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Performance evaluation of gang saw using hybrid ANFIS-DE and hybrid ANFIS-PSO algorithms

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Abstract

One of the most significant and effective criteria in the process of cutting dimensional rocks using the gang saw is the maximum energy consumption rate of the machine, and its accurate prediction and estimation can help designers and owners of this industry to achieve an optimal and economic process. In the present research work, it is attempted to study and provide models for predicting the maximum energy consumption of the gang saw during the process of soft dimensional rocks with the help of an intelligent optimization model such as random non-linear techniques, i.e. the Hybrid ANFIS-DE and Hybrid ANFIS-PSO algorithms based upon 4 physical and mechanical parameters including uniaxial compressive strength, Mohs hardness, Schimazek's F-abrasiveness factors, Young modulus, and an operational characteristic of the machine, i.e. production rate. During this research work, 120 samples are tested on 12 carbonate rocks. The maximum energy consumption of the cutting machine during this work is measured and used as a modeling output for evaluating the performance of cutting machine. Also meta-heuristic algorithms including DE and PSO algorithms are used for training the Adaptive Neural Fuzzy Inference System (ANFIS). In addition, the PSO algorithm has a higher ability in terms of model output and performance indices and has a superiority over the differential evolution algorithm. Furthermore, comparison between the measured datasets with the ANFIS-DE and ANFIS-PSO models indicate the accuracy and ability of the ANFIS-PSO model in predicting the performance of gang saw considering the machine's properties and the cut rock.

1. Introduction

The application of rock cutting instruments has been dramatically increased in the dimensional rock industry in two areas of mining and stone cutting factories. Having a full knowledge of the cutting process and the gang saw functions can increase the effectiveness and quality of the product. Two significant factors involved in this area include the final cost and the product quality. Generally, the cost of a rock plaque in rock cutting industries is highly influenced by the factors including instrumental costs (instruments' abrasion) and maximum energy consumption costs, and the purpose of optimization is to increase the ratio of the production rate to the two mentioned factors. There is a direct relationship between the production rate and the two factors diamond tools' abrasion and maximum energy consumption (MEC) so that not only the production rate but also the tools' abrasion and the maximum energy consumption will increase. For this reason, an ideal balance must be created between the production rate and tools' abrasion and the maximum energy consumption in the machine. There are different factors influencing the amount and type of cutting machines' function and the cutting machine's energy. Simultaneously,

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the most significant factors involved include the properties of rock, type and form of instruments, force or load being imposed, and other environmental parameters. Today, the development of technology and application of new cutting machines such as saws has opened-up a new path in the cutting process in stone processing plants so it can be predicted that for the next few years, these facilities (considering their superiority over circular diamond saws) will be totally replaced by circular diamond saws. Until the present time, complete and comprehensive studies have been conducted on the disk cutting instruments and diamond wire sawing. However, studies on the sawing equipment are at the preliminary levels since they are new to this area. In Lons' research work conducted in 1970, cutting forces and diamond segments' abrasion in the saw machine have been completely investigated. In this work, it was attempted to study the relationship between diamond abrasion and cutting forces, and based upon the results obtained, there was a weak relationship between the mentioned parameters [1]. Next, in the studies carried out by Wiemann et al. in 1982, the saw machine has been assessed. In their studies, it was found out that the diamond blades' tension significantly influenced the saw machine's cutting process. The results obtained indicated that tensile stress of tip of blade moved toward its bottom and its value varied in different measurement situations (front, middle, and end). At the end, in the sawing process, two significant factors influencing the cutting performance are the tension frequency change in diamond blades and the effect of supply rate on the blades' tensile stress [2]. In the studies of Jansen conducted in 1977, it was found out that deformation of diamond blades was a function of tension, eccentricity, friction coefficient, and geometric parameters of the blade [3]. Accordingly, the deviation change and tension of blade were investigated and calculated by Gerlach et al. in 1980 in a laboratory scale through a saw machine. The results of studies showed that geometric parameters, eccentricity, and tension of blade had influences on the blade diversion. In practice, the friction between segment and rock reduces the effective tension of blade; therefore, in the sawing process, the effective tension of blade can be a function of vertical forces in the direction of supply, which in the case of any change in the properties of rock, it also changes under different conditions [4]. In the research works conducted by Wang and Clausen in 2002, a carbonate rock sample was evaluated through single-point (single-segment) cutting instruments under different cutting conditions. In such a study, an analysis was conducted on the conditions of the contact surfaces between the rock and the diamond grain as well as the cutting mechanism of brittle failure. A CNC milling machine was used to conduct the cutting test. The cutting force Fc in the direction of cutting and the cutting force Ff perpendicular to the cutting direction have been calculated and recorded using a Kislter dynamometer (type-5019). During the test, two carbonate rocks were tested under the dry and wet cutting conditions. During the study, the cutting surfaces (the groove made by the contact of segment with the rock surface) were analyzed through a microscope [5]. In 2003, a computer simulation of this process was conducted by Wang and Clausen on the saw cutting process. The simulation of saw cutting is a practical alternative for design, especially for computation of the number of diamond grains and their distribution on the saw blades' segments. Simulation was implemented by the two softwares Visual Basic and Microsoft Access. In this simulation, the cutting forces in the blade, segment, and each diamond grain as well as the effective cutting edges were measured under different cutting conditions [6]. In the study of Wang in 2003, the theory of rock cutting process using the saw machine was evaluated. Thus the cutting motion of the blade and diamond grain was investigated. The studies indicate that the efficient number of diamond grains and the cutting depth depend on the status of segment and the height of the raised part of diamond grain. The cutting depth of diamond grain increases with increase in the supply rate, and reduction of crankshaft rotation per minute and the impact length. The maximum cutting depth of diamond grain depends on its status during the contact with the rock in one cutting impact. In the process of cutting, the contact surface between the blade and rock block will change per moment. The most important factors involved in the contact surface versus the cutting time include the segments' distribution, cutting length, and impact length [7]. Almasi et al. investigated 11 types of hard rock for developing a new rock classification based on the abrasiveness, hardness, and toughness of rocks, and with the multiple curvilinear regression analysis, the data was analyzed, and then validation of the model was conducted by considering the t-test, F-test, and coefficient of determination. The results obtained showed that this model was a reliable one as a prediction method in their case. [8]. The rock waste percentages produced from cutting rock blocks into slabs using gang saw machine were investigated by Alhaj. The results obtained showed an inverse relationship between the gang saw thickness and the volume waste percentages and productivity. In addition, the volume waste percentages altered around the ideal values of 26% for 2 cm, 19% for 3 cm, and 22% for the mixed 2 & 3 cm thicknesses [9]. Almasi et al. developed statistical and M5P tree models for the prediction of building stone cutting rate based on rock properties and device pullback amperage. The results obtained showed that in the comparison between the M5P tree technique and the statistical regression methods, the M5P tree model was more reliable than the statistical model in predicting the cutting rate [10].

