best values of ζ, β, N_{pop}, and N_{imp} were considered as 0.05, 1.75, 800, and 25, respectively.

Considering the used ICA parameters in this study, the proposed models for predicting RMSa values resulting from field recorded data sites are shown in Eqs. (16) and (17), respectively.

$$RMS_I = -2.207 - 2.671 \times DC_i^{-0.2683} + 5.862 \times FR_i^{0.176} - 15902.6 \times MH_i^{-9.471} - 6.7 \times YM_i^{-7.282} - 3.874 \times UCS_i^{-10.843} + 6.731 \times SF - a_i^{-50.576} \tag{16}$$

$$RMS_{II} = -0.1376 + 0.0567 \times DC_i^{0.2673} \times FR_i^{0.5466} \times MH_i^{-0.5277} \times YM_i^{0.5558} \times UCS_i^{0.4134} \times SF - a_i^{0.0045} \tag{17}$$

5 Results and Discussion

System vibration in rock sawing process depends on two groups, including controlled parameters related to operational parameters and tool characteristics and non-controlled parameters related to rock characteristics. Under the same working conditions, the cutting results are strongly affected by rock characteristics such as strength, hardness, and abrasiveness as well as

**Table 5** The value of statistical criteria for the predictive models

| Predictive model	Statistical criteria									
	MAPE		RMSE		VARE		VAF		CC	
	Model	Test	Model	Test	Model	Test	Model	Test	Model	Test
RMS_I	8.241	8.944	0.192	0.210	0.632	0.867	93.345	90.269	0.976	0.953
RMS_{II}	6.674	6.531	0.195	0.206	0.302	0.328	93.103	90.670	0.975	0.954
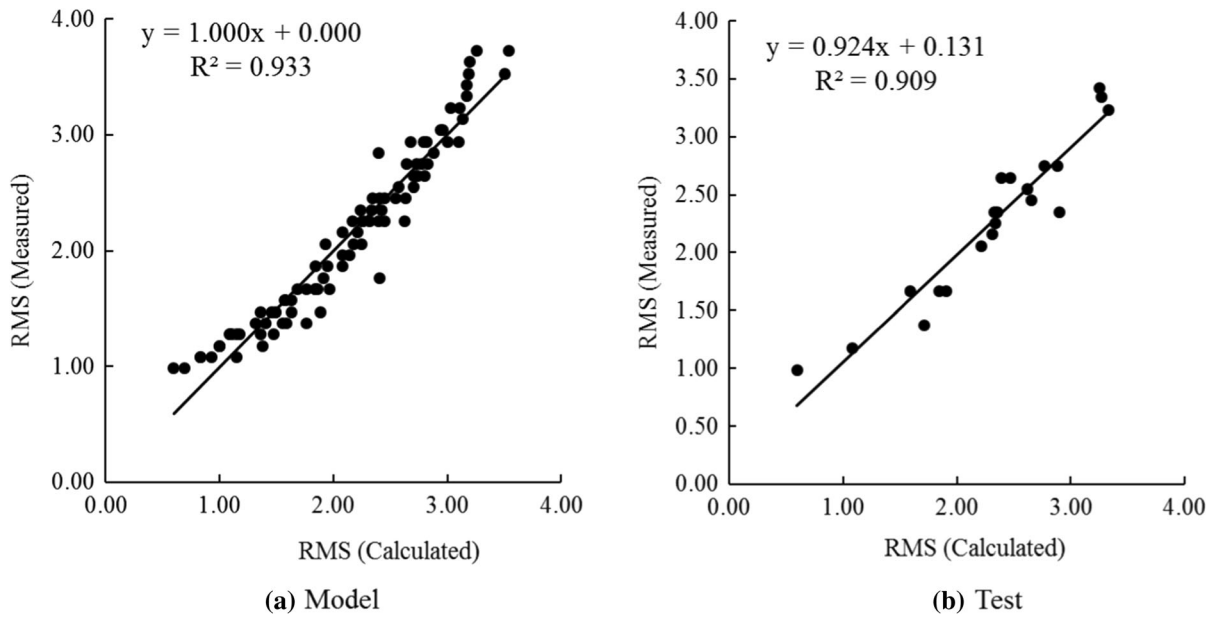
Fig. 6 Measured versus predicted RMS by model RMS$_I$ a. model data and b. test data

operational parameters such as feed rate and depth of cut. In the present research, two ICA models were presented for predicting the system vibration in terms of RMSa in 7 famous dimension stones in Iran. To develop the predictive models, 80% of the total data were randomly selected while the rest of the data (20%

