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Evaluation of Cutting Performance of Diamond Saw Machine Using Artificial Bee Colony (ABC) Algorithm

Masoud Akhyani [a] , Farhang Sereshki [a], Reza Mikaeil [b, *], Mohammad Taji [c]

[a] Faculty of Mining, Petroleum and Geophysics, Shahrood University of Technology, Shahrood, Iran.

[b] Department of Mining and Metallurgical Eng, Urmia University of Technology, Urmia, Iran

[c] Department of mining Engineering, Shahrood Branch, Islamic Azad University, Shahrood, Iran.

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ABSTRACT

Artificial Intelligence (AI) techniques are used for solving the intractable engineering problems. In this study, it is aimed to study the application of artificial bee colony algorithm to predict the performance of circular diamond saw of hard rocks. For this purpose, fourteen types of hard rocks were cut in laboratory using a cutting rig of 5 mm deep cut, feed rate of 40 cm/min and peripheral speed of 3000 rpm. Four major mechanical and physical properties of rocks such as uniaxial compressive strength (UCS), Schimazek abrasivity factor (SF-a), Mohs hardness (Mh), and Young's modulus (Ym) were determined in rock mechanic laboratory. Artificial bee colony (ABC) was used to classify the performance of circular diamond saw based on mentioned mechanical properties of rocks. Ampere consumption and wear rate of diamond saw were investigated to evaluate the result of ABC algorithm. Ampere consumption was determined during the cutting process and the average wear rate of diamond saw was calculated from the loss of width, length and height. Comparing the results of ABC and cutting performance (ampere consumption and wear rate of diamond saw) indicated the proper ability of metaheuristic algorithm such as ABC to evaluate the cutting performance

Keywords : *Ampere consumption, Cutting performance, Metaheuristic algorithm, Wear rate*

1. Introduction

Circular diamond saw has been widely used in dimension stone factories. Predicting the performance of circular diamond saw can be important in estimating the cost and finding the best designs of the plants. The performance of circular diamond saw is affected by many parameters such as the rock properties, sawing properties including saw operating and design characteristics, as well as the operating skills and work condition. Among these factors, sawing characteristics and operating skills can be controlled in the sawing process but the rock properties cannot be controlled in since they are related to the rock's physical and mechanical properties [1].

Since 2007, the relationship between rock features and sawability has been addressed in many studies. Table 1 provides a review of the most important and well-known conducted studies. According to Table 1, usually studied parameters consist of Uniaxial Compressive Strength (UCS), indirect Brazilian Tensile Strength (BTS), Schimazek abrasivity factor (SF-a), Mohs hardness (Mh), Young's modulus (Ym), Grain Size (GS) and Equivalent Quartz Content (EQC). These studies are indicative of the importance of these parameters in cutting performance of diamond saw machine.

In recent years, application of meta-heuristic methods in solving vague and complex systems has been significantly increased due to their ability in adapting optimization concepts to uncertainty problems in the modeling systems [32, 33-34]. Among meta-heuristic techniques, the Artificial Bee Colony Algorithm (ABC) is one of the most widely used evolutionary methods in the area of soft computing. This algorithm was first introduced by Karaboga and inspired by the bees' lifestyle, and their attempt to provide food was used for the optimization of different problems in the industry, transportation systems and traffic problems [35, 36, 37, 38, 39-40].

In this study, it is aimed to study the application of artificial bee colony algorithm for predicting the performance of circular diamond saw in sawing hard rocks based on important physical and mechanical properties of rocks.

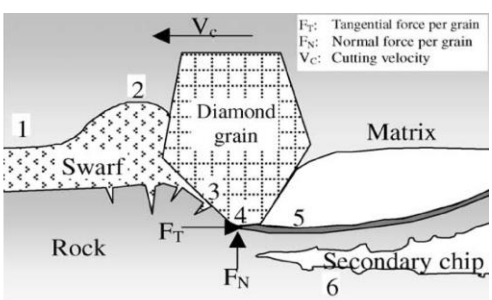
2. Sawing mechanism

Sawing chips form when a work-piece material is destroyed with the use of a circular diamond saw in a way that the saw cuts into the work-piece at a constant traverse rate as it rotates around its center with an angular speed. As a result, the surface of the work-piece is scratched and cracked with the removal of the materials from the segment surface by the diamond particles. There are two cutting mechanisms during these processes. First, tangential forces exert some stresses in front of a grain involved in the process. Therefore, tensile and compressive stresses produce a swarf. This mechanism is referred to as the primary chip formation. The swarf is forced out in front of and from beside the abrasive grain, which usually possesses a small size. The cutting progress should reach a certain minimum thickness of grinding since the rock shows an elastic behavior up to its ultimate stress. The compressive stress under the diamond deforms the rock cut. A brittle fracture as a critical tensile stress is achieved via an elastic revision caused by the load removal. This is the secondary chip formation process induced by a tensile stress as is illustrated in Fig. 1. Finally, the coolant fluid removes the swarf away [41].

