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Utilization of Soft Computing for Evaluating the Performance of Stone Sawing Machines, Iranian Quarries

Ahmad Aryafar [a, *], Reza Mikaeil [b], Sina Shaffiee Haghshenas [c], Sami Shaffiee Haghshenas [d]

[a] Department of Mining Engineering, Faculty of Engineering, University of Birjand, Birjand, Iran
[b] Department of Mining Engineering, Faculty of Engineering, Urmia University of Technology, Urmia, Iran
[c] Young Researchers and Elite Club, Islamic Azad University, Rasht Branch, Rasht, Iran
[d] Department of Civil Engineering, Islamic Azad University, Astara Branch, Astara, Iran

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ABSTRACT

The flourishing construction industry has led to a drastic increase in the dimension stone demand in the construction, mining and industry sectors. Assessment and investigation of mining projects and stone processing plants such as sawing machines is necessary to manage and respond to the sawing performance; hence, the soft computing techniques were considered as a challenging task due to stochastic optimization of this issue and to handle complex optimization problems. In this study, Particle Swarm Optimization (PSO) and Artificial Bee Colony (ABC) algorithms were used as soft computing techniques to classify dimension stones based on physical and mechanical properties and ampere consumption. For this purpose, a verity of dimension stones from 12 Iranian quarries were investigated. The studied dimension stones were classified into two and three separate clusters using the optimization clustering techniques. The results showed that the applied soft computing technique makes it possible to evaluate the performance of sawing machines in different complex conditions and uncertain systems.

Keywords : *Sawing machines, Particle Swarm Optimization (PSO), Artificial Bee Colony (ABC), ampere consumption, optimization clustering techniques*

1. Introduction

Nowadays, the optimization and solving of complex issues and uncertain systems have been provided through significant advances in the field of soft computing and data analysis. In recent years, these methods have been developed and used in other scientific and technical disciplines such as risk ranking, civil engineering, economics, operations research, and geotechnical and mining engineering [1, 2, 3, 4, 5, 6, 7, 8]. Meta-heuristic algorithms are one of the useful soft computing techniques for optimization of designing and implementation performance; hence, this paper presents application of Particle Swarm Optimization (PSO) and Artificial Bee Colony (ABC) techniques to evaluate the sawing performance based on stochastic optimization. Assessment of sawing performance is a multivariable complex issue that depends on several parameters. Due to the time, financial and other limitations in the simultaneous response and reaction to sawing machines, the classification scheme significantly helps successful implementation of the sawing performance by providing the possibility of a timely and appropriate planning to achieve the effective strategies. For this purpose, four effective rock properties on the sawing performance of quarrying machines such as Schmiazek factor (SF-a), hardness (H), uniaxial compressive strength (UCS) and Young modulus (E) were considered. Furthermore, the results were compared with ampere consumption of the sawing machines in 2 and 3 separate clusters. In this research, an application of two modern evolutionary techniques, namely Particle Swarm Optimization (PSO) and Artificial Bee Colony (ABC) algorithms are presented to evaluate the sawing performance of sawing machines. The remainder of the paper is organized as follows. In the two subsequent sections, a brief overview on the PSO and ABC algorithms has been provided. The dataset is analyzed and classified in section 4. In section 5, the application of meta-heuristic methods in classification of laboratory tests is evaluated.

2. Particle Swarm Optimization (PSO)

In the research operation and optimization issues, the Particle Swarm Optimization (PSO) is an optimization algorithm based on the movement and swarm intelligence technique proposed by [9]. This Meta heuristic algorithm was inspired by swarm of birds and shoals of fish, and has proved to be very efficient in complex optimization issues [10, 11]. This algorithm is capable of solving the most optimization problems such as optimization of mathematical functions, fuzzy system control, motion control of robots, neural network training and pattern recognition [12, 13, 14, 15, 16, 17]. Moreover, PSO is a suitable approach for optimization of energy and petroleum problems [18, 19, 20, 21, 22]. PSO is one of the impressive evolutionary algorithms that have been started by generation of initial population. In this algorithm, each solution is a particle. In fact, a set of solutions is a set of particles. In this process, the behavior of each particle can be affected by the behavior of neighboring particle or the general particle. These particles move around in the search-space and the rate equation guarantee the movement of particles towards the optimum area. This equation has three main elements as follows: the velocity vector, a particle keeps track of the best position that it has reached so far (pbest) and the globally best position (gbest) is the best value obtained so far by any particle in the neighborhood of that particle [23]. The swarm is updated in each iteration based on Equation (1) and (2) as follow:

$$V_i^{(k+1)} = w\,V_i^{k} + c_1 r_1.(pbest_i - X_i^{k}) + c_2 r_2.(gbest - X_i^{k}) \quad (1)$$