of whole data) were assigned for testing purposes. Specifically, 90 datasets from the whole 112 datasets were used to construct the predictive models and 22 data were used to test the constructed models. In the developed models, the DC (cm), FR (cm/min), MH (n), YM (GPa), UCS (MPa), and SF-a (N/mm) were
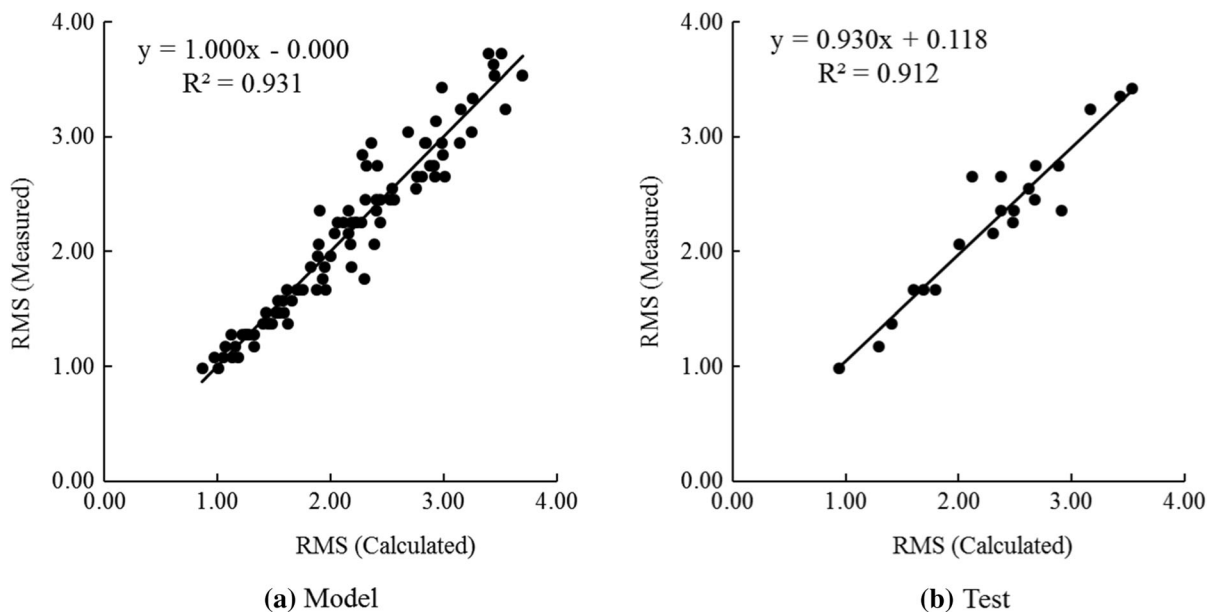
Fig. 7 Measured versus predicted RMS by model RMS$_{II}$ a. model data and b. test data
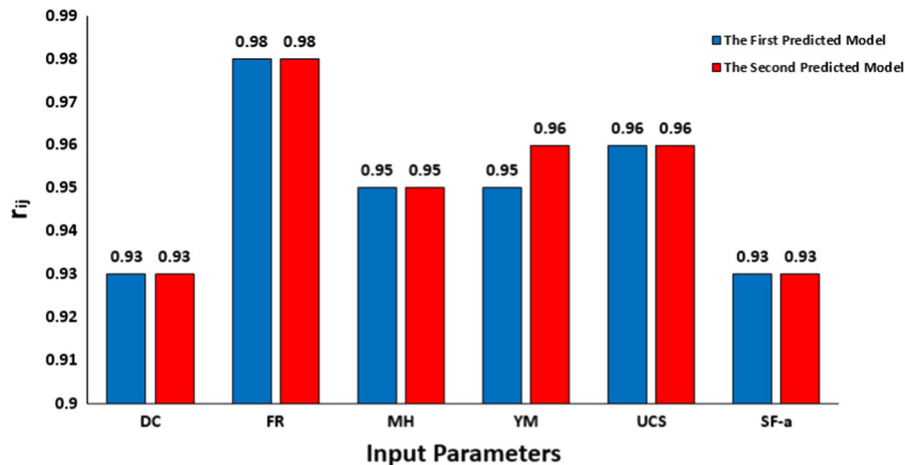
Fig. 8 The strength of the relation between input parameters and the predicted models

set as independent parameters, while RMS (m/s^2) was set as the dependent parameter. The performance of the models was controlled using statistical tests, i.e., Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), Variance Absolute Relative Error (VARE), Variance Account For (VAF), and Correlation Coefficient (CC). These indices can be computed using Eqs. (18, 19), respectively.