The main objective of the present work was to analyze the performance of the two hybrid algorithms for the cutting process and the performance of gang saw. In particular, the study focuses on the carbonate rocks' cutting process based on some important properties of the rocks and maximum energy consumption (MEC) of gang saws under uncertain conditions.

2. Gang saw machine

In this work, the location of investigations was Marble factories in the Mahallat area in Iran and the sawing operations (maximum energy consumption) of gang saws were calculated on twelve various carbonate rocks. The studies were conducted on the performance of machine operating in the same conditions (Figure 1). In Table 1, the machine operating properties during performance studies are provided.

Figure 1. Gang saw machine used in this case.

Table 1. Machine operating properties.

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

3. Methods and materials

In this section, in order to assess the performance evaluation of gang saw, some mechanical and physical properties were collected. The experimental studies and laboratory tests were carried out on the rock block samples, and the data was collected. Furthermore, two artificial intelligence (AI) techniques, namely Hybrid ANFIS-DE algorithm and Hybrid ANFIS- PSO algorithm, were considered as methods; more explanations are mentioned in the following sub-sections.

3.1. Methods

3.1.1. Adaptive neural fuzzy inference system

The artificial intelligence (AI) has provided a wide spectrum of intelligent methods and algorithms in the area of industrial developments and scientific and industrial optimizations [11-15]. In the meantime, the Adaptive Neural Fuzzy Inference System (ANFIS) is one of the special and complex methods with an appropriate capability in predicting complex, linear, and non-linear phenomena. In fact, the structure of ANFIS is the result of a complex combination of neural network with fuzzy rules formed by the multi-layer networks including nodes and directed communication links. This system was first provided by Jang, which turned to a powerful and useful tool for estimating real continuous functions in a limited range for each degree of accuracy due to the application of the learning power of artificial neural networks, on the one hand, and the use of the rules and fuzzy inference base, on the other hand [16-17]. It is also used as an intelligent dynamic system, and by processing the experimental data accurately, provides a very appropriate map of the input-output data [18-19]. The structure of an ANFIS model with 5 layers is shown in Figure 2.

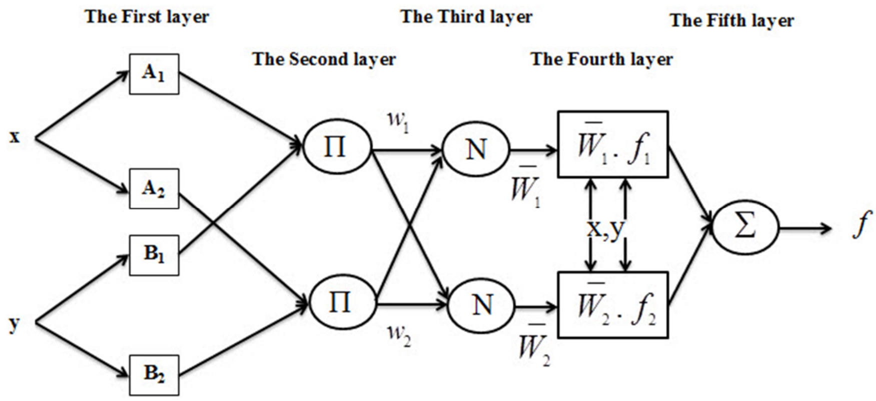

Figure 2. An architecture of ANFIS model.

According to this figure, the first layer includes input nodes, and in this layer, each node like i determines the degree of membership based on the membership functions (MFs) based on Equation (1) [20, 21].

$$Q_{l,i} = \mu A_i(x) \qquad for\ i = 1,2$$
$$or \tag{1}$$
$$Q_{l,i} = \mu B_i(y) \qquad for\ i = 3,4$$

where x and y are the inputs of the ith node, and A_i and B_i are the linguistic labels relating to this layer. Furthermore, $Q_{1,I}$ and μ are the membership degrees of the fuzzy set and the membership function, respectively.

In the second layer, a node is introduced under the title $\prod$ whose output value is obtained from the multiplication of input signals according to Equation (2). In fact, the output of each node indicates the firing strength of each rule.

$$Q_{2,i} = w_i = \mu A_i(x_i).\mu B_i(x_i) \qquad i = 1,2 \tag{2}$$

In the third layer, the node is introduced with label N, in which the ratio of firing strength rule for the ith node to the total firing strength rules is obtained according to Equation (3), which is introduced with the output of this layer under the title of normalized firing strengths ($\bar{W}_i$). Each node (i) in the fourth layer is in accordance with the node function according to Equation (3).

$$Q_{3,i} = \bar{W}_i = \frac{w_i}{\sum_{j=1}^{2} w_j} \qquad i = 1,2 \tag{3}$$

In Equation (4), the values for r_i, q_i, and p_i are a set of parameters for this node that are identified as inferential parameters [20-21].

$$Q_{4,i} = \bar{W}_i.f_i = \bar{W}_i(p_i x + q_i y + r_i) \tag{4}$$

In the fifth or last layer, there is only one node that is defined under the label of $\sum$, and according to Equation (5), all of the output signals of the fourth layer's nodes are introduced as the network output. Furthermore, in this layer, the fuzzy results produced are turned into a non-fuzzy output through a defuzzification process.

$$Q_{5,i} = \sum \bar{W}_i.f_i = \frac{\sum w_i f_i}{\sum w_i} \tag{5}$$

In the ANFIS modelling, there are many classic methods for training the model's fuzzy inference system. However, in this research work, in order to improve the training process of the fuzzy inference system, meta-heuristic algorithms were used for optimizing the influential parameters in the inference system. For this reason, two of the most commonly used meta-heuristic algorithms are used including Differential Evolution (DE) algorithm and Particle Swarm Optimization (PSO) algorithm, and coding is done in Matlab program for creating hybrid algorithms of ANFIS-DE and ANFIS-PSO in order to analyze the experimental data [20-22].