* Corresponding author Tel: +98-9155616379, *E-mail address:* aaryafar@birjand.ac.ir (A. Aryafar).

$$X_i^{(k)} = X_i^k + V_i^k \quad (2)$$

Where $V_i^{(k+1)}$ is a new velocity vector? The X_i^k and V_i^k are current position and the velocity of the i[th] particle, respectively. N is the size of swarm i=(1, 2, 3, ..., N) and k=(1, 2, 3, ...) determines the iteration number. (w) is the inertia weight that controls the impact of the previous velocity on the current velocity; r_1 and r_2 are a random number within the range [0, 1]. In addition, C_1 and C_2 are the acceleration constants. According to the empirical evidence, Equation (3) is established [24, 25].

$$c_1 + c_2 \le 4 \quad (3)$$

3. Artificial Bee Colony (ABC) algorithm

In order to solve complex problems and on the basis of swarm intelligence, Karaboga introduced Artificial Bee Colony (ABC) algorithm based on intelligent foraging behavior of honey bee swarm [26]. The honeybee swarm algorithm has three essential components: food sources, employed bees and unemployed bees (on lookers and scouts). The ABC model is an efficient technique for optimization problems. In the first step, a set of food sources are randomly selected. The employed bees start random search in the food zone (search space), and then, each worker bee randomly selects a neighbor bee and randomly moves towards it. This process was shown in Equation (4) [27, 28].

$$v_{ij} = x_{ij} + \phi_{ij}(x_{ij} - x_{kj})$$
$$k \in \{1, 2, 3, \ldots, BN\} \quad , \quad i \ne k \quad (4)$$
$$j \in \{1, 2, 3, \ldots, D\}$$

Where BN is the number of employed bees. v_{ij} is a new position of the first bee and x_{ij}, x_{kj} are the positions of the first bee and another bee (the neighboring bee), respectively. ϕ_{ij} is a random number between [1, -1]. This parameter controls the production of neighbor food sources around x_{ij}. (k) and (j) are randomly chosen indexes. (k) is different from (i) and is defined randomly. According to equation (1), as the difference between x_{ij}, x_{kj} reduces, the deviation of x_{ij} position will reduce. In fact, based on the value of ϕ_{ij}, movement occurs to the dimensions of one of the situations in the same direction or the opposite direction similar to PSO, however with a significant difference. In ABC, the algorithm creates variation through random selections and prevents them to be located in an optimal location. After completion of the search process, the onlookers evaluate the information of each employed bee with a probability that is proportional to the quality of nectar source, and then selects a food source. This possibility is obtained from Equation (5) [29, 30].

$$p_i = \frac{fit_i}{\sum_{n=1}^{SN} fit_n} \quad (5)$$

Where P_i is the probability value associated with the food source. fit_n and SN are considered the fitness value of the food sources corresponding to the i[th] bee and the number of available solutions (food sources), respectively. Finally, if the sources are finished or are not appropriate, the employed bees abandon them turning to the scout. If this process is not improved after several iterations, the position is deleted and a new position is randomly produced [31, 32, 33]. The Artificial Bee Colony (ABC) algorithm has been successfully applied to many areas such as complex problems in traffic studies [34, 35] and optimization of civil and electrical engineering projects [36, 37, 38].

4. Application of PSO and ABC in the Modeling

In this research, data clustering was conducted by the loyd's Algorithm (k-means clustering) based on the particle swarm optimization and the artificial bee colony algorithm. In fact, clustering is classification of components of a system based on their similarity. The Loyd's Algorithm is defined based on Equation (6). In this mathematical equation, d is the Euclidean distance between the centers of classes and each data under the study. In addition, K presents the number of classes in this classification, and (m) and (x) are the centers of classes and data under the study, correspondingly [39, 40, 41].

$$Obj.Function = \sum_{i=1}^{n} \min_{1 \le j \le k} d(x_i, m_j) \quad (6)$$

In this case, 12 different kinds of rocks were investigated through laboratory and field studies. In Table 1, 12 rock samples and 4 important parameters were shown as the clustering criteria. For laboratorial studies, the sample blocks were selected from the studied quarries. Standard tests were done to determine the mentioned physical and mechanical properties of rock. The Schimazek's F-abrasiveness factor was calculated using Eq. 7:

$$SFa = \frac{EQC \times Gs \times BTS}{100} \quad (7)$$

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 average uniaxial compressive strength was calculated for each studied dimension stones. The mean hardness of the studied rocks was determined based on the hardness their containing minerals using the Eq. 8:

$$Mean\ Hardness = \sum_{i=1}^{n} M_i \times H_i \quad (8)$$

Where M_i is the mineral content (%), Hi is the Mohs hardness, n is the total number of the minerals in the dimension stone. The tangent Young's modulus at a stress level of 50% of the ultimate uniaxial compressive strength was used, as well.

