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Development of Intelligent Systems to Predict Diamond Wire Saw Performance

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ABSTRACT

Assessment of wear rate is an inseparable section of the saw ability of dimension stone, and an essential task to optimization in the diamond wire saw performance. This research aims to provide an accurate, practical and applicable model for predicting the wear rate of diamond bead based on rock properties using applications and performances of intelligent systems. In order to reach this purpose, 38 cutting test results with 38 different rocks were used from andesites, limestones and real marbles quarries located in eleven areas in Turkey. Prediction of wear rate is determined by optimization techniques like Multilayer Perceptron (MLP) and hybrid Genetic algorithm –Artificial neural network (GA-ANN) models that were utilized to build two estimation models by MATLAB software. In this study, 80% of the total samples were used randomly for the training dataset, and the remaining 20% was considered as testing data for GA-ANN model. Further, accuracy and performance capacity of models established were investigated using root mean square error (RMSE), the coefficient of determination (R^2) and standard deviation (STD). Finally, a comparison was made among performances of these soft computing techniques for predicting and the results obtained indicated hybrid GA-ANN model with a coefficient of determination (R^2) of training = 0.95 and testing = 0.991 can get more accurate predicting results in comparison with MLP models.

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1. Introduction

There are several methods in dimension stone block. Nowadays, diamond wire saw with bead diamond is the most widely used process for dimension stone quarries.

In diamond wire cutting operations, the cutting action primarily includes the pulling of continuous loops of spinning wire mounted with diamond beads through the dimension stone. In this cutting operation, firstly the horizontal cutting is done for avoiding the gravity effect of dimension stone block. Then, vertical cuttings are done. The initial step for a vertical cutting is to drill two holes that intersect at a 90° angle. Then, the diamond wire threaded through these holes, and over the drive wheel, clamps at the two ends to form a continuous loop. The diamond wire cutting machine is mounted on a temporary track, along which it reverses to maintain tension in the wire as it cuts through the stone. Water is applied with the spin direction of the wire as a coolant and as a means of removing the particles of stone [1].

Diamond wire saw wear in rock cutting is one of the major criteria in determining the diamond wire saw life, energy consumption, production cost, and determine the cutting method selected for a given rock type. There are some important factors, which need to be considered to evaluate the wear rate of diamond wire saw. These factors can be divided into three key categories: (1) the characteristics of the diamond wire saw, (2) the operating parameters and (3) the characteristics of the cut rock. Many researchers have attempted to investigate the effect of these parameters on wear up to now. Some researchers have studied the wear of circular diamond saw blade, and diamond wire saw in rock cutting process [1–12]. In the field of diamond, wire saw wear, Özçelik et al. [1] studied the effects of textural properties on marble cutting with diamond wire. They evaluated the relationships between textural characteristics and wore rate. The results showed that decreasing grain size increases the wear rate. Also, there is a significant relationship between the texture coefficients and wear on diamond beads. This study indicated that textural characteristics could be considered in the selection and design of diamond beads in marble industry. Özçelik and Kulaksız studied the relationship between cutting angles and wear on diamond beads in diamond wire cutting process [11]. Özçelik et al. investigated the wear rate of diamond beads in the cutting of different rock types. They used the ridge regression method to evaluate the wear of beads in the cutting of different rock with different physical, chemical, mechanical and mineralogical-petrographical properties. They concluded that the developed statistical models could be used to determine diamond wire life and to cut efficiency [12]. Similarly, Özçelik applied the multivariate statistical analysis of the wear on diamond beads in the cutting of andesitic rocks according to physical and mechanical properties of rock [3]. Mikaeil et al. predicted the wear of diamond wire saw concerning the uniaxial compressive strength, Schimazek F-abrasivity factor, Shore hardness, and Young's modulus using the harmony search algorithm. The results showed that the applied algorithm could be used to evaluate the wear of diamond bead [4]. Almasi et al. carried out an investigation for the 11 types of igneous rocks based on the rock properties and production rate. For this purpose, they used linear and nonlinear regressions for analysis. The results indicated that the developed model could be a suitable system to predict the wear rate of diamond beads [13]. Mikaeil et al., investigated different carbonate rocks in some famous quarries located in Iran, according to some important mechanical and physical properties of stone such as elasticity modulus, similar quartz content and uniaxial compressive strength. They used the application of multivariate regression analysis to evaluate the performance of diamond wire saw [14].

All of these studies were simply studied the diamond bead wear with statistical analysis and metaheuristic algorithm. No study has been found relating to the influence of rock characteristics on the diamond bead wear rate in diamond wire sawing with soft computing such as artificial and intelligence algorithm. In this research, it is aimed to develop an accurate, practical and applicable model for predicting the wear rate of diamond bead based on rock properties using intelligent systems. The remainder of this paper is organized as follows. In Section 2, the methodology is briefly summarized. Section 3 presents the rock properties and laboratory testing of the case study. In Section 4, the development of the MLP and a combination of GA-ANN models for wear rate prediction are explained. Section 5 discusses and assesses the results and performances of moldings. Finally, Section 6 gives conclusions and recommendations for future work.

2. Methodology

The methodology of this study is organized as following steps.

Step 1: Quarries studies (Cutting of dimension stone with a diamond wire saw and determination of wear rate and sampling of stone blocks)

Step 2: Laboratory studies (Preparation of cylindrical specimens from stone samples and determination of physical and mechanical properties)

Step 3: Investigation of the relationship between wear rate and characteristics of rock with GA-ANN and MLP

Step 4: Evaluation of results

A flowchart followed in this study is illustrated in Figure 1.