3.1.2. Differential evolution algorithm

With increase in complexity and due to the existing uncertainties in solving problems in scientific and industrial areas, the need for using new optimization methods is inevitable. Meta-heuristic algorithms are one of the artificial intelligent methods in dealing with such problems

[23-27]. The DE algorithm is one of the meta-heuristic algorithms with a high ability in solving complex problems. This method was first introduced by Storn and Price [28-29]. The DE algorithm is one of the multi-purpose meta-heuristic algorithms that have an acceptable ability in engineering optimizations and mathematical problems' optimization. This algorithm starts working by creating an initial population and implements the algorithm by imposing four operators including initialization, mutation, cross-over and selection. The difference between this algorithm and others such as the genetic algorithm is how mutation and cross-over operators are placed and implemented [30]. In this way, in this algorithm, first the mutation operator and next the cross-over operator are implemented. The appropriate accuracy and speed in the applications of the DE algorithm have made this algorithm to be used in a wide range of problems. In a case study on the Queens Water Tunnel in New York City conducted by Yagiz and Karahan, a set of optimization algorithms were used for predicting the TBM penetration rate in rock mass. DE algorithm was one of the methods under investigation in this case study. The results obtained showed the proper performance of the optimization methods compared to other introduced methods [31]. The blast-induced fly-rock was analyzed by Dehghani and Shafaghi using the DE algorithm. By collecting, analyzing, and evaluating the parameters for approximately 300 blasting operations, they provided a prediction model based on this meta-heuristic algorithm, which showed a proper performance compared to the results of the empirical approaches [32]. The hybrid algorithms were used by Chen et al. for landslide spatial modeling. They used a combination of meta-heuristic algorithms including Differential Evolution (DE) algorithm, Genetic Algorithm (GA), and Particle Swarm Optimization (PSO) with ANFIS. The results obtained showed that these hybrid algorithms could be successful and efficient methods in managing and planning at regions with landslide risk [33].

3.1.3. Particle swarm optimization (PSO) algorithm

PSO algorithm is a meta-heuristic one, which is inspired by the collective intelligence and behavior of birds and fish. This algorithm was first provided by Kennedy and Eberhart based on simple mathematical relations and considering the movement pattern of birds for optimization of complex problems [34]. This algorithm starts to work by randomly creating an initial population (a group of particles). In fact, each particle shows a possible response. Each particle starts to move and search in the problem space in order to find the most appropriate point. In each step, this particle is fitted by its objective function and is placed toward the most appropriate direction to determine the most accurate and precise response. Each particle continues its movement each time using its experience and its neighbors in the problem search space. Other particles move toward a particle with the best position and correct their directions. Therefore, the movement of particles in the problem search space depends on three factors including the present position of particle X^k_i, the best location that a particle has experienced (Pbest), and the best location that all of the particles have experiences (Gbest). In fact, in each cycle, the aim is to identify a particle that finds the best momentary position in the problem and enters the community with a new position, and the other particles move toward it considering the superiority of the most appropriate particle in terms of location. This cycle continues until all particles gather together at the best point [35-36]. These calculations are introduced based on Equations (6) and (7).

$$V_i^{(k+1)} = w V_i^k + c_1 r_1.(pbest_i - X_i^k) + c_2 r_2.(gbest - X_i^k) \quad (6)$$

$$X_i^{(k)} = X_i^k + V_i^k \quad (7)$$

In Equation (6), i = (1,2,3,…,N), N is the population size (particle), and k = (1,2,3,…) is the iteration number in the algorithm process. $V_i^{(k+1)}$ is the new velocity vector for the ith particle. V^k_i indicates the existing velocity vector for the ith particle. $pbest_i$ is the best position that the ith particle has experienced, and gbest is the best position that all particles have experienced. In Equation (7), X^k_i is the present position of the ith particle and the new position of the ith particle. w is the weight inertia, which is used in the class of particles to ensure the convergence and is a suggestion in the range of 0.4-0.9. r_1 and r_2 are random numbers between 0 and 1. C_1 and C_2 are two fixed and positive values that are introduced as the personal learning factor and the global learning factor, respectively, and have a significant role in the algorithm's convergence controlling process. However, it is worth mentioning that the condition $c_1 + c_2 \leq 4$ must always be met [37]. In the recent years, the PSO algorithm, as a powerful tool, has been substituted with traditional optimization methods. In a study, a high-precision optimal model was provided by Hasanipanah et al. to predict the blast-produced ground vibration using the PSO algorithm. They performed modelling by collecting approximately 80 datasets, and compared them with the results obtained from other methods including the multiple linear regression (MLR) model and the United States Bureau of Mines (USBM) equation. Finally, the provided model was more capable than the other methods [38]. In a case study on three quarry sites in Malaysia, a model was provided by Hasanipanah et al. for predicting flyrock due to blasting using a meta-heuristic optimization technique. First, they studied and determined 5 influential parameters by studying and collecting data. Then by conducting enough analyses using the PSO algorithm, a very appropriate model was provided, which was better than the other linear methods [39]. Two linear and quadratic models were developed by Ghasemi using the PSO algorithm and a set of data on Sungun copper mine in Iran. The results obtained from optimization of the PSO algorithm for the quadratic model were better than those for the linear one [40].

3.2. Data collection

As mentioned earlier, the maximum energy consumption is a matter of concern for performance evaluation of gang saw in this case study; hence, MEC of any rock type from 12 different locations was recorded. Table 2 includes the locations and the names of the sawed rocks and the average of MEC.