* Corresponding author. Tel.: +989113278634. *E-mail address:* reza.mikaeil@gmail.com (R. Mikaeil).

Table 1. The main studies performed in the field of sawability using their own study parameters

Researchers	UCS	BTS	YM	MH	SF-a	GS	EQC
Buyuksagis,2007, [2]	•	•		•	•	•	•
Fener et al, 2007, [3]	•	•		•	•		
Tutmez et al, 2007, [4]	•	•		•	•		
Atici & Ersoy, 2009, [5]	•	•					
Mikaeil et al, 2011a, [6]	•	•					
Mikaeil et al, 2011b, [7]	•	•		•	•		
Mikaeil et al, 2011c 2011, [8]	•	•	•	•	•	•	•
Guney, 2011, [9]		•		•			
Mikaeil et al., 2011d, [10]	•			•	•	•	•
Mikaeil et al., 2011e, [11]	•	•	•	•	•	•	•
Ataei et al., 2012 [12]	•		•	•	•	•	•
Yurdakul & Akdas, 2012, [13]	•	•		•			•
Yasith et al, 2012, [14]	•	•		•			
Bilim, 2012, [15]	•			•			
Winkler, 2013, [16]						•	•
Karakurt et al, 2013, [17]	•						
Mikaeil et al, 2013, [18]	•	•	•	•	•	•	•
Engin et al,2013, [19]	•	•		•	•		
Bayram, 2013, [20]				•	•		
Sengun & Altihdag, 2013, [21]	•			•			
Aydin et al,2013, [22]	•			•			
Karakurt,2014a, [23]				•	•		
Mikaeil et al, 2014, [24]	•	•	•	•			
Karakurt,2014b, [25]					•		
Aydin et al, 2015, [26]	•						
Tumac, 2015, [27]				•			
Mikaeil et al, 2015, [28]	•		•	•	•		
Mikaeil et al, 2016a, [29]	•	•	•	•	•		
Aryanfar & Mikaeil, 2016, [30]	•	•	•	•			
Almasi et al, 2017b, [31]	•	•	•	•		•	•



1- Friction between swarf and matrix
2- Matrix erosion by swarf and chips
3- Primary chipping zone
4- Friction between stone and stone
5- Plastic deformation
6- Elastic deformation

Fig. 1. Observed Specific Ampere Draw versus estimated Specific Ampere for model 3 (test data).

3. Laboratory studies

To perform the laboratory tests, several blocks of rock samples were collected from the famous Iranian factories. These samples were selected based on their high usage in rock industry. To collect the rock samples, it was attempted to obtain sufficiently big specimens of each rock type for conducting every tests on the same piece (Fig. 2). To prepare the test specimens without any fractures, partings, or alteration zones, each block sample underwent an inspection for any probable macroscopic defects. The test samples were then prepared from these block samples. The main goals in mechanical and physical properties selection are to choose the minimum number of properties, avoid using equivalent parameters, and select only one parameter from a certain group. Therefore, the parameters selected in this paper to evaluate the sawability of hard rocks were as follows: Uniaxial Compressive Strength (UCS) Schimazek's F-abrasiveness (SF-a) factor Mohs Hardness (MH) Young's Modulus (YM) [18]. Based on the procedures suggested by ISRM standards [43], the Uniaxial Compressive Strength (UCS), Schmiazek Factor of abrasivity (SF-a), Mohs Hardness (MH), and Young's Modulus (YM) were measured. The physical and mechanical features of examined rocks are presented in Table 2.

Fig. 2. Some of prepared specimens for mechanical tests.

Table 2. The physical and mechanical characteristics of studied rocks.