Table 1. The samples mechanical and physical properties.

Samples No	Samples	Mohs Hardness	Young Modulus (GPa)	UCS (MPa)	SF-a
A_1	Red Granite	6.1	43.6	142	14.24
A_2	Black Granite	6.6	48.6	173	7.6
A_3	White Granite	5.95	35.5	145	24.25
A_4	Chocolate Granite Khoramdeh	5.65	28.9	133	10.42
A_5	Granite Pearl	5.6	31.2	125	8.5
A_6	Cream Marble Harsin	3.5	32.5	71.5	0.135
A_7	Pink Marble Anarak	3.2	33.6	74.5	0.109
A_8	Red Travertine	2.9	20.7	53	0.122
A_9	Travertine Haji Abad	2.9	21	61.5	0.124
A_{10}	Travertine Dareh Bokhari	2.95	23.5	63	0.127
A_{11}	Marble Salsali	3.1	31.6	73	0.105
A_{12}	Pink Marble Haftoman	3.6	35.5	74.5	0.173

In the first step, the pseudo-code of the loyd's Algorithm (k-means clustering) as the fitness function, and the other parts of the algorithms were written in the MATLAB software. The fitness function is the same for both algorithms. The considered limits in the clustering were an initial population of 50 and 100, a maximum iteration of 200 and 100, a minimum acceptance precision of ε_L=0.00001 for the PSO and ABC algorithms, respectively. Furthermore, the values of the parameters (initial population, maximum iteration) were analyzed in various modes selected for the suitable values. In this process, the numbers of clusters are considered two and three clusters based on experiences after several meetings and consultations with experts. In Tables 2 and 3, the optimization results of the samples by the PSO and ABC algorithms are shown, respectively. In addition, the process of calculations are shown in Figs 1-4.

According to the obtained results (Tables 1 and 2), it is clearly seen that the results of the optimum partition of PSO and the Artificial Bee Colony algorithms are the same. On the other hand, Figs 1-4 illustrate the samples position in the clustering for two clusters that are the same, even in the minimum cost per iteration of these two algorithms.

In the next analysis, the samples were classified into three clusters. The limits in the clustering including the initial population, the maximum iteration and the minimum acceptance precision are similar to the last analysis with two clusters. Accordingly, the RPI values and the wear rate for five clusters are summarized in Tables 4 and 5. The position of the samples with three clusters and the relationship between the best cost and the iteration are illustrated in Figs 5-8.

Table 2. Samples optimization and classification by the PSO and ABC algorithms with two clusters.

Samples	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}	A_{11}	A_{12}
Optimum Partition of PSO	0.171	0.374	0.506	0.183	0.209	0.733	0.747	0.9	0.872	0.845	0.764	0.711
	0.874	0.913	1.163	0.669	0.589	0.053	0.054	0.244	0.221	0.166	0.02	0.109
Classification of PSO			First Class						Second Class			
	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}	A_{11}	A_{12}
Optimum Partition of ABC	0.171	0.374	0.506	0.183	0.21	0.735	0.748	0.902	0.874	0.847	0.766	0713
	0.874	0.913	1.163	0.668	0.589	0.053	0.054	0.244	0.222	0.169	0.021	0.109
Classification of ABC			First Class						Second Class			
	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}	A_{11}	A_{12}

Table 3. Distance of clusters' centers from the criteria by the PSO and ABC algorithms with two clusters.