Rock blocks were collected from the factories for the purpose of laboratory tests. It was attempted to collect the rock samples large enough to obtain all of the test specimens of a given rock type from the same piece. Each block sample was investigated for macroscopic defects so that it would provide test specimens free from fractures, partings or alteration zones. Then the standard test samples were prepared from these block samples, and uniaxial compressive strength, Brazilian tensile strength, Mohs hardness, grain size, equal quartz content, Young modulus, and Schimazek's F-abrasiveness factor were studied. The summaries of the test results are provided in Table 3.

Table 2. The locations and names of studied rocks and maximum energy consumption.

Samples No.	Commercial name	Name of quarry	Average of MEC (Ampere)
A1	Hajiabad Travertine	Hajiabad	98.3
A2	Darebokhari Travertine	Kohbar	96.1
A3	Atashkoh Travertine	Atashkoh	104
A4	Chocolate Travertine	Kashan	86.9
A5	Abbas Abad Travertine	Abbas Abad	97
A6	Takab Travertine	Takab	93.7
A7	Azarshahr Travertine	Azarshahr	88.1
A8	Khalkhal Travertine	Khalkhal	85.5
A9	Harsin Marble	Harsin	110.3
A10	Kerman Marble	Mirzaei	105.5
A11	Ghorveh Marble	Ghorveh	104
A12	Laybid Marble	Laybid	105.5

Table 3. Information for studied rock properties in laboratory tests.

No.	Samples	UCS (MPa)	Mh	YM (GPa)	SF-a (N/mm)	Production rate (V)	MEC (Ampere)
A1	Tha	61.5	2.9	21	0.0361088	8	93
A1	Tha	61.5	2.9	21	0.0361088	11	95
A1	Tha	61.5	2.9	21	0.0361088	14	96
A1	Tha	61.5	2.9	21	0.0361088	17	97
A1	Tha	61.5	2.9	21	0.0361088	20	99
A1	Tha	61.5	2.9	21	0.0361088	23	100
A1	Tha	61.5	2.9	21	0.0361088	27	100
A1	Tha	61.5	2.9	21	0.0361088	30	100
A1	Tha	61.5	2.9	21	0.0361088	33	101
A1	Tha	61.5	2.9	21	0.0361088	37	102
A2	TDb	63	2.95	23.5	0.083106	8	94
A2	TDb	63	2.95	23.5	0.083106	11	94
A2	TDb	63	2.95	23.5	0.083106	14	95

Table 3. Continued.

A2	TDb	63	2.95	23.5	0.083106	17	95
A2	TDb	63	2.95	23.5	0.083106	20	96
A2	TDb	63	2.95	23.5	0.083106	23	96
A2	TDb	63	2.95	23.5	0.083106	27	97
A2	TDb	63	2.95	23.5	0.083106	30	97
A2	TDb	63	2.95	23.5	0.083106	33	98
A2	TDb	63	2.95	23.5	0.083106	37	99
A3	TAt	62.8	2.8	22.8	0.040651	8	98
A3	TAt	62.8	2.8	22.8	0.040651	11	100
A3	TAt	62.8	2.8	22.8	0.040651	14	103
A3	TAt	62.8	2.8	22.8	0.040651	17	103
A3	TAt	62.8	2.8	22.8	0.040651	20	103
A3	TAt	62.8	2.8	22.8	0.040651	23	103
A3	TAt	62.8	2.8	22.8	0.040651	27	105
A3	TAt	62.8	2.8	22.8	0.040651	30	106
A3	TAt	62.8	2.8	22.8	0.040651	33	109
A3	TAt	62.8	2.8	22.8	0.040651	37	110
A4	TShK	54.5	2.2	14.5	0.04788	8	85
A4	TShK	54.5	2.2	14.5	0.04788	11	85
A4	TShK	54.5	2.2	14.5	0.04788	14	85
A4	TShK	54.5	2.2	14.5	0.04788	17	86
A4	TShK	54.5	2.2	14.5	0.04788	20	86
A4	TShK	54.5	2.2	14.5	0.04788	23	87
A4	TShK	54.5	2.2	14.5	0.04788	27	87
A4	TShK	54.5	2.2	14.5	0.04788	30	89
A4	TShK	54.5	2.2	14.5	0.04788	33	89
A4	TShK	54.5	2.2	14.5	0.04788	37	90
A5	TAb	67	2.7	27	0.036432	8	94
A5	TAb	67	2.7	27	0.036432	11	94
A5	TAb	67	2.7	27	0.036432	14	95
A5	TAb	67	2.7	27	0.036432	17	96
A5	TAb	67	2.7	27	0.036432	20	96
A5	TAb	67	2.7	27	0.036432	23	97
A5	TAb	67	2.7	27	0.036432	27	99
A5	TAb	67	2.7	27	0.036432	30	99
A5	TAb	67	2.7	27	0.036432	33	100
A5	TAb	67	2.7	27	0.036432	37	100
A6	TTa	60	2.6	20	0.0196	8	90
A6	TTa	60	2.6	20	0.0196	11	90
A6	TTa	60	2.6	20	0.0196	14	91
A6	TTa	60	2.6	20	0.0196	17	92
A6	TTa	60	2.6	20	0.0196	20	92
A6	TTa	60	2.6	20	0.0196	23	95
A6	TTa	60	2.6	20	0.0196	27	95
A6	TTa	60	2.6	20	0.0196	30	96
A6	TTa	60	2.6	20	0.0196	33	98
A6	TTa	60	2.6	20	0.0196	37	98
A7	TAz	53	2.9	15	0.038528	8	85
A7	TAz	53	2.9	15	0.038528	11	86
A7	TAz	53	2.9	15	0.038528	14	86
A7	TAz	53	2.9	15	0.038528	17	86
A7	TAz	53	2.9	15	0.038528	20	87
A7	TAz	53	2.9	15	0.038528	23	88
A7	TAz	53	2.9	15	0.038528	27	90
A7	TAz	53	2.9	15	0.038528	30	90
A7	TAz	53	2.9	15	0.038528	33	91
A7	TAz	53	2.9	15	0.038528	37	92

Table 3. Continued.