Sample Number	UCS (Mpa)	Mh (n)	Ym (GPa)	BTS (Mpa)	EQc (%)	Gs (mm)	SF-a (N/mm)
1	157	5.6	37	15.46	52	1.13	9.1
2	138	6.1	29	8.15	64	1.14	5.95
3	141	6	41.5	10.15	61	1.25	7.74
4	173	5.7	46	15.98	35	1.43	7.99
5	155	5.7	39	13.1	55	2.06	14.84
6	150	5.7	43	11.28	55	2.16	13.4
7	185	5.3	49	17	55	1.16	10.84
8	239	6.4	52	18.86	66.5	0.77	9.65
9	199	5	49.5	16.14	37	0.91	5.44
10	145	5.95	36	9.2	64.3	4.1	24.25
11	173	6.6	49	15	60.06	0.87	7.6
12	133	5.65	29	8.3	32.2	3.9	10.42
13	125	5.6	31	7.4	30.3	3.8	8.5
14	142	6.1	44	8.52	57.65	2.9	14.24

4. Classification of studied rocks by Artificial Bee Colony (ABC) Algorithm

The performance of ABC algorithm was inspired by the honey bee colony procedure. The honey bee colony is generally composed of three sections, including food sources, employed and unemployed bees. In addition, unemployed bees are divided into two sections of onlooker bees and scout bees. In their behavior and lifestyle, honey bees use a complex communicative system. The relationship among bees is made through a dance language. The dance language includes a set of continuous motions done by bees. This dance, called waggle dance, contains information on the quality of source, location and position of bees. First, a set of food sources is randomly selected. Employed bees move toward the sources and compute their amount of honey. Then, these bees return to the hive and share their information with onlooker bees. In the second step, after the information exchange, each employed bee moves toward a source observed before and may select a new source near the previous one based on the information in its mind. Furthermore, scout bees search the surrounding environment for finding new food sources. If the food source is run out or bees leave there and move toward a new source, first the fitness of the new source (solution) is investigated based on the information of previous sources (solutions). If this fitness is more than the previous steps, the new source (solution) is maintained in the memory of the bee, otherwise the computation of the fitness of new food sources is another criterion for assessing the last and best source. This process continues until all the requirements are met (finding the most optimal solution). These steps are computed through Eq. 1.

$$v_{ij} = x_{ij} + \phi_{ij}(x_{ij} - x_{kj}) \qquad (1)$$
$$k \in \{1, 2, 3, \ldots\ldots, BN\} \quad , \quad i \neq k$$
$$j \in \{1, 2, 3, \ldots\ldots, D\}$$

Where v_{ij} is the position of the initial bee, and x_{ij} and x_{kj} are positions of the initial and other bees (neighbor bees), respectively. The less the value of $x_{ij} - x_{kj}$ is, the less the deviation from x_{ij} will be. Values k and j are randomly selected and BN is the number of employed bees which is equal to SN, food source number. In addition, variable k is different from variable i. ϕ_{ij} is a random number between interval [-1 & 1] and this variable controls the production of food sources around x_{ij}. In fact, in equation (1), it is attempted that in the next movements, the obtained initial position moves toward or against the value of index. ϕ_{ij}. The difference between this algorithm and other meta-heuristic ones such as PSO is that in this algorithm, considering the selection of random numbers from index. ϕ_{ij}, it is attempted to use diversity as much as possible and it prevents bees from being placed at optimum points [6, 44]. As mentioned, after the end of searching operations, onlookers investigate and evaluate the information obtained from employed bees and then considering the data analysis about the food sources, they select one of the food sources with a proper probability [34]. Eq. 2 computes this probability.

$$p_i = \frac{fit_i}{\sum_{n=1}^{SN} fit_n} \qquad (2)$$

Where P_i indicates a proper probability for the food source. SN is the number of food sources (the number of existing solutions). fit_i is the fitness function of food sources which corresponds to the i^{th} bee. If a food source is run out and or lacks a proper quality, employed bees leave it and turn into scout bees. It means that if in the fitness model, a point is not improved after several iterations, the local optimal point must be left and a new random point will be selected. Selection of a proper method and approach for solving complex systems depends on the condition and amount of complexity in the system. A wrong selection of modeling system not only finds a wrong solution for the problem, but also leads to more complexity and creates a reverse approach in solving the problem. Thus, in this research, considering that there is an uncertainty in the nature and characteristics of rocks on one hand, and an uncertainty in results obtained from experiments on the other hand, the Artificial Bee Colony Algorithm (ABC) is used for evaluation and investigation of results.

4.1. Modeling

In order to investigate and evaluate the experimental results obtained from this research, one of the most important applications of the Artificial Bee Colony Algorithm (ABC) is optimization which is used in data classification. In this procedure, based on eq. 3, Loyd's Algorithm (k-means) is used and fitted as the objective function in ABC algorithm in order to classify data [45].

$$Obj.Function = \sum_{i=1}^{n} \min_{1 \le j \le k} d(x_i, m_j) \qquad (3)$$

Where m_i is the center of cluster and k is the number of clusters. x_i is the data set and value of i is i=[1,2,3,...,n]. Furthermore, d is the Euclidean distance of the center of cluster to each member.