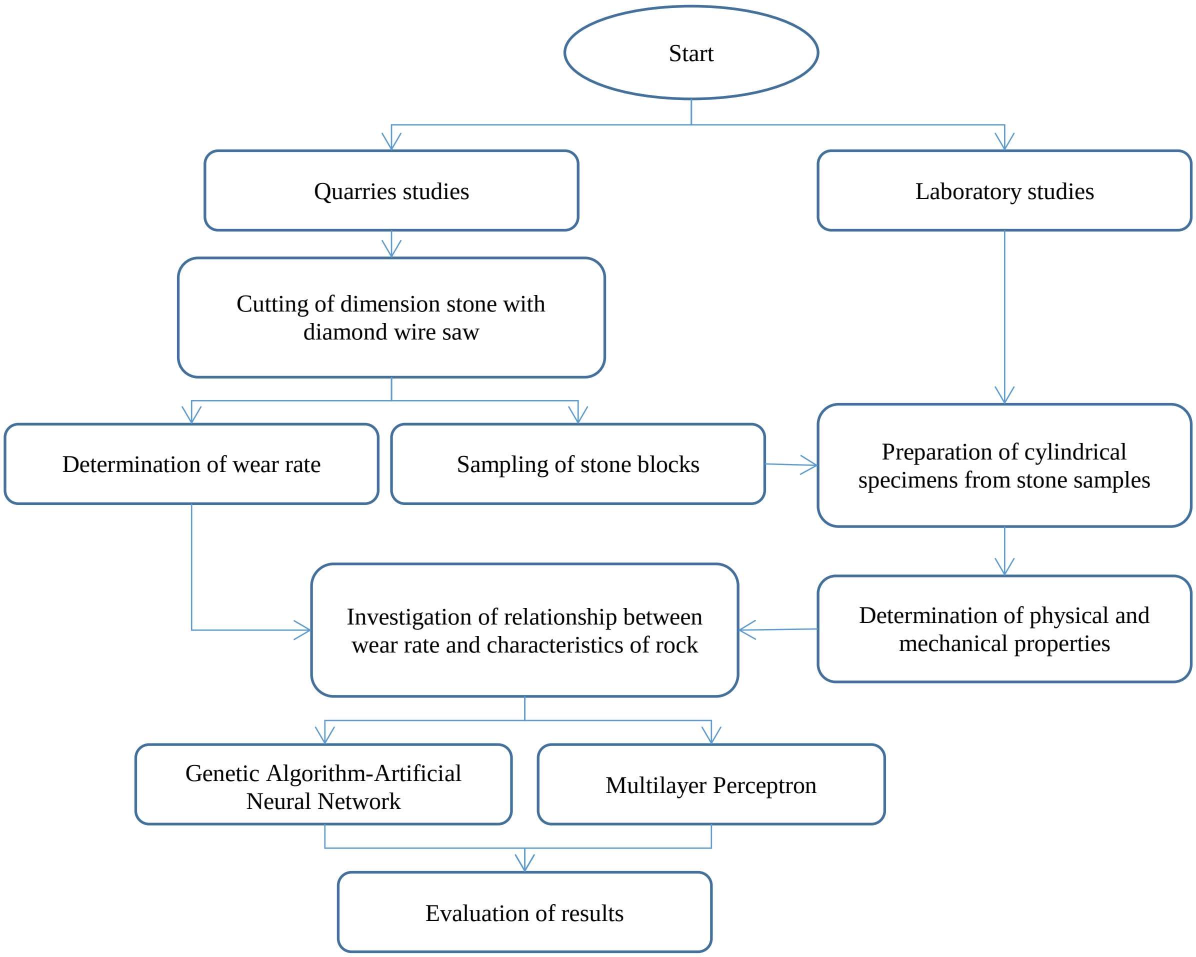

Fig. 1. Flowchart of study

3. Quarries and laboratory studies

This study has been performed at 38 quarries including a different type of rocks including andesites, limestones and real marbles in eleven areas in Turkey (Table 1). The extractions of andesite, limestones and real marble blocks have been achieved by diamond wire sawing. Wear rates of diamond beads for any rock types from 38 different localities have been recorded.

After quarries studies, experimental studies were done on rock block samples. To determine the main physical and mechanical properties of studied rocks, laboratory studies were done. Uniaxial compressive strength (UCS), Shore hardness (SH), Young modulus (YM) and Schmiazek F-abrasivity (SF-a) were selected as major rock characteristics. Results of laboratory tests for studied rock and quarries studies are given in Table (1).

Table 1
Diamond bead wear rate and characteristics of studied rock for evaluated deferent rocks.

Cutting No.		Sample	Cutting performance	Rock characteristics			
			WR (mm/m_2)	UCS (MPa)	SH	YM (GPa)	SFa (N/mm)
1	Andesite	Andesite1	0.00150	28.05	33.00	6.80	0.104
2		Andesite2	0.00230	47.39	39.93	7.60	0.134
3		Andesite3	0.00360	77.25	65.00	20.80	0.331
4		Andesite4	0.00340	84.02	63.62	23.50	0.290
5		Andesite5	0.00210	26.55	49.93	7.90	0.043
6		Andesite6	0.00560	67.41	67.00	15.50	0.531
7		Andesite7	0.00160	57.75	43.70	8.00	0.171
8		Andesite8	0.01570	87.53	61.38	30.56	0.313
9		Andesite9	0.01680	75.75	63.70	24.60	0.254
10		Andesite10	0.01590	81.35	62.48	25.40	0.292
11		Andesite11	0.00850	78.75	60.30	26.40	0.272
12		Andesite12	0.00800	82.50	61.20	28.30	0.320
13		Andesite13	0.00360	27.23	42.50	7.30	0.133
14		Andesite14	0.00220	51.92	41.20	7.76	0.203
15		Andesite15	0.00360	56.25	43.50	8.01	0.221
16	Limestone	Usak White	0.00370	69.00	47.00	12.20	0.021
17		Kozagac White	0.00280	42.00	40.00	12.10	0.034
18		Milas Lilac	0.00260	55.00	46.00	11.00	0.154
19		Afyon Cream	0.00300	64.00	46.00	11.80	0.014
20		Kutahya Lilac 1	0.00820	52.26	42.90	17.02	0.004
21		Kutahya Lilac 2	0.00980	79.00	43.05	17.50	0.004
22		Kutahya Violet	0.00820	63.49	43.25	21.14	0.004
23		Afyon Violet 1	0.00650	74.19	45.23	21.43	0.003
24		Afyon Violet 2	0.00490	51.84	41.60	15.96	0.003
25		Afyon Gray 1	0.00440	49.02	41.55	13.07	0.004
26		Afyon Gray 2	0.00440	45.57	39.85	15.72	0.003
27		Mugla Nacre	0.00290	28.68	50.45	12.74	0.003
28		Mugla White	0.00150	30.00	32.90	9.86	0.002
29	Real marble	Yesilova Beige	0.00310	70.50	56.00	9.90	0.014
30		Sivrihisar beige1	0.00370	72.00	60.00	12.50	0.014
31		Sivrihisar beige2	0.00380	70.00	62.00	13.20	0.013
32		Sivrihisar beige3	0.00390	68.00	58.00	12.20	0.012
33		Antalya Beige 1	0.00610	55.30	58.70	22.83	0.061
34		Antalya Beige 2	0.00850	65.80	58.15	25.24	0.104
35		Antalya Beige 3	0.00710	59.77	58.00	17.43	0.122
36		Antalya Beige 4	0.00820	56.75	59.48	20.35	0.370
37		Toros Black 1	0.01990	105.48	65.30	20.25	0.122
38		Toros Black 2	0.01573	110.77	64.75	17.94	0.121