A8	TKh	50.5	2.6	16.4	0.0333504	8	81
A8	TKh	50.5	2.6	16.4	0.0333504	11	81
A8	TKh	50.5	2.6	16.4	0.0333504	14	83
A8	TKh	50.5	2.6	16.4	0.0333504	17	83
A8	TKh	50.5	2.6	16.4	0.0333504	20	85
A8	TKh	50.5	2.6	16.4	0.0333504	23	87
A8	TKh	50.5	2.6	16.4	0.0333504	27	87
A8	TKh	50.5	2.6	16.4	0.0333504	30	89
A8	TKh	50.5	2.6	16.4	0.0333504	33	89
A8	TKh	50.5	2.6	16.4	0.0333504	37	90
A9	MHa	71.5	4.3	26	0.0604656	8	103
A9	MHa	71.5	4.3	26	0.0604656	11	104
A9	MHa	71.5	4.3	26	0.0604656	14	105
A9	MHa	71.5	4.3	26	0.0604656	17	106
A9	MHa	71.5	4.3	26	0.0604656	20	110
A9	MHa	71.5	4.3	26	0.0604656	23	112
A9	MHa	71.5	4.3	26	0.0604656	27	114
A9	MHa	71.5	4.3	26	0.0604656	30	115
A9	MHa	71.5	4.3	26	0.0604656	33	116
A9	MHa	71.5	4.3	26	0.0604656	37	118
A10	Mke	72	4	32	0.0550095	8	101
A10	Mke	72	4	32	0.0550095	11	101
A10	Mke	72	4	32	0.0550095	14	103
A10	Mke	72	4	32	0.0550095	17	103
A10	Mke	72	4	32	0.0550095	20	105
A10	Mke	72	4	32	0.0550095	23	106
A10	Mke	72	4	32	0.0550095	27	106
A10	Mke	72	4	32	0.0550095	30	108
A10	Mke	72	4	32	0.0550095	33	110
A10	Mke	72	4	32	0.0550095	37	112
A11	CGh	65	3.8	25	0.1674	8	100
A11	CGh	65	3.8	25	0.1674	11	101
A11	CGh	65	3.8	25	0.1674	14	101
A11	CGh	65	3.8	25	0.1674	17	103
A11	CGh	65	3.8	25	0.1674	20	104
A11	CGh	65	3.8	25	0.1674	23	105
A11	CGh	65	3.8	25	0.1674	27	106
A11	CGh	65	3.8	25	0.1674	30	106
A11	CGh	65	3.8	25	0.1674	33	107
A11	CGh	65	3.8	25	0.1674	37	107
A12	CLa	63.5	3.9	23.5	0.145796	8	101
A12	CLa	63.5	3.9	23.5	0.145796	11	102
A12	CLa	63.5	3.9	23.5	0.145796	14	103
A12	CLa	63.5	3.9	23.5	0.145796	17	105
A12	CLa	63.5	3.9	23.5	0.145796	20	105
A12	CLa	63.5	3.9	23.5	0.145796	23	106
A12	CLa	63.5	3.9	23.5	0.145796	27	106
A12	CLa	63.5	3.9	23.5	0.145796	30	108
A12	CLa	63.5	3.9	23.5	0.145796	33	109
A12	CLa	63.5	3.9	23.5	0.145796	37	110

4. Modeling and discussion

In order to provide an intelligent optimization model for estimating MEC in a rock cutting machine, after conducting the experimental tests on 120 rock samples, 5 important and influential factors in the performance of cutting machine were selected, which included uniaxial compressive strength (UCS), Mohs hardness (Mh), Schimazek's F-abrasiveness factors (SF-a), Young modulus (YM), and production rate (V), respectively, and were used as the modelling inputs. In addition, MEC of the machine was measured during the required experiments conducted on 120 samples, and was used as a modelling output for evaluating the performance of the cutting machine. Then 84 samples (70%) were utilized for constructing the model as the train data, and 36 samples (30%) were used as the test data for evaluation of the degree of accuracy and robustness.

In this work, two modellings were used through random non-linear techniques including the Hybrid ANFIS-DE and Hybrid ANFIS-DE algorithms. Similarly, in order to determine the efficiency and ability of the prediction models, three performance indices were used according to Equations (8)-(10) including value account for (VAF), root mean square error (RMSE), and coefficient of determination (R^2).

$$VAF = \left[1 - \frac{\mathrm{var}(x_i - y_i)}{\mathrm{var}(x_i)}\right] \quad (8)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - y_i)^2} \quad (9)$$

$$R^2 = \frac{[\sum_{i=1}^{n}(x_i - x_{mean})^2] - [\sum_{i=1}^{n}(x_i - y_i)^2]}{[\sum_{i=1}^{n}(x_i - x_{mean})^2]} \quad (10)$$

where n is the number of datasets in the model, and x_i and y_i are the values predicted from the output model and the output model, respectively. The significant point in the study of performance indices is that the closer the VAF value to 100, the better the performance of the model. In addition, the closer the RMSE value to zero and the R^2 value to 1, the better the performance of the model. FIS type is Sugeno. Also the number of fuzzy rules was determined using a trial-error method; some models of the set of fuzzy rule combinations were employed for dataset. Accordingly, some characterizations used in the ANFIS structure are shown in Table 4.

Table 4. Characteristics of the best structure of ANFIS model.