In fact, the aim of this section is to develop an integrated approach using the ABC and Loyd's Algorithms (k-means). They belong to an appropriate optimized classification, and therefore, the two classification methods are combined.

In the first step of modeling, the pseudo code of ABC algorithm and its objective function are written. Then, the algorithm's control parameters such as the maximum number of iterations, the population size (colony size) and the minimum acceptable error are considered as 300, 50 and $\varepsilon_L = 0 \cdot 00001$, respectively. These control parameters of algorithm are important to a suitable optimization which are selected by experts' suggestions and previous studies [46]. Hence, in this study, these control parameters were selected after several experts' consultation meetings. In addition, obtained results from laboratory tests on 14 rock samples and four major rocks properties were introduced for evaluation of classes classified as input data in the algorithm. Based on the experienced technicians' suggestions, in the next step, the classification of 2, 3 and 4 classes are analyzed and investigated using the software. According to the obtained results, the most proper classification is obtained for the fourth class. The obtained results from the ternary classification are shown in Tables 3 and 4 for the minimum acceptable error and the amount of optimization of each data in the class, respectively.

Table 3. Precision level and calculation termination in 300th iteration.

Result	$\varepsilon_L = \tilde{U}^{(n)} - \tilde{U}^{(n-1)}$	$\tilde{U}^{(n)}$	$\tilde{U}^{(n-1)}$	Step (n)
Continue	0.0541 > 0.00001	107.1023	107.0482	185
Continue	0 < 0.00001	107.0482	107.0482	186
Stop	0 < 0.00001	107.0482	107.0482	300

Based on the results of Table 3, the algorithm reached the most acceptable possible error in the 185th iteration and this value remained constant by the end of iterations. In fact, the convergence obtained in the 185th iteration remains constant until the 300th iteration, indicating the ability of this algorithm in the fast convergence and its stability. Furthermore, the process of convergence is shown in Fig. 3.

Table 4. Optimization and classification of rock's samples by ABC algorithm.

Rock Samples	Optimum Partition				Classification	
A1	9.029	25.326	25.879	82.757	First Class	A1
A2	18.191	46.105	6.548	103.015		A3
A3	10.708	39.327	14.944	97.952		A5
A4	24.367	7.42	43.99	65.659		A6
A5	5.428	26.719	25.391	84.639		A10
A6	2.594	30.271	22.786	88.984		A14
A7	36.201	5.439	56.287	53.524	Second Class	A4
A8	89.895	59.494	109.116	1.834		A7
A9	50.556	20	69.777	39.57		A9
A10	12.599	39.31	21.048	96.069		A11
A11	25.315	7.385	45.233	65.469	Third Class	A2
A12	20.674	50.468	1.889	107.883		A12
A13	27.137	57.337	7.43	115.311		A13
A14	8.732	38.1	18.335	96.896	Furth Class	A8

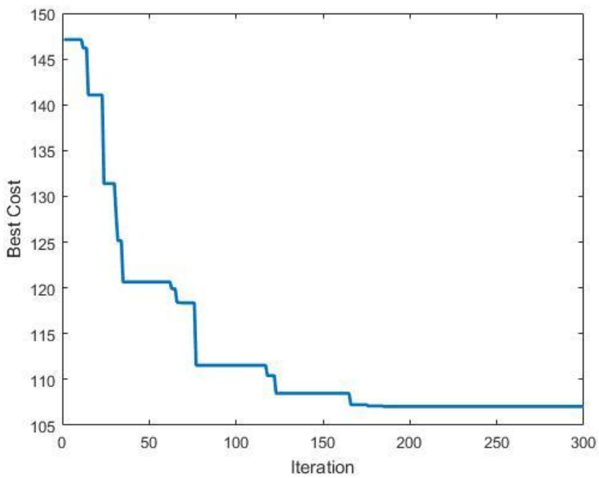


Fig. 3. The minimum cost per iteration by ABC algorithm.

Based on the results obtained from Table 3, 14 rocks were classified by ABC algorithm in 4 classes as 6 samples in the first class, 4 samples in the second class, three sample in the third one and 1 sample in the fourth class. We carried out an optimized classification of 38 different dimension (decorative) stones in 4 separate clusters, according to four important parameters such uniaxial compressive strength (UCS), Schimazek abrasivity factor (SF-a), Mohs hardness (Mh), and Young's modulus (Ym). Also applying the meta-heuristic algorithm made it possible to evaluate the cutting performance of diamond saw with various operating parameters. More discussions can be obtained in the area of validation of results obtained from this data classification process.

5. Discussion

In this section, the result of ABC were verified by ampere consumption and wear rate of circular diamond saw. Therefore, the following four main steps were performed.