4. Prediction of wear rate through statistical and intelligent techniques

In the present study, two intelligent systems, namely GA- ANN and MLP are proposed to create a precise equation for the prediction of diamond wire saw performance, and then a comparison of their performances are conducted and discussed. Some statistical functions indices, i.e., root mean square error (RMSE), the coefficient of determination (R^2) and standard deviation (STD) were computed to check for assessment and evaluating the accuracy and performance capacity of models as shown in Eqs.1 to 4, respectively.

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

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

$$STD = \sigma = \sqrt{\frac{1}{n}[\sum_{i=1}^{n}\left(\left|\frac{x_i - y_i}{x_i}\right| - mean\left|\frac{x_i - y_i}{x_i}\right|\right)]} \tag{3}$$

Where n explains the number of data sets. The y_i and x_i are the forecasted and measured wear rate values, respectively. Note that, in modeling with high and acceptable accuracy, the values of RMSE, $R^{2,}$ and STD should be close to 0, 1 and 0, respectively.

4.1. Multilayer perceptron (MLP)

The soft computing acts as a huge incentive to solve complex problems [15–17]. Artificial neural networks have a special place among soft computing methods considering their high ability in complex and imprecise data analysis and processing. The performance of the human brain and neural systems considering million years of evolution can be used as the most complete and efficient pattern for the recognition of the surrounding events. In recent decades, neural networks have had a great impact on the development and modeling of industrial problems, as well as the control and optimization of the production process. One of the most practical and appropriate types of neural networks is the multilayer perceptron network used with a special type of learning algorithm in optimization problems. In a multilayer perceptron network, the linear relationship between input and output vectors is shown through connections between neurons in each node and previous and next layers. The weight of network is determined through the minimum error between input and output data and or through the end of a number of teachings to a predetermined value [18,19]. Different methods are used for teaching artificial neural networks, among which the backpropagation algorithm is one of the most efficient and appropriate methods for teaching the multi-layer perceptron neural network and has the maximum consistency with this network. Therefore, for learning weights of a multi-layer perceptron network, the back propagation rule is used. This method was proposed by Wiliams Rumelhalt in 1986. In this method, using the gradient descent, it is attempted to minimize the square error between network outputs and objective function [20,21]. In fact, the error produced by the comparison between output data and estimated data must be smaller than the mean square error (MSE), or the root mean square error (RMSE); otherwise, the network must be propagated back in order to correct weights and reduce errors. The computation of output sensitivity to weights is started from the end of the network, and finally, weights are updated at once. The network's output error is computed in Eq (5) based on BP:

$$E(\vec{W}) = \frac{1}{2} \sum_{d \in D} \sum_{k \in outputs} (t_{kd} - o_{kd})^2 \tag{5}$$

where $E(\vec{W})$ is the total output error, d is training samples, k is output data set, t_{kd} and o_{kd} are kth value of the objective function (corresponding to the kth output unit) for dth training sample and kth value of output function (corresponding to the kth output unit) for dth training sample, respectively.

4.1.1. MLP modeling

In this work, Multilayer Perceptron (MLP) is utilized to build a prediction model for the assessment of diamond wire saw performance from the samples of stones as data set using the MATLAB software. The same datasets are used in three simulations in this study. Wear rate was considered as the dependent variable (output), and the uniaxial compressive strength (UCS), Schmiazek F-abrasivity (SF-a), Shore hardness (SH), and Young's modulus (YM) were considered as the independent variables (input). The dataset of 38 different varieties of dimension stones from Turkey quarry mines is considered in the current study, while 26 data points (70%) are utilized for constructing the model as train data, 8 data points (20%) are used as test data and the rest data points (4 data points) are considered as validation data for evaluation of the degree of accuracy and robustness.

The number of hidden layers and the number of neurons in each hidden layers are two important factors in the MLP structure. Hence; in this modeling by the contribution of experimental equations and after several simulations conducted, N_i =4 and N_0 =1 are considered for the number of input neuron and number of output neuron, respectively. Furthermore, hidden layer size is used as a range of 1-10 with one hidden layer for more accurate computing. Some of these equations are shown in Table (2).

Table 2
The equations for determining the number of neuron in the hidden layer [22].