ANFIS parameter	Value
Input membership function	Gaussianmf
Output membership function	Linear
Inputs/outputs	[5 1]
Rules	[1 * 10 struct]
Input	[5 * 1 struct]
Output	[1 * 1 struct]
Number of input MFs	[10 10 10 10 10]
Number of output MFs	10
And method	prod
Or method	probor
Defuzz method	wtaver

4.1. Hybrid ANFIS-DE algorithm

In this section, after determining the hybrid ANFIS-DE algorithm code in MATLAB software, the algorithm's control parameters are required in order to implement an appropriate convergence process and provide an accurate high-efficient model. These parameters have a significant role in the convergence process and the ability to estimate the proposed model. According to the past studies, some control parameters such as cross-over probability are considered as 0.1 and several modellings in different states are done to determine an appropriate value for other control parameters of the algorithm, for example, Max iteration considered the values 150, 250, 350, 450, 550, and 750 in different models. In addition, the initial population is implemented for the values of 25, 45, 65, 85, and 100 in different modellings [33], [41]. Table 5 shows a comparison of modellings with different Max iterations and initial populations. In these modellings, 70% and 30% of datasets are used as the model training data and the model test data, respectively [42-43]. Considering the results of Table 5, although the conducted modellings are acceptable, the model No. 17 has been accepted as an optimization model due to the better performance indices such as VAF = 93.29, RMSE = 2.31, and R^2 = 0.94 compared to the other models provided by the hybrid ANFIS-DE. Figure 3 shows the coefficient of determination (R^2) for MEC obtained from the cutting machine and MEC obtained from the prediction model for the hybrid ANFIS-DE algorithm.

Table 5. Comparison of performance indices of each ANFIS-DE model.

Model No.	Max Iteration	Initial Population	VAF	RMSE	R^2
1	150	25	86.63	2.84	0.88
2	150	45	87.72	2.76	0.89
3	150	65	46.23	8.11	0.46
4	150	85	86.71	2.83	0.89
5	150	100	90.67	2.82	0.89
6	250	25	84.57	2.83	0.86
7	250	45	91.34	2.44	0.91
8	250	65	87.42	2.84	0.86
9	250	85	87.34	2.84	0.89
10	250	100	87.8	2.83	0.87
11	350	25	87.23	2.84	0.89
12	350	45	86.23	2.84	0.88
13	350	65	86.81	2.87	0.88
14	350	85	87.13	2.83	0.89
15	350	100	88.63	2.58	0.9
16	450	25	86.87	2.85	0.88
17	450	45	93.29	2.31	0.94
18	450	65	87.18	2.83	0.89
19	450	85	86.75	2.82	0.89
20	450	100	87.23	2.77	0.89
21	550	25	86.54	2.84	0.88
22	550	45	88.82	2.76	0.89
23	550	65	87.78	2.81	0.89
24	550	85	87.98	2.77	0.89
25	550	100	88.4	2.73	0.89
26	750	25	86.7	2.86	0.88
27	750	45	88.53	2.78	0.89
28	750	65	87.59	2.78	0.89
29	750	85	86.26	2.85	0.89
30	750	100	88.66	2.71	0.9

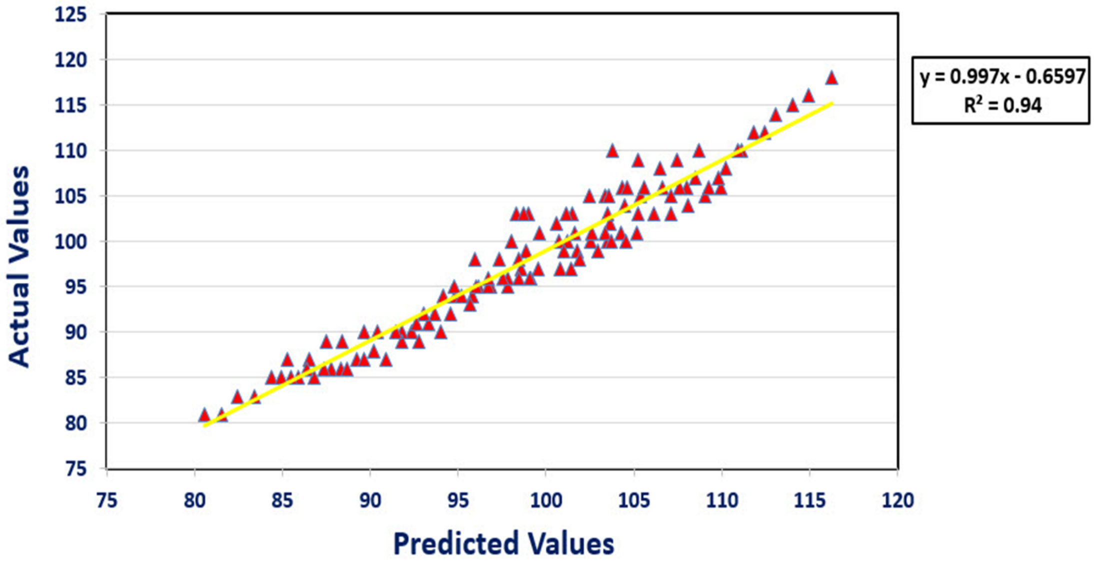

Figure 3. Predicted values versus actual values for the 17th model using Hybrid ANFIS-DE algorithm.

4.2. Hybrid ANFIS-PSO algorithm

As mentioned above, in this work, in addition to the hybrid ANFIS-DE algorithm, another hybrid algorithm called "hybrid ANFIS-PSO algorithm" was used as a random technique with a high flexibility. For this reason, in order to build the structure of the hybrid ANFIS-PSO algorithm, after creating the required codes in MATLAB software for ANFIS, the PSO algorithm was used for ANFIS training and obtaining a highly accurate response. In the next step, the control parameters were determined for this system. Some of the control parameters including Inertia Weight (w) = 1, Inertia Weight Damping Ratio (wdamp) = 0.99, Personal Learning Coefficient (C1) = 1, and Global Learning Coefficient (C2) = 2 were considered according to the comments made by experts and the previous studies [44-45]. They are significantly important in the algorithm's convergence process. Furthermore, various models were created based on Max Iteration = 150,250,350,450,550, and 750, and initial population = 25,45,65,85, and 100, and the results obtained from these models and their performance indices were tabulated in Table 6. In these models, the proportion of training and test models were 70% and 30% of the total dataset, respectively [42, 43].

According to the data in Table 6, although the provided models have acceptable accuracy and proper ability for predicting the rate of MEC, model No. 28 shows appropriate performance indices with values VAF = 99.65, RMSE = 0.5, and R^2 = 0.997, and is selected as a winner model in these modellings. Figure 4 shows the diagram of coefficient of determination (R^2) for the MEC obtained from the cutting machine and the MEC obtained from the model obtained using the hybrid ANFIS-PSO algorithm.