Step 1. Preparing the fully-instrumented laboratory cutting rig

Step 2. Monitoring and calculating the ampere consumption during the sawing tests

Step 3. Calculating the average wear rate of diamond saw from loss of width, length and height

Step 4. Comparing ABC results and cutting performance (ampere consumption and wear rate of circular diamond saw).

To perform the cutting tests, a fully-instrumented laboratory sawing rig was prepared (Fig. 4). It consisted of 3 major sub-systems, i.e., a sawing unit, instrumentation, and a personal computer. A small side-sawing machine with a maximum spindle motor power of 4 kW was employed to conduct the sawing tests. Cutting parameters included feed rate, cut depth, and controlling the peripheral speed in the monitoring system.

In this study, a circular diamond saw of a 250-mm diameter, and a steel core of 50-mm thickness were utilized. Eighteen pieces of impregnated diamond segments with a size of 35 mm×2.5 mm×6.0 mm were brazed to the periphery of a circular steel core, which had a standard narrow radial slot. Two different saws were applied to 14 rock types in this study. The diamond had a grit size of about 50/60 US mesh at concentration 35. Ampere consumption and wear rate of diamond saw were selected as criteria to evaluate the result of ABC algorithm. Ampere consumption was determined during the cutting process using a digital ampere meter. The average wear rate of diamond saw was calculated from loss of width, length and height using a digital micrometer (Fig. 5). The ABC result and cutting performance parameters such as wear rate of circular diamond saw and ampere consumption are given in Table 5.

Fig. 4. A fully-instrumented laboratory cutting rig.

Fig. 5. A digital micrometer to determine the wear rate.

Table 5. The ABC result and cutting performance parameters.

Rock Samples	Cutting performance		Classification
	Wr (mm^3)	I (A)	
A1	4.50E-07	15.5	First Class
A3	8.00E-07	15.4	
A5	5.00E-06	15.7	
A6	2.50E-06	15.6	
A10	3.00E-06	15.7	
A14	1.60E-06	15.6	
A4	1.56E-06	16.1	Second Class
A7	1.50E-06	16.2	
A9	1.00E-06	16.6	
A11	2.20E-06	15.8	
A2	5.00E-07	15.2	Third Class
A12	6.00E-07	15.4	
A13	4.00E-07	15.5	
A8	7.20E-06	17	Fourth Class

Confirmation of the applied metaheuristic algorithm were conducted by comparing the ABC results with those of cutting performance parameters (wear rate and ampere consumption). According to Table 4, the studied rocks were classified into four classes. Samples 1, 3, 5, 6, 10 and 14 were classified in the first class. All of these samples except sample 3, had a medium value of ampere consumption ranging from 15.5

to 15.7 A. However, the wear rates of diamond saw for sample 1 and 3 did not match this class. Similarly, samples 4, 7, 9 and 11 were classified in the second class with medium both wear rate (with a range of 1E-6 to 3E-6 mm^3) and ampere consumption (with a range of 15.8 to 16.6 A). The third class has a good performance of cutting with the lowest wear rate and ampere consumption. Sample 8 with a high value of wear rate and ampere consumption has been classified in fourth class. This sample had a very poor cutting performance. Based on experts comments, the classification accuracy in proposed method is about 92.85% (only 1 fault in 14 samples). In order to compare the results with other methods, based on our best knowledge, no research paper was found on this topic but a similar work, [1] has reported a maximum accuracy of about 84.6% in its classification. This means that metaheuristic method is better than mathematical and theoretical classification in this topic.

6. Conclusion

In this study, the application of metaheuristic algorithm was studied to evaluate the performance of circular diamond saw in hard rocks sawing process. A total of fourteen types of hard rocks were analyzed at a constant operation condition in laboratory. Artificial bee colony (ABC) was used to classify the performance of circular diamond saw based on four major mechanical properties of rocks such as uniaxial compressive strength (UCS), Schmiazek abrasivity factor (SF-a), Mohs hardness (Mh), and Young's modulus (Ym). Studied rocks were classified into four classes. Validation of applied metaheuristic algorithm was conducted by comparing the class of each rock with wear rate and ampere consumption. The results of comparison between ABC results and ampere consumption and wear rate of diamond saw showed that the ABC algorithm is properly capable to evaluate the cutting performance only by testing the mechanical properties. For future studies, it is recommended to use other optimization techniques including a combination of Artificial Neural Network and Imperialist Competitive Algorithm (ANN-ICA), Differential Evolution (DE), Genetic Algorithm (GA) for more effectively sensitivity analysis. It leads to the fact that we can overcome complex problems by using these new approaches as the appropriate solution.

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