	PSO		ABC	
	C_1	C_2	C_1	C_2
MH	0.896	0.485	0.897	0.486
YM	0.756	0.641	0.756	0.641
UCS	0.809	0.413	0.811	0.413
SF-a	0.495	0.005	0.496	0.005

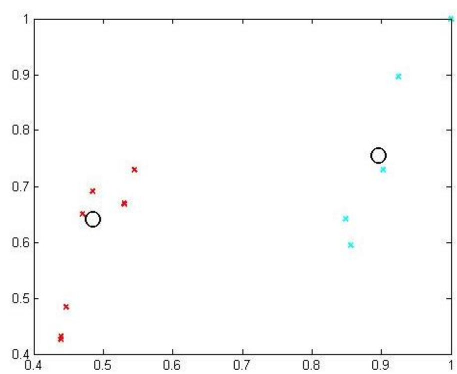

Fig. 1. Samples position in clustering by PSO for two clusters

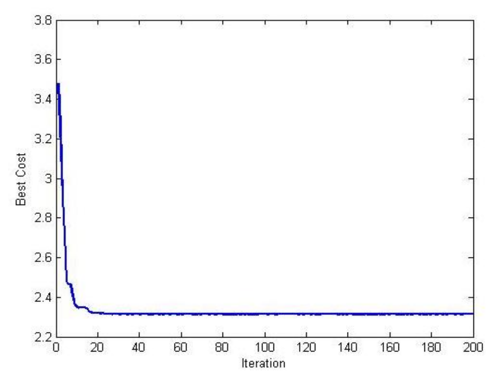

Fig. 2. Minimum cost per iteration by PSO for two clusters

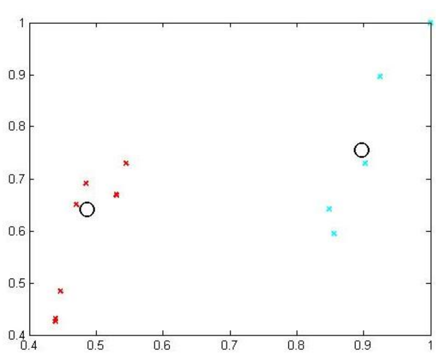

Fig. 3. Samples position in clustering by ABC for two clusters

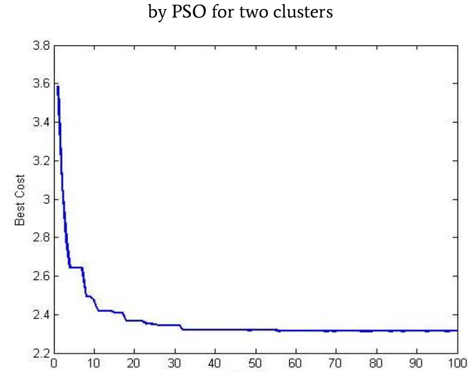

Fig. 4. Minimum cost per iteration by ABC for two clusters

Table 4. Samples optimization and classification by the PSO and ABC algorithms with three clusters.

Samples	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}	A_{11}	A_{12}
Optimum Partition of PSO	0.273	0.406	0.593	0.106	0.105	0.649	0.665	0.81	0.78	0.755	0.681	0.631
	0.446	0.762	4e-08	0.592	0.667	1.145	1.155	1.257	1.236	1.218	1.165	1.131
	0.874	0.913	1.163	0.669	0.589	0.053	0.054	0.244	0.221	0.169	0.2	0.109
Classification of PSO		First Class			Second Class				Third Class			
	A_1	A_2	A_4	A_5	A_3	A_6	A_7	A_8	A_9	A_{10}	A_{11}	A_{12}
Optimum Partition of ABC	0.184	0.363	0.519	0.181	0.208	0.729	0.741	0.898	0.868	0.841	0.759	0.707
	1.031	1.105	1.258	0.774	0.713	0.281	0.297	0.001	0.049	0.082	0.254	0.345
	0.854	0.889	1.15	0.649	0.567	0.021	0.064	0.261	0.24	0.189	0.059	0.086
Classification of ABC			First Class				Second Class			Third Class		
	A_1	A_2	A_3	A_4	A_5	A_8	A_9	A_{10}	A_6	A_7	A_{11}	A_{12}

Table 5. Distance of clusters' centers from criteria by the PSO and ABC algorithms with three clusters.

	PSO			ABC		
	C_1	C_2	C_3	C_1	C_2	C_3
MH	0.877	0.902	0.485	0.876	0.439	0.528
YM	0.697	0.73	0.671	0.754	0.426	0.649
UCS	0.782	0.838	0.413	0.835	0.306	0.408
SF-a	0.411	1	0.005	0.483	0.004	0.004