Researchers	Heuristic
Hecht-Nielsen [23]	$\leq 2 \times N_i + 1$
Hush [24]	$3N_i$
Kaastra and Boyd [25] Kannellopoulas and Wilkinson [26]	$2N_i$
Ripley [27]	$(N_i + N_0)/2$
Paola [28]	$\frac{2 + N_0 \times N_i + 0.5N_0 \times (N_0^2 + N_i) - 3}{N_i + N_0}$
Wang [29]	$2N_i/3$
Masters [30]	$\sqrt{N_i + N_0}$

N_i: Number of input neuron, N_0: Number of the output neuron

Different studies are conducted about conventional gradient descent techniques. Levenberg–Marquardt (LM) is one of the most effective and accurate algorithm based on the suggestion of Hagan and Menhaj [31]. Therefore, Levenberg–Marquardt (LM) learning algorithm is considered in constructing MLP models for training net. In this study, the tansig and purelin are considered as transfer functions of the hidden layers and output, respectively. The effects of hidden layer size on the results of RMSE, $R^{2,}$ and STD. are shown in Tables (3), and ranking of each model are listed in Table (4) based on a simple ranking method [32,33].

Table 3
Effects of hidden layer size on statistical functions performance in MLP network.

Model No.	Hidden Layer Size (HLS)	The Results of Network for R^2			The Results of Network for RMSE			The Results of Network for STD.		
		Training	Validation	Testing	Training	Validation	Testing	Training	Validation	Testing
1	1	0.54	0.99	0.7	0.0026	0.0021	0.0048	0.0027	0.0024	0.0042
2	2	0.73	0.81	0.56	0.0027	0.0028	0.0018	0.0027	0.0031	0.0019
3	3	0.7	0.21	0.14	0.0028	0.0042	0.0023	0.0029	0.0044	0.0018
4	4	0.8	0.84	0.8	0.0021	0.0036	0.003	0.0021	0.0039	0.0028
5	5	0.83	0.78	0.73	0.002	0.0037	0.0023	0.002	0.0031	0.0023
6	6	0.96	0.97	0.54	0.0011	0.0028	0.0049	0.0011	0.0022	0.0042
7	7	0.76	0.84	0.77	0.0024	0.0022	0.0027	0.0024	0.0025	0.0025
8	8	0.95	0.55	0.92	0.0011	0.0035	0.0021	0.0011	0.0038	0.0017
9	9	0.7	0.92	0.88	0.0028	0.0011	0.0022	0.0028	0.0011	0.0021
10	10	0.67	0.99	0.91	0.0027	0.0018	0.002	0.0026	0.002	0.0021

Table 4
Ranking of each model using MLP network.

Model No.	Hidden Layer Size (HLS)	The Ranking of Network for R^2			The Ranking of Network for RMSE			The Ranking of Network for STD.			Total rank
		Training	Validation	Testing	Training	Validation	Testing	Training	Validation	Testing	
1	1	2	10	4	6	8	3	5	7	3	48
2	2	5	6	3	5	6	10	5	5	8	53
3	3	4	3	1	4	2	6	3	2	9	34
4	4	7	7	6	8	4	4	8	3	5	52
5	5	8	5	5	9	3	6	9	5	7	57
6	6	10	9	2	10	6	2	10	8	3	60
7	7	6	7	7	7	7	5	7	6	6	58
8	8	9	4	10	10	5	8	10	4	10	70
9	9	4	8	8	4	10	7	4	10	4	59
10	10	3	10	9	5	9	9	6	9	4	64

Furthermore, Fig (2) shows a correlation of determination between measured and predicted wear rate that there is a reasonable R^2 with a coefficient higher than 0.88. Figs(3) and (4) present RMSE values and the histograms of errors for training, validation, and testing steps for all datasets in the eighth model using MLP, respectively. According to the statistical functions and their total rank in Table (4), the model number 8 indicates higher performance capacities compared to other models with hidden layer size of 8 and a total rank of 70.

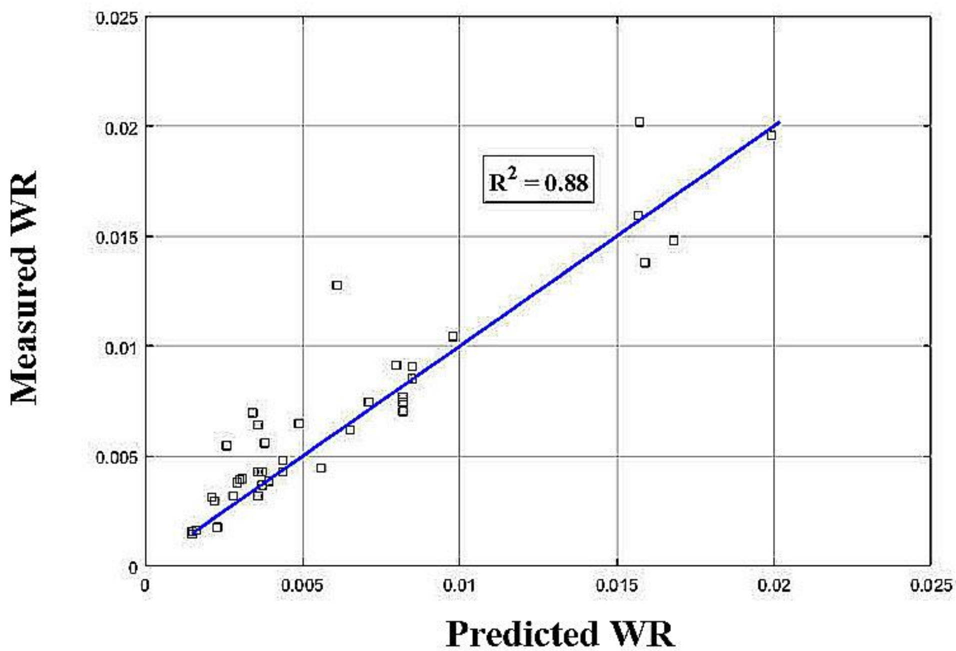

Fig. 2. R^2 of predicted and measured WR values for all data set using the MLP model.