$$MAPE = \frac{1}{n} \times \left[\sum_{i=1}^{i=n} \left| \frac{RMS_{Meas}^i - RMS_{Esti}^i}{RMS_{Meas}^i} \right| \right] \times 100 \tag{18}$$

$$RMSE = \sqrt{\frac{1}{n} \times \sum_{i=1}^{i=n} \left(RMS_{Meas}^i - RMS_{Esti}^i \right)^2} \tag{19}$$

$$VARE = \mathrm{var}\left(\left| \frac{RMS_{Meas} - RMS_{Esti}}{RMS_{Meas}} \right| \right) \times 100 \tag{20}$$

$$VAF = \left[1 - \frac{\mathrm{var}(RMS_{Meas} - RMS_{Esti})}{\mathrm{var}(RMS_{Meas})} \right] \times 100 \tag{21}$$

$$CC = \frac{\sum_{i=1}^{i=n} \left[\left(RMS_{Meas}^i - \overline{RMS_{Meas}^i} \right)\left(RMS_{Esti}^i - \overline{RMS_{Esti}^i} \right) \right]}{\sqrt{\sum_{i=1}^{i=n} \left(RMS_{Meas}^i - \overline{ROP_{Meas}^i} \right)^2 \times \sum_{i=1}^{i=n} \left(RMS_{Esti}^i - \overline{RMS_{Esti}^i} \right)^2}} \tag{22}$$

The results of these statistical criteria for two predictive models and test data are reported in Table 5.

Note that lower values of MAPE, RMSE, and VARE, and higher values VAF and CC indicate the best approximation. As can be seen in Table 5, when considering the obtained results of the MAPE for the RMS$_{II}$ model, the value of 6.674 was observed, while this value for the RMS$_I$ model was 8.241. These values reveal a higher accuracy of the RMS$_{II}$. The scatter plot comparing measured and predicted RMS values for the RMS$_I$ and RMS$_{II}$ is shown in Figs. 6 and 7. Considering the obtained results of R^2 for the RMS$_I$ and RMS$_{II}$ models, the value of 0.93 was observed for the model data, the results revealed the high accuracy of both models. The value of R^2 for test data is 0.9, which has also acceptable accuracy.

Finally, in order to assess the effectiveness of input parameters on the predicted RMS, a sensitivity analysis was also performed using the cosine amplitude method based upon Eq. (23). Where r$_{ij}$ represents the strength of the relation, n is the number of dataset, and the x$_{ik}$ and y$_{ij}$ denotes input parameters and the predicted output, respectively (Yang and Zhang 1997).

$$r_{ij} = \frac{\sum_{k=1}^{n} (x_{ik} \times y_{jk})}{\sqrt{\sum_{k=1}^{n} x_{ik}^2 \sum_{k=1}^{n} y_{ik}^2}} \tag{23}$$

The results of sensitivity analysis for two models are shown in Fig. 8. According to the results, the feed rate had a high impact on the predicted RMS with strength of the relation being equal to 0.98 in both models. Then, the Mohs hardness, Young's modulus, and uniaxial compressive strength had almost equal effects on the predicted output in two models. However, the depth of cut and Schimazek's

F-abrasivity with a correlation of 0.93, had the lowest effect on the predicted output. Finally, it is worth mentioning that the proposed equations in this study can only be used in studied quarries and circular diamond saw, in the other word, they are unique models.

6 Conclusion

The production cost in dimension stone factory is affected by numerous factors such as diamond saw, energy consumption, maintenance, labor, water, and polishing pads, filling material, and packing. Also, the level of system vibration has a great impact on the maintenance cost. Thus, controlling the system vibration level can help reduce the maintenance cost. In the present study, two predicted models based on the imperialist competitive algorithm (ICA) were developed for predicting the system vibration in the dimension stone sawing process in 7 famous quarries in Iran. In the developed models, the depth of cut (cm), feed rate (m/s), Mohs hardness, Young's modulus (GPa), uniaxial compressive strength (MPa), and Schimazek's F-abrasivity (N/cm) were set as independent parameters, while Root Mean Square (m/s^2) was set as the dependent variable. The performance of the developed predictive models was controlled by statistical functions, i.e., Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), Variance Absolute Relative Error (VARE), Variance Accounted For (VAF), and Correlation Coefficient (CC). Finally, the results of models showed that ICA was able to assess the vibration of different rocks in the carbonate group with a low acceptable error and the models can be applied for rock vibration estimation in practice. Furthermore, the modeling of vibration in sawing processes can be a reliable system for high benefit and low-cost models for industrial applications and enables factory managers to have an accurate prediction of maintenance and energy costs. For future work, it is recommended to consider other operational parameters that also affect the vibration, such as the blade flatness and tensioning or the water flow and then comparing results with each other.

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