Table 6. Comparison of performance indices of each ANFIS-PSO model.

Model No.	Max Iteration	Initial Population	VAF	RMSE	R^2
1	150	25	98	0.99	0.97
2	150	45	95.88	1.71	0.95
3	150	65	98	1.16	0.98
4	150	85	97.32	1.37	0.97
5	150	100	95.86	1.71	0.95
6	250	25	97.62	1.29	0.97
7	250	45	97.16	1.41	0.97
8	250	65	94.5	1.94	0.95
9	250	85	98.4	0.97	0.98
10	250	100	97.45	1.33	0.97
11	350	25	95.2	1.86	0.95
12	350	45	98.6	0.86	0.98
13	350	65	99.1	0.77	0.99
14	350	85	98.8	0.94	0.98
15	350	100	98.31	1.08	0.98
16	450	25	97.05	1.44	0.97
17	450	45	99	0.93	0.99
18	450	65	97.36	1.36	0.99
19	450	85	99.2	0.75	0.991
20	450	100	98.78	0.93	0.98
21	550	25	98.88	0.89	0.98
22	550	45	99.35	0.67	0.992
23	550	65	99.01	0.84	0.99
24	550	85	99.1	0.82	0.99
25	550	100	98.8	0.9	0.99
26	750	25	98.14	1.14	0.98
27	750	45	98.76	0.94	0.99
28	750	65	99.65	0.5	0.997
29	750	85	99.2	0.71	0.992
30	750	100	99.28	0.71	0.992

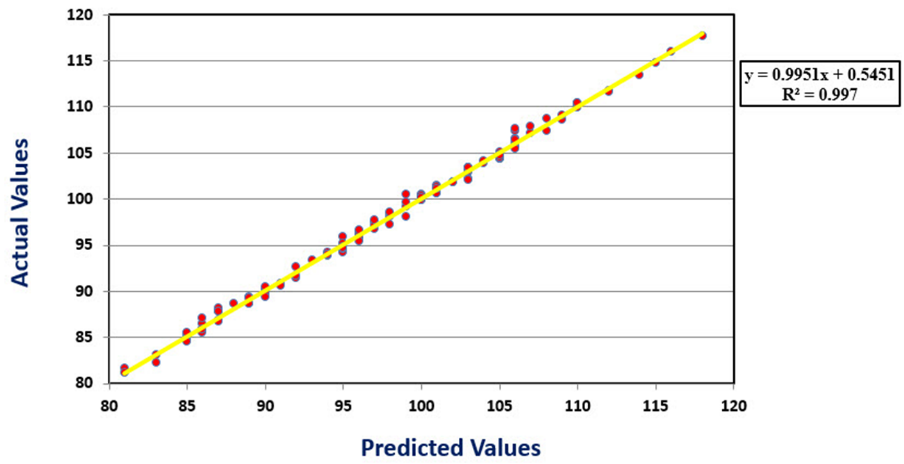

Figure 4. Predicted values versus actual values for the 17th model using Hybrid ANFIS-PSO algorithm.

4.3. Discussion

Based upon the results obtained from the models predicted based on Tables 5 and 6, it is obvious that the meta-heuristic algorithms of Differential Evolution (DE) algorithm and Particle Swarm Optimization (PSO) algorithm are successful algorithms for ANFIS training. Although the results of analyses and competition between the two algorithms were very close, the PSO algorithm had a better ability in terms of the model outputs and performance indices, indicating its superiority over the DE algorithm. Similarly, a comparison between the measured dataset with ANFIS-DE predicted and ANFIS-PSO predicted is shown in Figures 5 and 6, respectively, indicating the precision and ability of the ANFIS-PSO model.

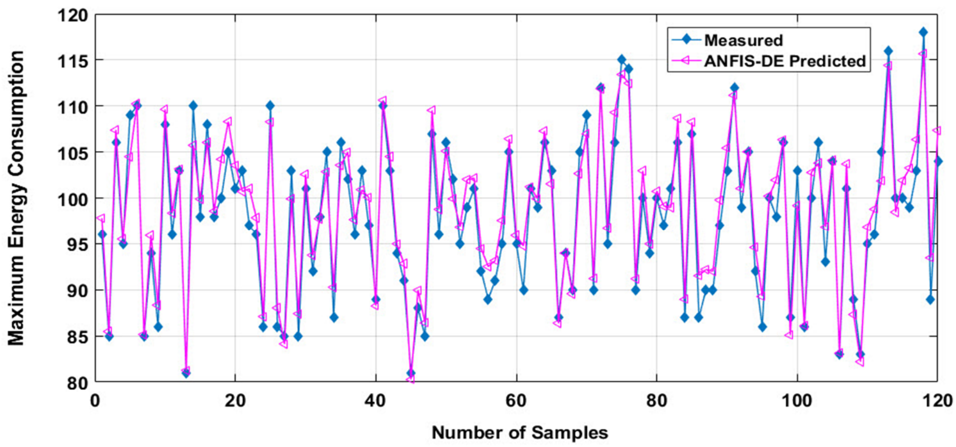

Figure 5. Comparison between measured and predicted MEC by ANFIS-DE model for dataset.

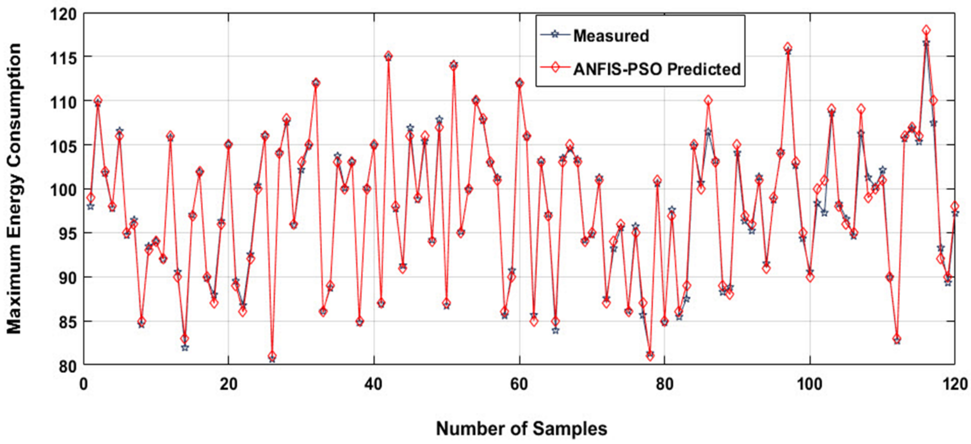

Figure 6. Comparison between measured and predicted MEC by ANFIS-PSO model for dataset.