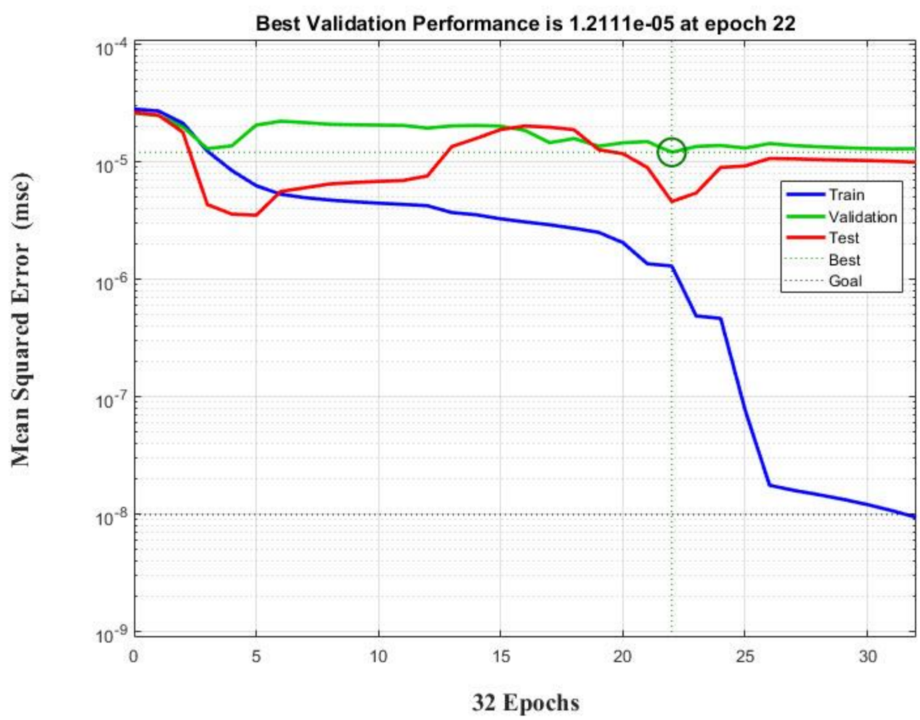

Fig. 3. RMSE values for training, validation and testing steps.

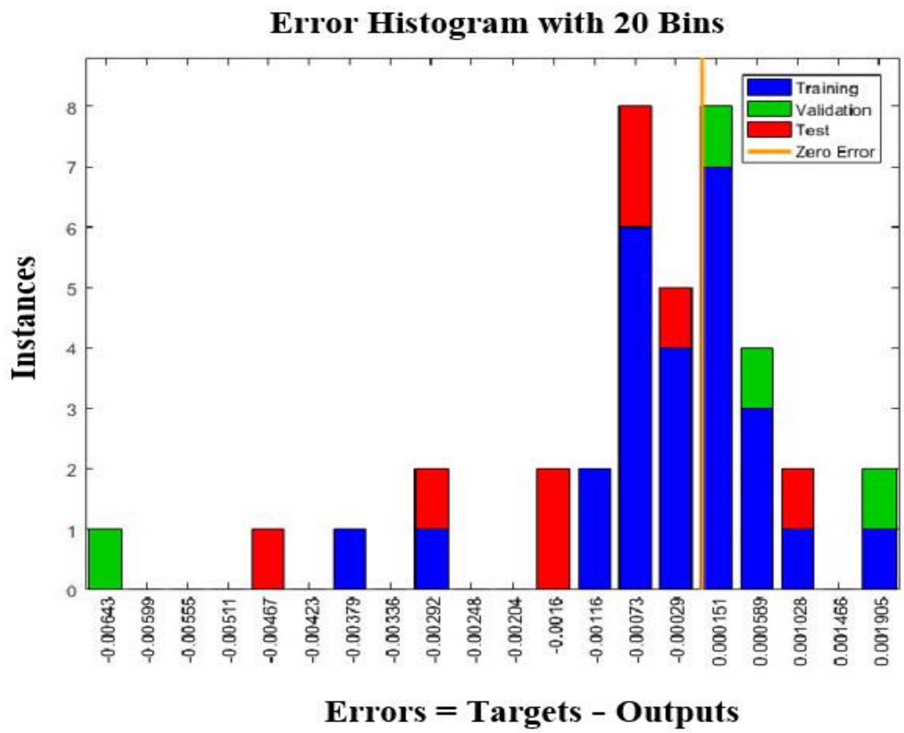

Fig. 4. Histograms of errors for all data set using the MLP model

4.2. Hybrid GA-ANN algorithm

In recent years, Meta-heuristic algorithms have attracted the interest of researcher in many engineering fields and industry. These algorithms are the precise scientific tools instead of statistical methods to deal with the uncertain systems [34–36]. A genetic algorithm is a population-based algorithm like particle swarm optimization, firstly proposed by John Holland in 1975 at the University of Michigan [37]. The GA is a Meta-heuristic algorithm that is suitable for dealing with complex problems, especially when the goal is to find an optimization result. The genetic algorithm can model the qualitative and quantitative aspects of uncertain systems in the industry. The genetic algorithm (GA) was inspired by Darwin's principle of natural evolution. The optimization and searching method in this algorithm is based on the principle of natural biological evolution and inheritance rules.