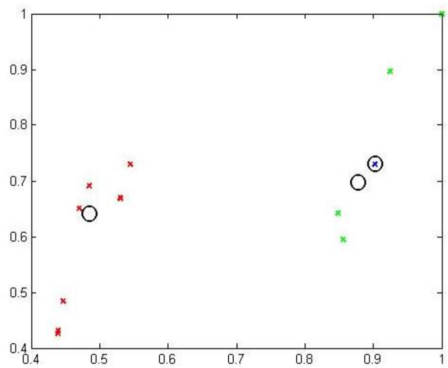

Fig. 5. Samples position in clustering by PSO for three clusters

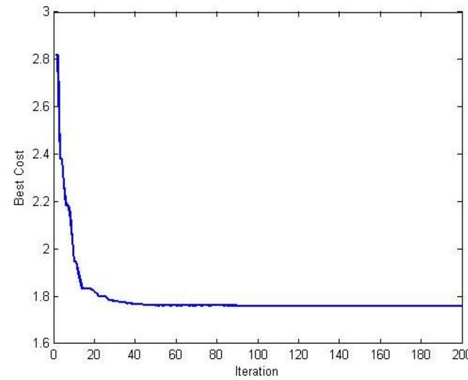

Fig. 6. Minimum cost per iteration by PSO for three clusters

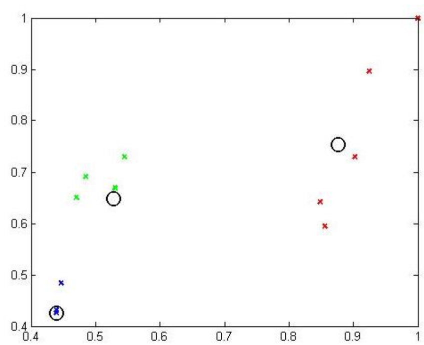

Fig. 7. Samples position in clustering by ABC for three clusters

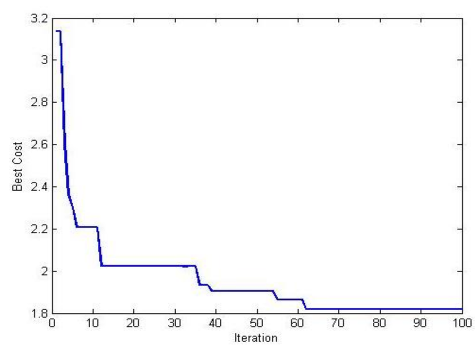

Fig. 8. Minimum cost per iteration by ABC for three clusters

5. Validation of results

To validate the clustering results, laboratorial studies were carried out. The studied dimension stones were sawn using a fully instrumented laboratorial sawing rig at a feed rate of 100 cm/min and a depth of cut of 15 mm. During the sawing test, the ampere consumption was recorded as a criterion for evaluating and validating the clustering results. The results are given in Table 6.

Table 6. The ampere consumption of the studied rocks.

Samples	Fr=100cm/min Dc=15mm	Classification of PSO		Classification of ABC	
		(2 clusters)	(3 clusters)	(2clusters)	(3clusters)
A_1	8	First Class	First Class	First Class	First Class
A_2	7.5	First Class	First Class	First Class	First Class
A_3	7.5	First Class	First Class	First Class	First Class
A_4	7	First Class	First Class	First Class	First Class
A_5	7	First Class	Second Class	First Class	First Class
A_6	6.3	Second Class	Third Class	Second Class	Third Class
A_7	6.5	Second Class	Third Class	Second Class	Third Class
A_8	6.2	Second Class	Third Class	Second Class	Second Class
A_9	6.2	Second Class	Third Class	Second Class	Second Class
A_{10}	6.3	Second Class	Third Class	Second Class	Second Class
A_{11}	6.3	Second Class	Third Class	Second Class	Third Class
A_{12}	6.3	Second Class	Third Class	Second Class	Third Class

As it is seen in Table 6, the studied dimension stones were accurately classified by both of the PSO and ABC algorithms into two geological groups of hard and soft dimension stones. However, ABC was able to classify the soft studied stones correctly into two classes including travertine and marble. The results of laboratorial tests in terms of ampere consumption also confirmed it, because the value of ampere average in all three classes is different.

6. Conclusion

In this research, the application of the PSO and ABC algorithms was studied to classify the dimension stones based on physical and mechanical properties such as uniaxial compressive strength, Schmiazek F-abrasivity, Mohs hardness scale, and Young's modulus. A variety of dimension stones from 12 Iranian quarries located were studied. The studied dimension stones were accurately classified into two geological groups including the hard and soft dimension stones. In three clusters, ABC was able to classify the soft studied stones correctly into two classes including travertine and marble. The results of laboratorial tests in terms of ampere consumption also have a good agreement with the predicted classes. The obtained results showed that the applied algorithms can be reliably used to evaluate the performance of sawing machines in different complex conditions and uncertain systems.

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