As mentioned earlier, prediction and assessment of MEC is very notable for performance evaluation of gang saw during the process of cutting soft dimensional rocks. Hence, the aim of the present work was to develop a precise model for predicting MEC by 120 samples from 12 carbonate rocks. In this regard, 120 samples were monitored, and the values for MEC, UCS, Mh, SF-a, YM, and production rate (V) were measured. According to the results obtained, the presented study can be discussed as follows:

- A variety of models were developed using ANFIS-DE and ANFIS-PSO with different control parameters. As it can be seen, the performance indices for dataset describe its high capability for predicting MEC. Although all the proposed models and datasets have the proper results, the model No. 17 for ANFIS-DE and the model No. 28 for ANFIS-PSO obtained the maximum value of performance indices among other models.
- In comparison between the ANFIS-DE and ANFIS-PSO models, the ANFIS-PSO method can provide a higher performance capability for prediction of MEC.
- These methods are the precise scientific tools instead of statistical methods to deal with uncertain systems.
- It should be noted that the proposed models should be used only for Iranian carbonate rocks with some particular properties, namely UCS, Mh, SF-a, YM, and production rate (V).

5. Conclusions

One of the most important steps in designing the dimensional rock cutting process is the prediction of the performance of cutting machines. The accurate prediction of cutting machines in the stone cutting factories leads the designers and owners of this industry toward a desired process with the maximum operational power. In the present research work, it was attempted to study and predict the maximum energy consumption (MEC) of the gang saw during the process of cutting soft dimensional rocks using soft computing and considering the physical and mechanical properties of the rock sample and the production rate of gang saw. For this reason, after conducting studies on the rock mechanics of 12 carbonate rock samples, 120 cutting tests were conducted in the rock processing factory under different operational conditions, and MEC of the machines was recorded as a criterion for the performance of the gang saw. The results obtained showed that meta-heuristic algorithms such as the Differential Evolution (DE) and Particle Swarm Optimization (PSO) algorithms had the ability for ANFIS training. However, although these two algorithms showed appropriate efficiencies in the process of model training, the PSO algorithm had much ability in terms of model outputs and performance indices. The coefficient of determination (R^2) equal to 0.997, VAF = 99.65, and RMSE = 0.5 for dataset suggests the superiority of the ANFIS-PSO approach in predicting MEC, while these values were obtained as $R^2 = 0.94$, VAF = 93.29, and RMSE = 2.31 for the ANFIS-PSO method, respectively. Furthermore, a comparison between the measured dataset with ANFIS-DE predicted and ANFIS-PSO predicted indicates the accuracy and ability of the ANFIS-PSO model in predicting MEC of the gang saw considering the production rate of the gang saw and the physical and mechanical properties of carbonate rocks including uniaxial compressive strength (UCS), Mohs hardness (Mh), Schimazek's F-abrasiveness factors (SF-a), and Young modulus (YM). Future research works are required to focus on comparing the ANFIS-DE and ANFIS-PSO models with other hybrid algorithms and machine learning methods within the framework of this application.

Conflict of interest

The authors have no conflict of interest.

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ارزیابی عملکرد دستگاه برش اره با استفاده از الگوریتم‌های هیبریدی ANFIS-DE و ANFIS-PSO

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چکیده:

نرخ شدت جریان مصرفی بیشینه یکی از مهم‌ترین و مؤثرترین معیارها در روند برش سنگ‌ها است. تخمین و پیش‌بینی صحیح از این معیار می‌تواند به طراحان و صاحبان این صنعت در به دست آوردن یک روند بهینه و اقتصادی کمک کند. در پژوهش حاضر، سعی شده است تا به بررسی و مطالعه مدل‌هایی برای پیش‌بینی شدت جریان مصرفی بیشینه دستگاه برش اره به کمک یک مدل بهینه‌سازی هوشمند نظیر تکنیک‌های تصادفی غیرخطی یعنی الگوریتم‌های هیبریدی ANFIS-DE و ANFIS-PSO بر اساس ۴ پارامتر فیزیکی و مکانیکی شامل: مقاومت فشاری تک‌محوری، سختی موهس، سایندگی شیمازک، مدول الاستیسیته و یک مشخصه عملیاتی ماشین برش سنگ یعنی نرخ تولید پرداخته شود. در طی این پژوهش ۱۲۰ نمونه از ۱۲ نوع سنگ کربناته مورد آزمایش‌های آزمایشگاهی قرار گرفت. همچنین در طی این پژوهش، شدت جریان مصرفی بیشینه دستگاه برش اندازه‌گیری شده و به عنوان خروجی مدل‌سازی برای ارزیابی عملکرد دستگاه برش اره مورد استفاده قرار گرفته است. همچنین الگوریتم‌های فرا ابتکاری شامل DE و PSO برای آموزش سیستم استنتاج فازی عصبی تطبیقی (ANFIS) مورد استفاده قرار گرفتند. به علاوه، الگوریتم PSO از توانایی بالاتری بر اساس خروجی‌های مدل و شاخص‌های عملکرد نسبت به الگوریتم DE داشت. علاوه بر این، مقایسه بین داده‌های اندازه‌گیری شده با مدل ANFIS-DE و مدل ANFIS-PSO، دقت و توانایی مدل ANFIS-PSO را در پیش‌بینی عملکرد دستگاه برش اره با توجه به مشخصه‌های دستگاه و برش سنگ نشان داد.

کلمات کلیدی: دستگاه برش اره، جریان مصرفی بیشینه، نرخ برش، ANFIS-DE، ANFIS-PSO.