In the genetic algorithm, numbers are expressed in terms of binary strings and converged toward the range of solutions during the stepwise algorithm's implementation using the probability distribution function. The population to population searching is a technique for obtaining an optimal solution. Also, in problems with a complex hypothesis space with the unknown effect of components on the general hypothesis, GA can be used for searching and finding an approximate solution for an optimal answer. GA has a significant flexible nature compared to other Meta-heuristic algorithms and is formed based on the natural selection mechanism and stochastic techniques. Furthermore, in this algorithm, differentiation is not required, and only the objective function and basic information fitting methods are used. In GA, each set of chromosomes and each replication of algorithm are called population and generation, respectively. GA first fits the existing population in each replication by determining the initial population and using the fitness function and then starts optimization. In fact, the compatibility of the initial population is computed and assessed through the objective function. Next, the new generation (population) is produced based on GA operators, i.e., reproduction, crossover, and mutation. The fitness steps for answers and production of new generations continue until an optimal answer is reached. GA has a wide range in the optimization and solution of complex and uncertain problems. The landslide was evaluated and studied by Terranova et al. The results and the subsequent validation showed that the genetic-algorithms-based hydrological model was a reliable approach for their research. [38]. The flood risk management was done by Woodward et al. using a multi-objective genetic algorithm. The results indicated that the simulations were very suitable [39].

Also, one of the most important applications of GA is teaching neural networks. Since GA can run away from trapping in local optimums, does not depend on any special structure of the network and is applied for any defined structure, it can be considered as a proper and efficient tool for being combined with neural networks and teaching neural networks. Therefore, in this research, the wear rate is anticipated using a GA and ANN combination for optimizing the performance of diamond wire saw. Figure (5) shows a combination of GA-ANN structure.

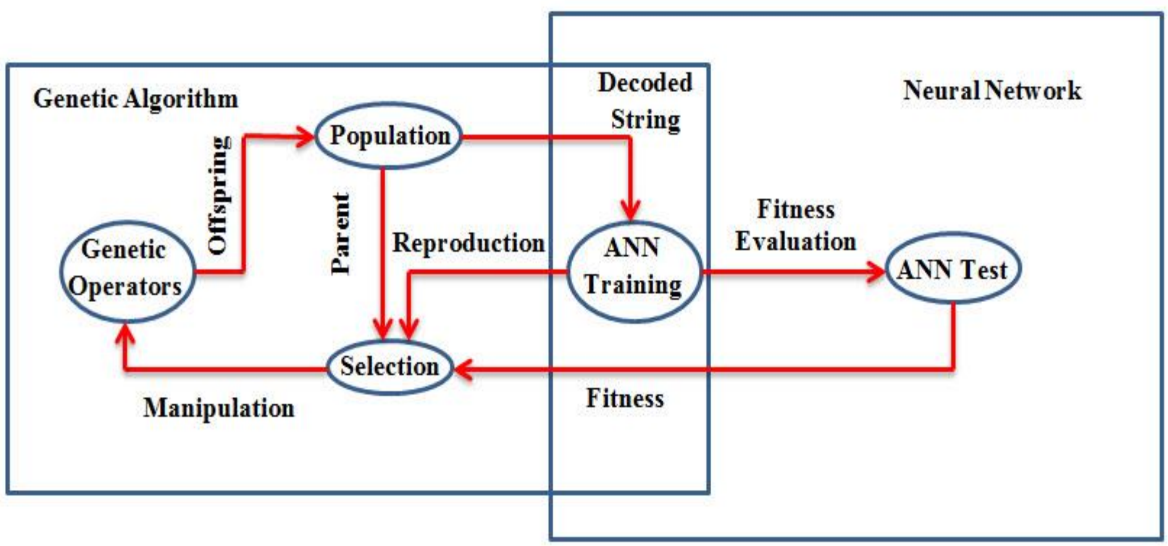

Fig. 5. The structure of the hybrid GA-ANN flowchart [40]

In recent years, different studies were conducted in different scientific areas using a hybrid GA-ANN algorithm. Armaghani and Khandelwal proposed a model for the anticipation of the drilling rate index using GA and neural network and used on the rock strength characteristics [41]. Good anticipation of the pile bearing capacity was done by Momeni et al. by developing a hybrid algorithm model. In their study, they obtained answers with very good accuracy by combining GA and ANN [42]. A model for the anticipation of flyrock and back break in open pit mines was proposed by Monjezi et al. based on GA-ANN, and a model with high efficiency was developed for anticipation with the minimum possible error and the maximum correlation coefficient [43].

4.2.1. Hybrid GA-ANN algorithm modeling

As mentioned, the predicting diamond wire saw performance in this study is based on four important measures of rocks which the same datasets performed in the assessment of MLP simulations were applied. A hybrid GA-ANN algorithm is considered as a flexible predicting method. This technique is based on artificial intelligence for solving complex issues and uncertain systems, which is one of the most efficient soft computing methods. Hagan and Menhaj (1994) introduced more details for the hybrid GA-based ANN model [31].

In order to obtain a high level of precision in data analysis and predicting process, it is necessary to determine the appropriate control parameters. Hence; firstly the pseudo-code of the hybrid GA-ANN algorithm is written in MATLAB software. Some parameters can define based on visual observations and suggestion of previous studies [31,44]. The recombination percent (RP) was determined at 15%, the mutation percent (MP) and cross-over percent (CP) were fixed at 35% and 50%. The maximum number of generation (G_{Max}) and population size are two of the effective factors in during algorithm implementation process. In the next step, in order to obtain the optimum G_{Max} value, the efficacy of the number of generation on the network performance for RMSE as statistical functions is carried out for deferent population size as a range of 50-500 with G_{Max} = 500. The result of the analysis is illustrated in Fig (6). Based on the results, it is obvious that the optimum G_{Max} was set to be 400 because the network performance is unchanged after this value of G_{Max}. Furthermore, the ANN structure is determined based on Table (2).

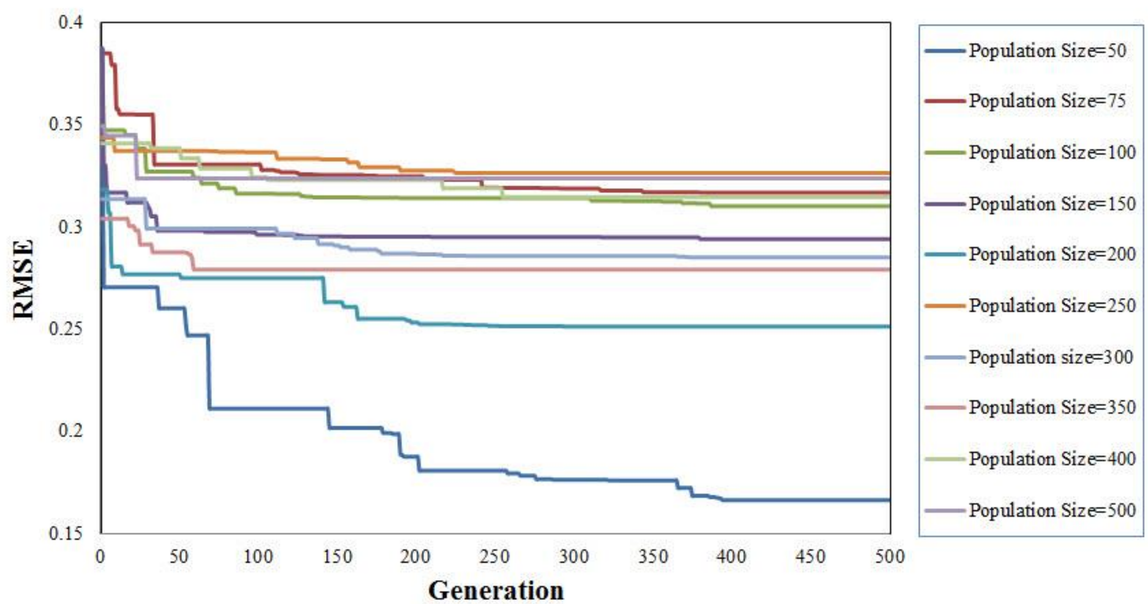

Fig. 6. The efficacy of the number of generation on the network performance based on RMSE

In the final step, in order to determine the optimum population size in GA-ANN algorithm, 10 hybrids GA-ANN models are constructed for the optimum G_{Max} = 400, the results of root mean square error (RMSE), coefficient of determination (R^2) and standard deviation (STD) are listed in Table (5). The models are ranked according to the suggestion of Zorlu et al. (2008) as a simple ranking approach [33].

Table 5
Effects of population size on statistical functions performance in Hybrid GN-ANN algorithm.

Model No.	Population Size	The Results of Network for R^2		The Results of Network for RMSE		The Results of Network for STD.	
		Training	Testing	Training	Testing	Training	Testing
1	50	0.89	0.25	0.168	0.489	0.459	0.435
2	75	0.69	0.64	0.261	0.375	0.376	0.384
3	100	0.67	0.81	0.2	0.55	0.264	0.337
4	150	0.64	0.62	0.299	0.357	0.389	0.375
5	200	0.68	0.68	0.31	0.264	0.418	0.442
6	250	0.89	0.24	0.174	0.495	0.443	0.389
7	300	0.75	0.56	0.264	0.41	0.467	0.595
8	350	0.7	0.37	0.297	0.417	0.444	0.447
9	400	0.65	0.7	0.276	0.348	0.374	0.407
10	500	0.49	0.69	0.319	0.318	0.455	0.467

The results of the ranking shown in Table (6). As shown in Table (6), the third model has the highest rank among other models with the rank of 44. Therefore, Figs (7) and (8) illustrate the value of R^2 and the graphical comparison between measured and predicted wear rate using a hybrid model for test data set of the third simulation, respectively.

Table 6
Ranking of each model using Hybrid GN-ANN algorithm.

Model No.	Population Size	The Ranking of Network for R^2		The Ranking of Network for RMSE		The Ranking of Network for STD.		Total rank
		Training	Testing	Training	Testing	Training	Testing	
1	50	10	2	10	3	2	5	32
2	75	7	6	7	6	8	8	42
3	100	5	10	8	1	10	10	44
4	150	3	5	3	7	7	9	34
5	200	6	7	2	10	6	4	35
6	250	10	1	9	2	5	7	34
7	300	9	4	6	5	1	1	26
8	350	8	3	4	4	4	3	26
9	400	4	9	5	8	9	6	41
10	500	2	8	1	9	3	2	25

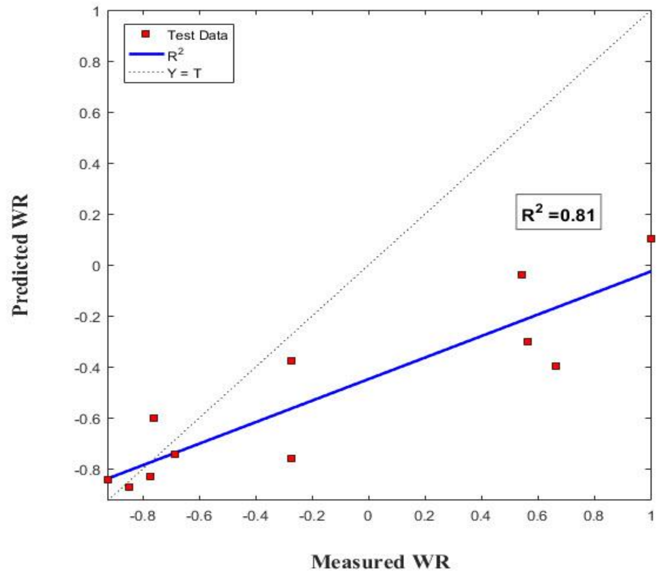

Fig. 7. R^2 between measured and predicted wear rate using hybrid GA-ANN model for Test data.

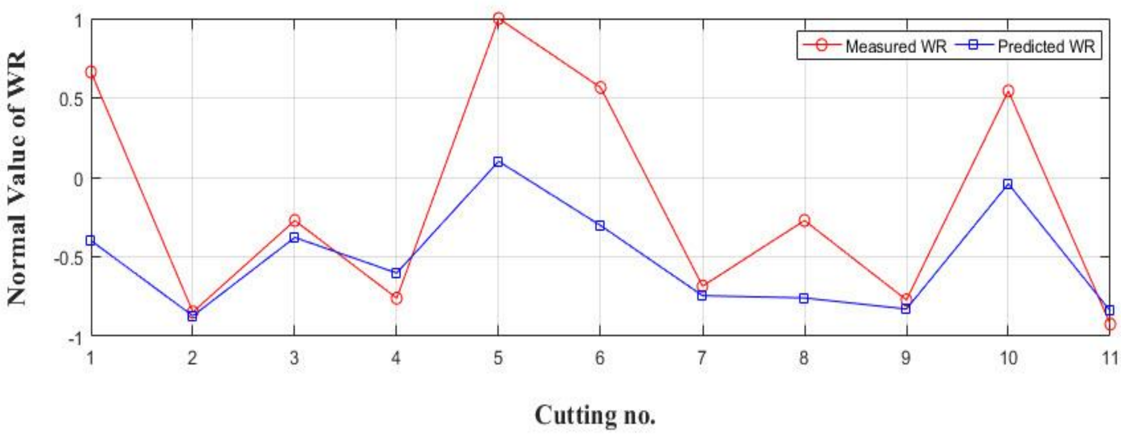

Fig. 8. The graphical comparison between measured and predicted wear rate using hybrid GA-ANN model for test data.

5. Evaluation of the results and discussion

Assessment of diamond wire saw performance had been considered as one of the most notable topics to study in mining engineering and rock mechanics. Investigation of effective parameters on the diamond wire saw performance is frequently encountered with complex and non-linear problems; hence, soft computing techniques are the approaches that are suitable for dealing with complex and uncertain processes. In this research, in order to investigate the applications and performances of each optimization technique for predicting diamond wire saw performance, after implementation simulations, the most appropriate structures of MLP and hybrid GA-ANN model were determined. Based on the optimum models, all the datasets were randomly selected to 4 various datasets. Also, 80% of samples were used randomly for the training dataset, and the remaining 20 % was considered as testing data in each simulation. In Tables (7), the results of

R^2, RMSE, and STD. of ANN and GA-ANN methods and final ranking are shown. Finally, Table (8) listed shows the final ranking of all simulations.

Table 7
Ranking of each model for 4 datasets randomly selected using MLP and hybrid GN-ANN.

Optimization Techniques	Model No.	Value of R^2	Score of R^2	Value of RMSE	Score of RMSE	Value of STD.	Score of STD.	Total Score
MLP	Train 1.	0.8	3	0.0014	3	0.0016	3	9
	Train 2.	0.88	4	0.001	4	0.001	4	12
	Train 3.	0.62	1	0.0034	2	0.0034	2	5
	Train 4.	0.65	2	0.0049	1	0.0048	1	4
	Test 1.	0.91	4	0.0013	4	0.0015	4	12
	Test 2.	0.77	2	0.0044	2	0.0017	3	7
	Test 3.	0.81	3	0.006	1	0.007	1	5
	Test 4.	0.5	1	0.004	3	0.0033	2	6
GA-ANN	Train 1.	0.968	3	0.11	4	0.88	1	8
	Train 2.	0.95	4	0.15	3	0.54	4	11
	Train 3.	0.95	4	0.18	2	0.73	3	9
	Train 4.	0.889	2	0.31	2	0.74	2	6
	Test 1.	0.652	2	0.31	4	0.55	2	8
	Test 2.	0.991	4	0.61	1	0.53	3	8
	Test 3.	0.601	1	0.43	3	0.11	4	8
	Test 4.	0.881	3	0.56	2	0.6	1	6

Table 8
The final ranking of each model using two optimization techniques.

Optimization Techniques	Simulation No.	Total Score
MLP	1	21
	2	19
	3	10
	4	10
Hybrid GA-ANN	1	16
	2	19
	3	17
	4	12

Based on the results of Tables (7) and (8), the first model in MLP simulation and the second model in GA-ANN simulation obtained the highest score according to statistical functions. The first MLP simulation has the highest total rank with 21 among other MLP simulations. Also, the second GA-AAN simulation obtained the most score in other GA-ANN simulations with rank=19. In comparison between the best MLP and hybrid GA-ANN simulations, the high and reasonable R^2 values between the model predictions and the measured data for training = 0.95 and testing =0.991 using the hybrid GA-ANN method describes its high capability in the prediction of diamond wire saw performance.

6. Conclusion

In this research, the aim is to develop prediction models for assessment of diamond wire saw performance using two optimization approaches including MLP and hybrid GA-ANN algorithm. This work compared the application and performance of the hybrid GA-ANN algorithm with MnLR on the database of 38 different varieties of dimension stones from Turkey quarry mines. Four important physical and mechanical rock characteristics on the cutting process, namely wear rate from diamond wire cutting machine was set as output data, and uniaxial compressive strength, Schmiazek F-abrasivity, Shore hardness, and Young's modulus were considered as input data set. From the results found in this study, it can be concluded that the performance of the hybrid GA-ANN algorithm is superior to MLP in terms of some model performance indices such as RMSE, $R^{2,}$ and STD. The comparison was made between the three simulations based upon the performance indices, hybrid GA-ANN algorithm with a coefficient of determination (R^2) of training = 0.95 and testing = 0.991 was selected as the best predictive model. Also, it outperforms MLP based on robustness and solution quality for simulation some problems involved in rock mechanics engineering. From what has been discussed above, it can be concluded that hybrid GA-ANN algorithm is a reliable system simulation technique for predicting the performance of diamond bead with the highly acceptable level of accuracy and it can be applied as an appropriate alternative which has a wide application in management and planning for costs and designs of quarries. In future research, prediction of diamond wire saw performance can also be investigated and improved the using ICA-ANN, PSO-ANN, Hybrid Harmony Search (HS-BFGS) and Grey Wolf Optimizer (GWO) and other performance indicators such as the mean absolute percentage error (MAPE) and value account for (VAF).

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